Pergamon

Pattern Recognition, Vol. 31, No. 12, pp. 1873–1881, 1998

0031-3203/98 $19.00 + 0.00

PII: S0031-3203(98)00076-4

COMPARING FACE IMAGES USING THE MODIFIED HAUSDORFF DISTANCE

BARNABÁS TAKÁCS*

Virtual Celebrity Productions, 3679 Motor Ave. Suite 200, Los Angles, CA 90034, U.S.A

(*Received* 23 *April* 1997; *in revised form* 18 *May* 1998)

Abstract—We introduce a novel methodology applicable to face matching and fast screening of large facial databases. The proposed shape comparison method operates on edge maps and derives holistic similarity measures, yet, it does not require solving the point correspondence problem. While the use of edge images is important to introduce robustness to changes in illumination, the lack of point-to-point matching delivers speed and tolerance to local non-rigid distortions. In particular, we propose a face similarity measure derived as a variant of the Hausdorff distance by introducing the notion of a neighborhood function (N) and associated penalties (P). Experimental results on a large set of face images demonstrate that our approach produces excellent recognition results even when less than 3% of the original grey-scale face image information is stored in the face database (gallery). These results implicate that the process of face recognition may start at a much earlier stage of visual processing than it was earlier suggested. We argue, that edge-like retinal images of faces are initially screened "at a glance" without the involvement of high-level cognitive functions thus delivering high speed and reducing computational complexity. © 1998 Pattern Recognition Society. Published by Elsevier Science Ltd. All rights reserved.

Digital libraries   Face recognition   Modified Hausdorff distance

1. INTRODUCTION

Automated processing of face images has been receiving increasing attention during the last few decades.[1,2] Current approaches require computer systems to look through many stored sets of characteristics ("the gallery") and pick the ones that match best the features of an unknown individual ("the probe"). A central problem in this process is determining the extent to which two faces are similar or differ from one another. We have recently been investigating comparison functions that obey metric properties and operate on binarized face images. In particular, we propose a face similarity measure derived from the Hausdorff distance[3,4] and show that this approach produces good recognition results even when less than 3% of the original grey-scale face image information is stored in the gallery.

The underlying motivations for our approach originate from the observation that humans achieve at least a basic level of categorization of faces "at a glance" even when images of very low resolution are used. In fact, experimental evidence shows that resolution of 16×16 pixels is minimally required for detecting a pattern as a face, and that 4 bits of grey-scale information is enough for recognition when images of 32×32 pixels are used.[15] Furthermore, psychological studies have indicated that line drawings of objects are recognized as quickly and almost as accurately as photographs[6–8] suggesting a holistic theory of encoding in which distinctive aspects of a face are represented by comparison with a norm.[9] These evidences implicate that the process of face recognition may start at the level of early vision where edge-like retinal images of faces are screened at a very high speed, thus reducing the computational complexity needed to perform high-level cognitive functions.

In this paper, we introduce a novel methodology applicable to face matching and fast screening of large facial databases. The proposed shape comparison method operates on edge maps and derives holistic similarity measures, yet, it does not require the solution of the correspondence problem. While the use of edge images is important to introduce robustness to changes in illumination, the lack of point-to-point matching delivers speed and tolerance to local non-rigid distortions.

For the scope of this paper, we limit our attention to the characteristics of the matching process itself and assume that a face detection and segmentation algorithm has already been applied to the entire image. However, the recognition results presented correspond to a system operating in a fully automatic manner. The remainder of this paper is organized as follows: In Section 2 we briefly review the state-of-the-art in face recognition technology and assess the advantages and disadvantages of individual techniques. Section 3 discusses the Hausdorff distance as a metric, and introduces a new measure of object similarity, called the "doubly" modified Hausdorff

*Tel: (310) 253-5131/Ext. 212; Fax: (310) 253-5139; E-mail: TakacsB@virtualceleb.com, URL: http://chagall. gmu.edu/FORENSIC/barna.html.

distance (M2HD). We have built an automated face recognition (AFR) solution centered around the proposed M2HD measure. The brief description of this system, including face detection, normalization and template generation methods, can be found in Section 4. Experimental results and the conclusions of our research are presented in Sections 5 and 6, respectively.

2. FACE RECOGNITION

Face recognition is challenging because of the inherent variability of the image formation process in terms of image quality, geometry, occlusion, and disguise. Automatic processing for face recognition usually begins with the detection of a pattern as a face, and proceeds with normalization of the face image to account for geometry and illumination changes. This can be done using information regarding the bounding box of the face and/or the location of prominent facial features, such as the eyes. Finally, matching is performed by means of appropriate image representations and classification algorithms. In most practical scenarios there are two possible recognition tasks to be considered.

- *Match/Identification*: An image of an unknown individual is compared to a set of known images in order to find the best match or to establish the identity of the subject in the picture. The size of the gallery, as well as the number of probes is typically 100–1000, but in many applications it may involve thousands of images. Rather than a single identity, the output can also be a subset of possible matches consisting of the best candidates ranked according to their similarity. This feature becomes important when searching digital image libraries such as police mugshot files.
- *Surveillance/Verification*: The automated face recognition system is now involved with detection, rather than exact identification, by checking whether a given probe belongs to a relatively small gallery, such as a set of criminals. Should detection occur, the system alerts security personnel for further action. The surveillance system is flooded with possibly hundreds of faces per minute (e.g. airport security) and most of the faces, if not all of them, correspond to false positives. The limit case when the gallery includes just one subject corresponds to verification (e.g. bank ATMs, home security).

