

# HUMAN FACE RECOGNITION USING A SPATIALLY WEIGHTED HAUSDORFF DISTANCE

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## ABSTRACT

The edge map of a facial image contains abundant information about its shape and structure, which is useful for face recognition. To compare edge images, Hausdorff distance is an efficient measure that can determine the degree of their resemblance, and does not require a knowledge of correspondence among those points in the two edge maps. In this paper, a new modified Hausdorff distance measure is proposed, which has a better noise immunity capability and better discriminant power. As the different facial regions have different relative importance for face recognition, the modified Hausdorff distance is weighted according to a weighted function derived from the spatial information of the human face; hence crucial regions are emphasized for face identification. Experimental results show that the distance measure can achieve recognition rates of 82%, 93%, and 97% for the first, the first three, and the first five likely matched faces, respectively.

## 1. INTRODUCTION

Face recognition has a wide application in the fields of commerce and law enforcement, particularly in criminal identification, credit card verification, security systems, scene surveillance, and area access control [1], [2], [3]. It is a non-contact personal identification technique that has advantages over contact identifications such as fingerprints and iris texture. Under some circumstances, such as crowd surveillance, face recognition is the only feasible method of automatic identification. It does not require every person entering a restricted area to leave his or her fingerprints or to gaze at a camera closely.

Some classic technologies for face recognition such as the geometrical measurement method [1], Karhunen-Loeve transform based method [4], elastic graph matching [5], [6] and, more recently, neural networks [7], [8] have been used, and other efficient methods have also been proposed [9], [10], [11].

Experimental results from physiology and psychophysics have shown that the edges of an object contain important information about its shape and structure [12] and can be used in face recognition. Humans have the ability to categorize faces "at a glance", and can recognize the line drawings of objects as quickly and almost as accurately as photographs [13]. It is suggested that the edge-like retinal images of faces are useful and efficient in face identification at the level of early vision. Moreover, in [9], the template matching method using edge-like maps has been shown to have a better performance than the feature-based techniques. As an image feature, edges have the advantages of simplicity of presentation and robustness to

illumination change. Takács [13] introduced a method of comparing face images using a modified Hausdorff distance, which is a similarity measure derived as a variant of the Hausdorff distance.

In this paper, a face recognition method is proposed that utilizes a modified type of Hausdorff distance by incorporating the spatial information of a human face. In order to evaluate this new method, 240 face images extracted from a public face database, the ORL database, are tested. The experimental results show that the modified Hausdorff distance measure proposed in this paper has a better discriminant power and can achieve a higher recognition rate than other existing Hausdorff distance measures.

This paper is organized as follows. Section 2 introduces the basic concept of Hausdorff distance, its advantages, and limitations. A new modified Hausdorff distance is defined in Section 3. Section 4 presents the experimental results concerning recognition rates and the discriminant power of this modified Hausdorff distance method. Finally, conclusions are given in Section 5.

## 2. HAUSDORFF DISTANCE

Hausdorff distance is a *max-min* distance that measures the extent to which two images are similar or different to one another based on their edge maps. Therefore, Hausdorff distance can be used as a measure to determine the degree of resemblance between two objects [14]. Given two finite point sets  $A = \{a_1, \dots, a_n\}$  and  $B = \{b_1, \dots, b_q\}$  Hausdorff distance is defined as follows:

$$H(A, B) = \max \{ h(A, B), h(B, A) \} \quad (1)$$

$$\text{where } h(A, B) = \max_{a \in A} \min_{b \in B} \|a - b\| \quad (2)$$

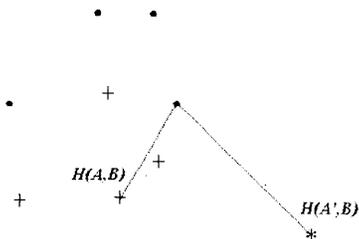
$\|\cdot\|$  is an underlying norm on the points of  $A$  and  $B$ . The function  $h(A, B)$  is called directed Hausdorff distance from  $A$  to  $B$ . It identifies the point  $a \in A$  that is farthest from any points of  $B$  and measures the distance from the point  $a$  to its nearest neighbor in  $B$ . Thus, Hausdorff distance measures the mismatch between the two point sets and can be used as a measure for shape comparison.