Strategies for face recognition vary significantly depending on the task (see above) and the characteristics of the image acquisition process (for recent detailed reviews the interested reader is referred to references (2) and (1). Recognition tasks are commonly approached from an *abstractive* or *holistic* perspective.

Abstractive methods extract and measure discrete local features and employ statistical pattern recognition for retrieval and identification. These techniques are based on the premise that a face can be recognized even when the details of its individual features are no longer resolved. The remaining information is, in essence, purely geometrical and represents spatial configurations of facial landmarks by defining their relative placement and distance relations. The description of the face using such measurements is the earliest technique applied to the face recognition problem.[10–15]. D*eformable templates* and the related elastic snake models[16–18] provide another alternative to abstractive recognition. A deformable template is a parametrized geometric model of the face or part of it to be recognized, together with a measure of how well it fits the image data. Variations in the parameters correspond to allowable deformations and the similarity of any two faces is measured by a cost function associated with template deformations implemented as graph matching (see also reference (19)). The corresponding cost (fitness) function employed typically consists of two terms, one measuring the resemblance between the landmarks corresponding to an unknown face and those describing the database, and the other term measuring how well the spatial structures linking the landmarks can align.

Holistic techniques attempt to identify faces via global representations. Characteristic of this approach are template matching,[20,21,14] neural networks, principal component analysis (PCA),[22] singular value decomposition (SVD),[23] and eigenspaces.[24,25] The common purpose of all these methods is data reduction achieved by means of exploiting the statistical regularities of the pattern space. In other words the goal is to derive an optimal basis set of feature vectors (e.g. equivalent of a "face-space") where unknown face patterns can be encoded with a small number of coefficients. The vector space is usually orthogonal, eigenspaces being one example, but non-orthogonal spaces have been contemplated as well.[26,27] The technique renders itself to connectionist implementations based on architectures such as multilayer networks using backpropagation (BP) learning, time-delay neural networks (TDNN), self-organizing feature maps (SOFM) and radial basis functions (RBFs).[28–30]

In the following sections, we introduce a computational model which uses a low-dimensional, reduced feature representation and employs local measurements tolerant to non-rigid deformations to perform matching (abstractive-like). Based on these local features it provides a global measure of face similarity (holistic), yet, without the explicit need to solve the point-to-point correspondence problem. We demonstrate that the proposed comparison measure allows for rapid and efficient processing over large image data sets making it ideal for a variety of real-world applications, including searching digital image libraries, police mugshot files, and surveillance video.

3. THE MODIFIED HAUSDROFF DISTANCE

The use of the Hausdorff distance for binary image comparison and computer vision was originally proposed by Huttenlocher and colleagues.[3] In their paper the authors argue that the method is more tolerant to perturbations in the locations of points than binary correlation techniques since it measures proximity rather than exact superposition. Unlike most shape comparison methods, the Hausdorff distance can be calculated without the explicit pairing of points in their respective data sets, A and B. Furthermore, there is a natural allowance to compare partial images and the method lends itself to simple and fast implementation. Formally, given two finite point sets $A = \{a_1, \ldots, a_p\}$, and $B = \{b_1, \ldots, b_q\}$, the Hausdorff distance is defined as

$$H(A,B) = \max\left(h(A,B), h(B,A)\right), \tag{1}$$

where

$$h(A,B) = \max_{a \in A} \min_{b \in B} \|a - b\| . \tag{2}$$

In the formulation above $\|.\|$ is some underlying norm over the point sets A and B. In the following discussion, we assume that the distance between any two data points is defined as the Euclidean distance. $H(A,B)$ can be trivially computed in time $O(pq)$ for point sets of size p and q, respectively, and this can be improved to $O((p+q)\log(p+q))$. The function $h(A,B)$ is called the *directed* Hausdorff distance from set A to B. It identifies the point $a \in A$ that is farthest from any point of B and measures the distance from a to its nearest neighbor in B. In other words, $h(A,B)$ in effect ranks each point of A based on its distance to the nearest point in B and then uses the largest ranked such point as the measure of distance (the most mismatched point of A). Intuitively, if $h(A,B) = d$, then each point of A must be within distance d of some point of B, and there also is some point of A that is exactly distance d from the nearest point of B. For practical implementations, it is also important (due to occlusion or noise conditions) to be able to compare portions of shapes rather than providing exact matches. To handle such situations, the Hausdorff distance can be naturally extended to find the best *partial distance* between sets A and B. To achieve this, while computing $h(A,B)$, one simply has to rank each point of A by its distance to the nearest point in B and take the Kth ranked value. This definition provides a nice property, that is it automatically selects the K "best matching" points of set A that minimizes the directed Hausdorff distance.[3]