Huttenlocher *et al.* [14] introduced Hausdorff distance to the application of image comparison. Shape comparison methods based on Hausdorff distance do not require any explicit correspondence between the model and the image data set. In fact, it does not build one-to-one pairing between the model and the image feature points. Comparing two objects using Hausdorff distance has the advantages of simplicity in algorithm and efficiency in computation. Due to the fact that edges are the

only feature used, this distance measure is also robust to illumination change. Moreover, Hausdorff distance is a match methodology without the requirement of point-to-point correspondence, so the measure is insensitive to local non-rigid distortions. Different modified Hausdorff distance measures have been proposed such that they can provide a more reliable and robust distance measure than the original one. For face recognition, Takács [14] further improved the modified Hausdorff distance by introducing the notion of neighborhood function ( $N_b^a$ ) and associated penalty ( $P$ ), which is called "doubly" modified Hausdorff distance ( $M2HD$ ).

The use of Hausdorff distance in face recognition has its own problems. As Hausdorff distance is a *max-min* distance, it is sensitive to the noise in an image. The presence of a few outliers can cause a serious error in the computation of Hausdorff distance in spite of the fact the two objects may be very similar. For example, in Fig. 1, the correct Hausdorff distance between the point set  $A$  and the point set  $B$  should be  $H(A, B)$ . However, due to the presence of an outlier point (\*), this Hausdorff distance will become  $H(A', B)$ , which is much larger than  $H(A, B)$ . It is well known that edge detection is an ill-posed problem by itself, and the definition of edge is usually ambiguous [12]. Consequently, it is very difficult to differentiate between an edge point and a noise point, and it is a challenging task to detect all the edges of an object while at the same time excluding all the wrong edges or outliers. These outliers or noise points may have a significant effect on shape comparison if Hausdorff distance measure is used directly.

In this paper, a modified Hausdorff distance measure incorporated with facial structure is introduced such that a more robust and better discriminant measure for face recognition can be achieved.



+ : Point set  $A$ ; • : Point set  $B$ ; \* : An outlier of point set  $A$ .

**Figure 1.** The influence of an outlier point to the computed Hausdorff distance.  $H(A, B)$  and  $H(A', B)$  are the Hausdorff distances between point set  $A$  and set  $B$  (excluding outlier point), and between point set  $A'$  and set  $B$  (including outlier point), respectively.

### 3. THE SPATIALLY WEIGHTED HAUSDORFF DISTANCE

In human face recognition, the different facial regions have different amounts of importance. For example, the eyes and mouth regions on a face are crucial features for identification and are more important than other parts of the face [1], [9]. However, the traditional Hausdorff distance does not consider the relative importance between different facial regions, and makes no distinction between all parts of a face region. We therefore propose a new Hausdorff distance measure in this

paper that is specific to face recognition and emphasizes the importance of the crucial facial features, including the eyes and mouth regions.

The modified Hausdorff distance measure proposed in this paper is based on the assumption that the various facial regions have different amounts of importance, whereby the eyes and mouth play the most important role in face recognition. A weighted function defined according to the spatial position of the respective regions of the facial features is used in this new formulation; hence this modified Hausdorff distance measure is called Spatially Weighted Hausdorff Distance ( $SWHD$ ). The following is the definition of the new Hausdorff distance:

Given two finite point sets  $A = \{a_1, \dots, a_p\}$  and  $B = \{b_1, \dots, b_q\}$ , the spatially weighted Hausdorff distance is defined as follows:

$$H(A, B) = \max(h_{sw}(A, B), h_{sw}(B, A)) \quad (3)$$

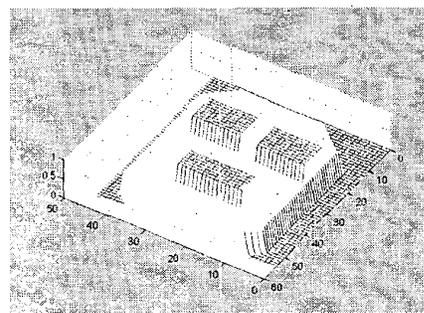
$$h_{sw}(A, B) = \frac{1}{N_a} \cdot \sum_{N_a} w(b) \min_{b \in B} \|a - b\| \quad (4)$$

$N_a$  is the number of points in set  $A$ ;  $w(x)$  is a weighted function, whose definition is:

$$w(x) = \begin{cases} 1 & x \in R_i \\ w_v & x \in R_u \\ 0 & x \in R_b \end{cases} \quad (5)$$

where  $R_i$  represents the important facial regions, such as the eyes and mouth, which should be emphasized;  $R_u$  is the unimportant facial regions, such as the facial regions other than the important facial regions; and  $R_b$  is the background region that contains no facial parts. With this weighted function, an edge point that occurs in the background will be ignored. Those points in the unimportant facial regions,  $R_u$ , will be suppressed by a weighted value,  $w_v$ , which is less than one. Those points in the important facial regions,  $R_i$ , are fully counted.