Realizing that there could be many different ways to define the directed ($h(A,B)$, $h(B,A)$) and undirected ($H(A,B)$) distances between two point sets A and B, Dubuisson and Jain revised the metric and investigated 24 different distance measures based on their behavior in the presence of noise. In reference (4) they redefine the original definition of $h(A,B)$ proposing an improved measure, called the modified Hausdorff distance (MHD), which is less sensitive to noise. Specifically, in their formulation

$$h(A,B) = \frac{1}{N_a} \sum_{a \in A} \min_{b \in B} \|a - b\| , \tag{3}$$

where $N_a = p$, the number of points in set A. In their paper, the authors argue that even the K^{th} ranked Hausdorff distance of Huttenlocher present some problems for object matching under noisy conditions, and conclude that the modified distance proposed above has the most desirable behavior for real-world applications.

In this paper, we adopt the MHD formulation of Dubuisson *et al.* and further improve its performance by introducing the notion of a *neighborhood function* (N_B^a) and associated *penalties* (P). Specifically, we assume that for each point in set A, the corresponding point in B must fall within a range of a given diameter. This assumption is valid under the conditions that (i) the input and reference images are normalized by appropriate preprocessing algorithms, and (ii) the non-rigid transformation is small and localized. Let N_B^a be the neighborhood of point a in set B, and an indicator $I = 1$ if there exists a point $b \in N_B^a$, and $I = 0$ otherwise. The complete formulation of the "doubly" modified Hausdorff distance (M2HD) can now be written as

$$d(a,B) = \max\left(\mathrm{I} \min_{b \in N_B^a} \|a - b\|, (1 - \mathrm{I})P\right), \tag{4a}$$

$$h(A,B) = \frac{1}{N_a} \sum_{a \in A} d(a,B), \tag{4b}$$

$$H(A,B) = \max(h(A,B), h(B,A)). \tag{4c}$$

The notion of similarity encoded by this modifed Hausdorff distance is that each point of A be near some point of B and *vice versa*. It requires, however, that all matching pairs fall within a given neighborhood of each other in consistency with our initial assumption that local image transformations may take place. If no matching pair can be found, the present model introduces a penalty mechanism to ensure that images with large overlap are easily distinguished as well. *As a result, the proposed modified Hausdorff measure (M2HD) is ideal for applications, such as face recognition, where although overall shape similarity is maintained, the matching algorithm has to account for small, non-rigid local distortions.*

4. MATCHING FACE IMAGES USING M2HD

Centered around the modified Hausdorff (M2HD) distance introduced in the preceding section we have developed an Automated Face Recognition (AFR) system. The specific implementation of the model uses a three-stage processing strategy depicted in Fig. 1. *Preprocessing* consists of (i) face detection and (ii)

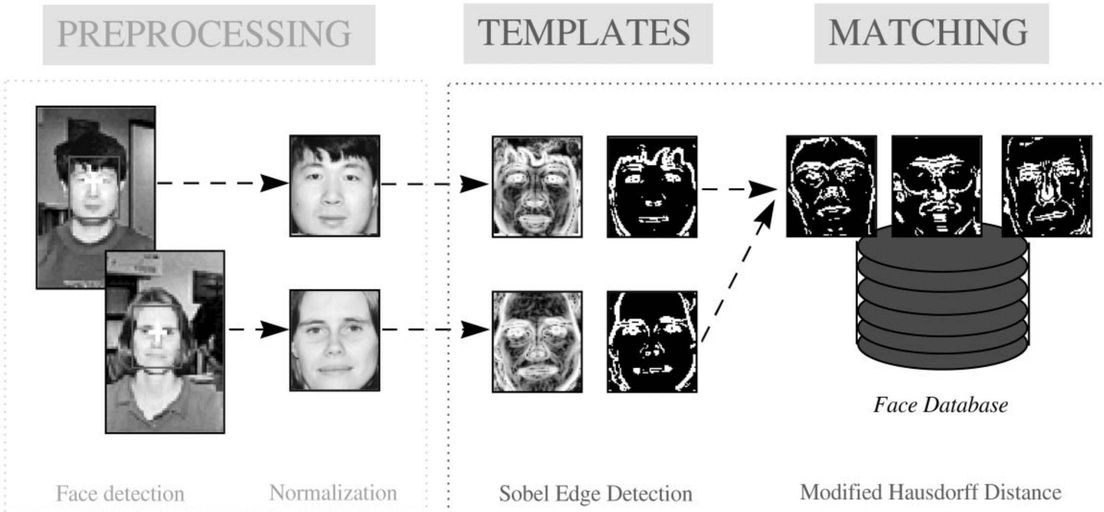

Fig. 1. Overall architecture of the automated face recognition (AFR) system.

normalization with respect to geometry. To implement this stage, one could use any of the variety of algorithms published in the literature. The specific algorithm employed here is based on a biologically motivated approach (called visual filters) and is summarized in the following section. At the second stage of processing the normalized grey-scale input is converted to binary template representation by means of edge detection (Sobel operator) followed by appropriate thresholding. Finally, the generated binary template is matched against a large database of faces and the results are ranked according to the measure of similarity.

4.1. *Automatic face detection and normalization*

The specific face detection scheme, used as a preprocessor in our experiments, implements *optimal visual filters* responsive to face/eyepair patterns.(27,31,32,36) By using a bank of multi-resolution face detectors the method was able to reliably locate anchor points of interest and to provide accurate size estimates for geometric normalization purposes. In particular, the face filters were implemented via self-organizing feature maps (SOFM) and constructed using biological principles (retinal sampling and feature extraction) borrowed from the human visual system (HVS). Initially, a training set consisting of 100 retinal face templates were extracted from frontal images in the *FERET* database (33) and used to train the SOFMs. During face detection, the input was scanned pixel by pixel using a retinal sampling grid while the similarity of the current template to those encoded in the memory was registered. For the particular application in hand, we could assume that there was only one face present in the image at a time, so after a complete scan, the location giving the maximum similarity could be used as the primary candidate for the face itself. The output of this process for six subjects is shown in Fig. 2. The original face images are shown above including a mark indicating the location of the strongest response of the face filters. The normalized images are rendered below. For each subject a pair of images are displayed exhibiting a wide range of imaging conditions. The algorithm produced good normalization and alignment of facial landmarks using only a single anchor point on each face. The normalized face images are now ready to be passed on to the classification stage, discussed next.

4.2. *Binary template generation and classification*

The proposed classification method employs binary edge images to encode faces in the database. This offers a great reduction in storage requirements and significant increase during distance calculations. Specifically (see Fig. 3), the normalized grey-scale input image (*a*) is first convolved with 3×3 Sobel operator (*b*), and subsequently thresholded using an adaptive technique to obtain a binary edge image (*c*). The Sobel kernel,(34) represented in matrix form by horizontal and vertical operators as shown below, was used to compute the components of local image gradient.

$$\left(\left\|\begin{pmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{pmatrix}\right\| + \left\|\begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix}\right\|\right)/2 \qquad (5)$$

The threshold (Th) to obtain the binary outputs was selected adaptively for each image such that the pixel ratio (R) of ON vs OFF bits in the image corresponded to a preset percentage. Finally, the binary templates were further scaled to $K \times L$ pixels and subjected to comparison with templates in the database.

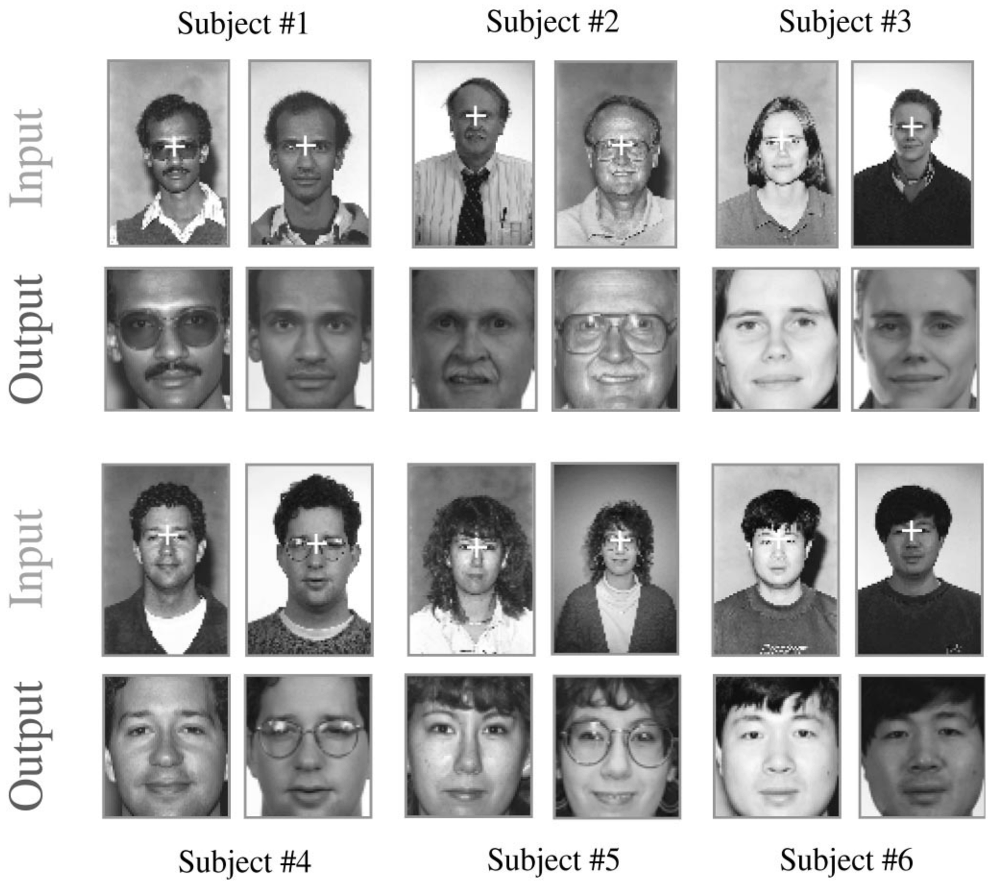

Fig. 2. Face detection and normalization using visual filters (see text).

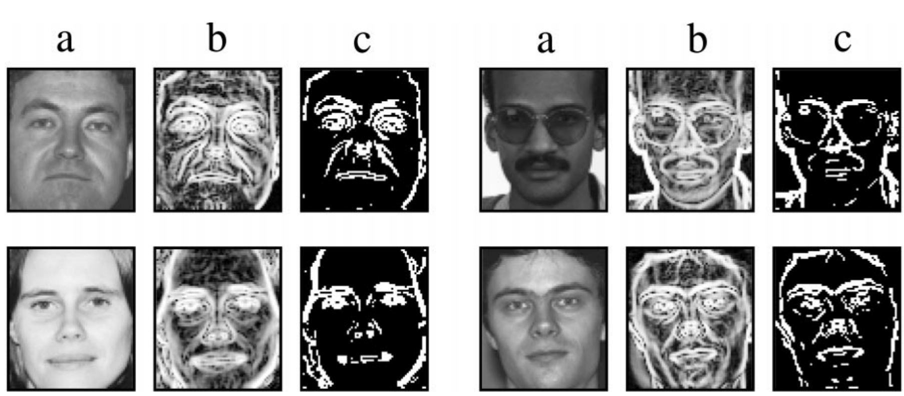

Fig. 3. Binary template generation results for four subjects. (a) original grey-scale image (b) output of Sobel operator (c) thresholded binary image (R = 20%).

5. EXPERIMENTAL RESULTS

To demonstrate the applicability of the proposed M2HD-based face recognition and matching algorithm, we applied our method to a large set of facial mugshot photographs. A total number of *150 subjects* corresponding to *320 images* were selected from the US Government *FERET* database (currently storing around 8500 images corresponding to different poses of over 1100 subjects and exhibiting a wide range of viewing conditions and individual characteristics), which is collected and maintained at George Mason University to provide a standard testbed for face recognition applications.[33,35]

In the experiments face location was carried out by the automatic detection algorithm described in Section 4.1 using full-resolution (256×384) 8-bit grey-scale images. The subsequent normalization and edge detection stages produced 64×72 binary output, further scaled to size $KxL = 32 \times 36$ templates to be stored in the database.

To evaluate overall recognition performance and analyze parameter sensitivity, we have conducted a set of experiments during which we varied R, N, and P corresponding to the pixel ratio, neighborhood size, and penalty values, respectively. Each test cycle consisted of matching all 320 images in the database against the remaining 319 templates using the modified Hausdorff distance (M2HD) metric. The results were then ranked and arranged in ascending order of their measured similarity with respect to the current input. After extensive testing we found that optimal recognition performance was achieved when using parameters $R = 20\%$, $N = 2$, and $P = 2$, respectively. Specifically, the system reached *92%* accuracy in correctly identifying the input (recognition mode), and the matching face was included among the best 5, 10, and 30 ranked candidates in 96.9%, 98.1%, and 99.7% of the cases, respectively (Fig. 4).

Note, that this high performance was achieved using extremely low data rates. Specifically, the normalized grey-scale images require $64 \times 72 = 4608$ bytes. The binary templates, however, use only $KxL/8 = 144$ bytes worth of information, *meaning that fast screening and over* 99.7% *recognition accuracy could be achieved while using less than* 3% *information of the original data*! The high performance achieved when using the best 30 candidates indicates that the proposed algorithm successfully screened out/eliminated 90% of all faces in the data base "at a glance" prior to the use more accurate and computationally expensive matching strategies.

To test the sensitivity of the M2HD algorithm we plotted the behavior (error rates) as a function of varying parameters (Figs 5–7). The curves *ERRx* (where $x = 1,5,10,30$) correspond to different receiver operator characteristics (ROC). As an example, *ERR1* indicates the error rate for the recognition task, and *ERR5* means the percentage of those erroneous cases where the correct match was not included within the $x = 5$ best ranking candidates.

In the first experiment (Fig. 5) we varied the neighborhood size (N) while keeping the penalty value ($P = 2$) and pixel ratio ($R = 20\%$) fixed. As it is seen the algorithm shows stability over a wide range of possible values. The *ERR1* performance quickly drops to 8%, while the *ERR30* performance remains under 1% for all values. Figure 6 shows the ROC curves corresponding to different pixel ratios (R). It is clear that there is an increasing number of mismatched cases both (i) when there is not enough information remaining to discriminate one face from another ($R < 15\%$), and (ii) when the high overlap of template images causes confusion. Finally, Fig. 7 plots the operational characteristics as a function of varying penalty (P). Error rates without using penalties ($R = 0$) are relatively high. However, they drop very quickly when small values comparable to the neighborhood's area are taken on.

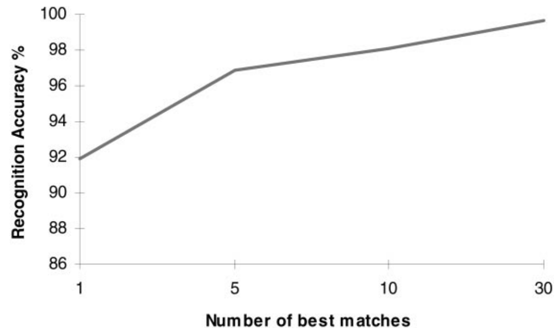

Fig. 4. Recognition accuracy as a function of the number of highest ranking candidates. [N = 2,P = 2, R = 0.2].

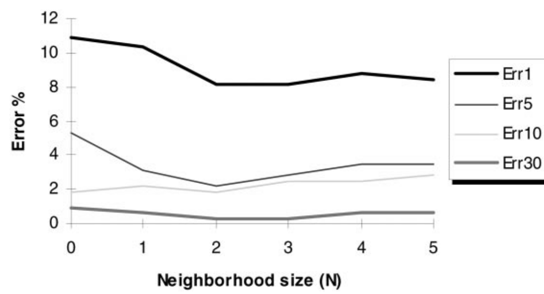

Fig. 5. Error percentages as a function of neighborhood size (N) [P = 2, R = 0.2].

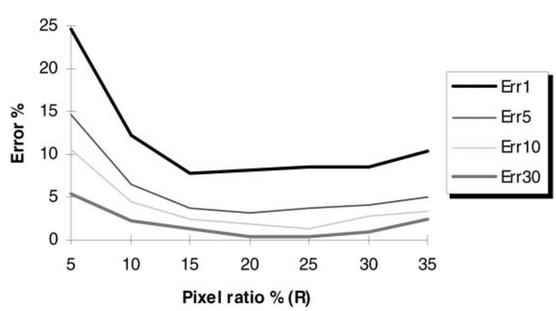

Fig. 6. Error percentages as a function of pixel ratio (R) [P = 2, N = 2].

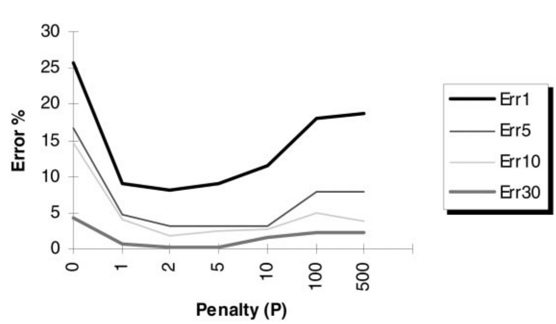

Fig. 7. Error percentages as a function of penalty (P) [N = 2, R = 0.2].

To conclude this section we would like to demonstrate to what extent the proposed M2HD measure

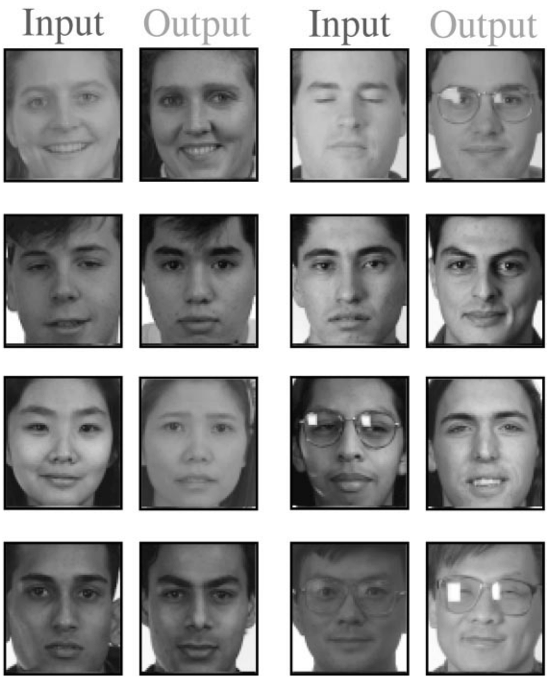

Fig. 8. Incorrect recognition results. Can *YOU* tell the difference?

produces "incorrect" recognition results. Figure 8 shows eight incorrectly identified subjects of the total 26 mistakes the algorithm produced when using the best parameter set ($P = 2$, $N = 2$, $R = 20\%$). The input to the recognizer module is shown on the left, the corresponding outputs are on the right. The original and matched faces show a great amount of similarity to the human observer. In fact, some of them are rather hard to tell apart. Can *YOU* tell the difference?

6. CONCLUSIONS AND FUTURE RESEARCH

We have introduced, in this paper, a novel measure of shape similarity and demonstrated its applicability to successfully address face recognition tasks including face matching and fast screening of large facial databases. The proposed approach operates on edge maps and derives holistic similarity measures using a modified Hausdorff distance, called M2HD. Specifically, we introduced the notion of local neighborhood and associated penalties yielding to a matching algorithm that allows for large tolerance to local, non-rigid distortions without the explicit need to address the point-to-point correspondence problem. The method produces accurate results and lends itself to fast implementation.

To evaluate the performance of the proposed algorithm we experimented with a large set of face images (150 subjects/ 320 images) selected from the FERET database. A fully automated face detection and normalization system was used as a preprocessor to generate grey-scale reference templates both for training and testing. These normalized images were then transformed into low-resolution binary templates while keeping less than 3% of the original information. A set of parametric experiments was subsequently carried out to establish the operational characteristics of the proposed method. The method reached 92% accuracy in correctly identifying the input (recognition mode), and the matching face was included among the best 5, 10, and 30 ranked candidates in 96.9%, 98.1%, and 99.7% of the cases, respectively (surveillance mode).

These results implicate that the process of face recognition may start at a much earlier stage of visual processing than it was earlier suggested. We argue, that edge-like retinal images of faces are initially screened "at a glance" without the involvement of high level cognitive functions thus delivering high speed and reducing computational complexity.

In its current form the proposed method is sensitive to large variations in pose and does not offer rejection mechanisms. We are currently improving the algorithm to overcome these difficulties by means of view-based face libraries and hybrid recognition strategies that employ multiple samples and edge-noise models. Future experiments will focus on parametric assessment of the behavior of our method as a function of increasing database size.

7. SUMMARY

Current approaches to automated face processing require computer systems to look through many stored sets of characteristics ("the gallery") and pick the ones that match best the features of an unknown individual ("the probe"). A central problem in this process is determining the extent to which two faces are similar or differ from one another. We have recently been investigating comparison functions that obey metric properties and operate on binarized face images.

This paper introduces a novel methodology applicable to face matching and fast screening of large facial databases. The proposed face similarity measure is derived from the Hausdorff distance by introducing the notion of a local neighborhood function (N) and associated penalties (P). The specific implementation operates on edge maps and computes holistic similarity, yet, it does not require resolving the data point correspondence of input vs reference templates. While the use of edge images is important to introduce robustness to changes in illumination, the lack of point-to-point matching delivers speed and tolerance to local non-rigid distortions.

The underlying motivations for our approach originate from the observation that humans achieve at least a basic level of categorization of faces "at a glance" even when images of very low resolution are used. Psychological studies have also indicated that

line drawings of objects are recognized as quickly and almost as accurately as photographs suggesting a holistic theory of encoding in which distinctive aspects of a face are represented by comparison with a norm.

Experimental results on a large set of face images (150 subjects/320 images) demonstrate that our approach produces excellent recognition results even when less than 3% of the original grey-scale face image information is stored in the face database. Specifically, the method reached 92% accuracy in correctly identifying the input (recognition mode), and the matching face was included among the best 5, 10, and 30 ranked candidates in 96.9%, 98.1%, and 99.7% of the cases, respectively (surveillance mode). These results implicate that the process of face recognition may start at a much earlier stage of visual processing than it was earlier suggested. We argue, that edge-like retinal images of faces are initially screened "at a glance" without the involvement of high-level cognitive functions thus delivering high speed and reducing computational complexity.

REFERENCES

1. A. Samal and P. A. Iyengar, Automatic reecognition and analysis of human faces and facial expressions: a survey, *Pattern Recognition* **25**(1) 67–77 (1992).
2. R. Chellappa, C. L. Wilson and S. Sirohey, Human and machine recognition of faces: A survey, *Proc. IEEE* **83**(5), (1995).
3. D. P. Huttenlocher, G. A. Klanderman and W. J. Rucklidge Comparing Images Using the Hausdorff Distance, *IEEE Trans. Pattern Anal. Machine Intelligence* **15**(9), 850–863 (1993)
4. M. Dubuisson and A. K. Jain, A modified Hausdorff distance for object Matching, *Proc.* 12*th Int. Conf. on Pattern Recognition* (*ICPR*), Jerusalem, Israel, (1994).
5. A. Samal, Minimum resolution for human face detection and Identification, *Proc. SPIE/SPSE Symp. Electronic Imaging*, (1991).
6. I. Biederman, Recognition-by-components: A theory of human image understanding, *Psychol. Rev.* **94,** 115–145 (1987).
7. I. Biederman and J. Gu, Surface versus edge-based determinants of visual recognition, *Cognitive Psychology* **20,** 38–64 (1988).
8. V. Bruce, *et al.*, The importance of 'mass' in line drawings of faces, *Appl. Cognitive Psychol.* **6,** 619–628 (1992).
9. G. Rhodes, S. Brennan and S. Carey, Identification and ratings of caricatures: implications for mental representations of faces, *Cognitive Psychology* **19,** 473–497 (1987).
10. A. J. Goldstein and L.D. Harmon, Identification of human faces, *Proc. IEEE* **59**(5), 748–760 (1971).
11. Y. Kaya and K. Kobayashi, A basic study on human face recognition, in *ht. Conference on Frontiers of Pattern Recognition*, S. Watanabe Ed., (1972).
12. T. Kanade, Computer Recognition of human faces, in *Interdisciplinary Systems Research.* Birkhauser Basel, Switzerland (1977).
13. I. Craw, H. Ellis and J. R. Lishman, Automatic extraction of face-features, *Pattern Recognition Lett.* **5,** 183–187 (1987).
14. R. Brunelli and T. Poggio, Face recognition: features versus templates, *IEEE Trans. Pattern Anal. and Machine Intelligence* **15**(10), 1042–1052 (1993).
15. I. J. Cox, J. Ghosn and P. N. Yianilos, Feature-based face recognition using mixture distance, NEC Research Institute TR95–09 (1995).
16. A. L. Yuille, Deformable templates for face recognition, *J. Cognitive Neurosc.* **3**(1), 59–70 (1991).
17. M. Köküer, Automatic facial feature recognition and location, *University of Helsinki*, *Technical Report* (1992).
18. E. D. Petajan, Automatic Interpretation of human faces and hand gestures using flexible models, *Proc. Int. Workshop on Automatic Face- and Gesture-Recognition* (*IWAFGR*), Zürich, Switzerland (1995).
19. J. Buhmann, *et al.* Object recognition with Gabor functions in the dynamic link architecture, in *Neural Networks for Signal Processing*, B. Kosko. ed., Prentice-Hall. Englewood Cliffs, NJ (1992).
20. R. J. Baron, Mechanisms of human facial recognition, *Int. J. Man-Machine Studies* **15,** 137–178 (1981).
21. D. J. Beymer, Face recognition under varying pose, MIT A.I Memo No. 1461 (1993).
22. G. W. Cottrell and M. Fleming, Face Recognition Using Unsupervised Feature Extraction, *Proc. Int. Neural Network Conference*, **1,** pp. 322–325 (1990).
23. Z. Hong, Algebraic feature extraction of image for recognition, *Pattern Recognition* **24**(3), 211–219 (1991).
24. M. Turk and A. Pentland, Eigenfaces for recognition, *J. Cognitive Neurosci.* **3,** 71–86 (1991).
25. A. P. Pentland, B. Moghaddam and T. Starner, View-based and Modular Eigenspaces for Recognition, *Proc. Computer Vision and Pattern Recognition*, Seattle, USA (1994).
26. J. Daugman, An information-theoretic view of analog representations in the Striate cortex, in *Computational Neuroscience*, E.L Schwartz, ed., MIT Press, Cambridge, MA (1990).
27. B. Takács and H. Wechsler, Visual Filters for face recognition, *Proc. 2nd Int. Conf. on Automatic Face- and Gesture Recognition*, Killington, VT, USA. (1996).
28. D. Valentin, H. Abdi, A. J. O'Toole and G. W. Cottrell, Connectionist models of face processing. A survey, *Pattern Recognition* **27**(9), 1209–1230 1994.
29. F. F. Soulie and E. Viennet, Multi-modular neural network architectures for pattern recognition: applications in optical character recognition and human face recognition, TR Laboratorie de Recherches en Informatique, Paris XI, Orsay (1993).
30. J. Lampinen and E. Oja, Clustering properties of hierarchical self-organizing maps, *J. Mathem. Imaging Vision*, **2,** 261–272 (1992).
31. B. Takács and H. Wechsler, Locating facial features using SOFM, *Proc. 12th Int. Conf. on Pattern Recognition* (*ICPR*), Jerusalem, Israel (1994).
32. B. Takács and H. Wechsler, Detection of faces and facial landmarks using retinal filter banks, *Pattern Recognition*, **30**(10), 1623–1636.
33. S. Gutta *et al.*, Benchmark studies on face recognition, *Proc. Int. Workshop on Automatic Face- and Gesture-Recognition* (*IWAFGR*), Zürich, Switzerland (1995).
34. V. S. Nalwa, *A Guided Tour of Computer Vision* Addison-Wesley, Reading, MA (1993).
35. A. T. DePersia and P. J. Phillips, The FERET Program: overview and accomplishments, *Proc. Int. Workshop on Automatic Face- and Gesture-Recognition* (*IWAFGR*), Zürich, Switzerland (1995)
36. B. Talors and H. Wechsler, A dynamic and multiresolution model of visual attention and its application to facial land mark detection. *Computer Vision and Image Understanding*, **10**(1), 63–73.

About the Author—BARNABÁS TAKÁCS born in 1966 in Budapest, Hungary. He received his B.Sc. in Informatics and Electrical Engineering from the Technical University of Budapest, in 1991, an M.Sc. in Computer Science from the University of Houston, Texas, in 1992 and his Ph.D. in 1996 from the Institute for Computational Sciences and Informatics (CSI) at George Mason University in Fairfax, Virgina, USA.

Dr. Takács is currently with Virtual Celebrity Productions, a Los Angeles-based production company dedicated to create and animate photo-realistic humans called Digital Clones™. At VCP he acts as Director of Vision/Image Analysis and is responsible for system design and project management including high accuracy facial- and body motion tracking and automatic creation of digital clones.

He was previously affiliated with WaveBand Corporation (Torrance, California) where he worked as a research scientist and project manager. His responsibilities included system design, algorithm development and project management of novel visual technologies applied to 3D invariant object recognition. Specific areas include (i) automatic target recognition (ii) millimeter-wave radar landing systems, (iii) automotive collision avoidance radars and (iv) concealed weapon detection.

Dr. Takács is the recipient of the "Foundation for Hungarian Technical Progress" award in 1990, and several scholarships (including support from the European Community for 1991-92, and ENST, Paris, France, for 1992). He is the author of over 25 technical papers.

For more information please click on *http://chagall.gmu.edu/FORENSIC/barna.html* or send email to TakacsB@virtualceleb.com.