Fig. 2 illustrates a 3D representation of the spatially weighted function. In our method, the position of the two eyes is identified first by using the integral projections technique. Integral projection is a simple and useful technique for the extraction of facial features, and has been used successfully [9]. After detecting the two eyes, a rectangular face window, the two eye windows and the mouth window can be set by means of anthropometric measure [11]. In order to avoid interference from the background and noise, the four corners of the face picture are considered as the non-facial regions and are discarded. In normal situations, these regions do not contain any useful facial edge.



**Figure 2.** The 3D graph of a spatially weighted function  $w(x)$ .

In this weighted function, the weight of the eyes and mouth regions (important region  $R_i$ ) has a value of 1; the weight of the background region,  $R_b$ , is 0; and the weight of the remaining face region,  $R_w$ , is 0.5. Due to the weighted function, only those edge points in a face region are considered when computing the Hausdorff distance. Those important regions for recognition have a higher weight (i.e., 1); therefore, this modified Hausdorff distance is more effective in capturing the salient features of human faces. Because the weight of the background is 0, the noise points and non-facial points in these areas will be ignored, resulting in a better noise immunity capability.

#### 4. EXPERIMENTAL RESULTS

The input to our face recognition system is a facial image. Firstly, the face region is normalized according to the inter-distance of the eyes, and the weighted function for the input face can then be generated. Based on the position of the two eyes, we can also estimate the face region, which is in the form of a rectangle, as shown in Fig. 2. The corresponding edge map of the face region is then produced and two human faces, one from the input and the other from the face gallery, are compared using the spatially weighted Hausdorff distance. The block diagram of our face recognition system is depicted in Fig. 3.

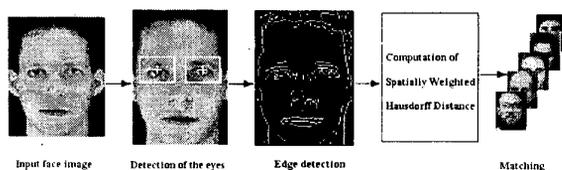


Figure 3. Block diagram of the SWHD face recognition system.

##### 4.1 Recognition rates

We used the ORL face database (from the Oliver Research Laboratory in Cambridge, U.K.) in the experiment. There are 400 different face images corresponding to 40 distinct subjects in the database. The face images of each subject were captured at different times, under slightly different lighting conditions, with different facial expressions (open/closed eyes, smiling or non-smiling), different facial details (glasses or no-glasses) and different orientations. In our experiment, an upright frontal view of each of the 40 subjects with suitable scale and normal facial expression was chosen as our database (the gallery). Among the rest of the faces, 6 images for each of the 40 subjects were selected to form a pool of 240 faces as a testing set (probe set).

In the experiment, the recognition rates based on the Hausdorff distance ( $HD$ ), the 'doubly' modified Hausdorff distance ( $M2HD$ ), and the spatially weighed Hausdorff distance ( $SWHD$ ) are evaluated and compared. Figure 4 illustrates the cumulative recognition rates of these three methods. The  $SWHD$  scheme proposed in this paper achieves the best recognition performance, and has a significant improvement over the other two methods, especially for the recognition rate  $P(1)$ . The recognition rates,  $P(1)$ , for  $HD$ ,  $M2HD$ , and  $SWHD$  are 47%, 73% and 82%, respectively.

As mentioned above, Hausdorff distance ( $HD$ ) is a  $max-min$  distance and a few outliers may cause a serious error even if the two point sets are similar. Noise, non-homogeneous background,

and imperfect edge detection algorithm all can produce some outliers and error edges, which will adversely affect the recognition performance if Hausdorff distance measure is used directly.

The  $M2HD$  scheme can further improve the modified Hausdorff distance. This method is based on an assumption that for each point in set  $A$ ; the corresponding point in  $B$  must fall within a range of a given diameter. However, in our experiment, the testing face images within the database have different facial expressions and head orientations. It is obvious that different perspective variations and changes of facial details (i.e., glasses or no-glasses) will produce significant non-rigid transformation. Consequently, although a good result was obtained in some face databases, the recognition rate of this  $M2HD$  scheme is not optimized for the face database used in our experiment.

The  $SWHD$  scheme proposed in this paper utilizes the *a priori* knowledge of a human face in the face recognition process. In measuring the distance between two point sets, we emphasize the important regions on a human face such as the eyes and mouth. Thus, the effect of noise and error edges occurring in unimportant regions and the background will be weakened and depressed.

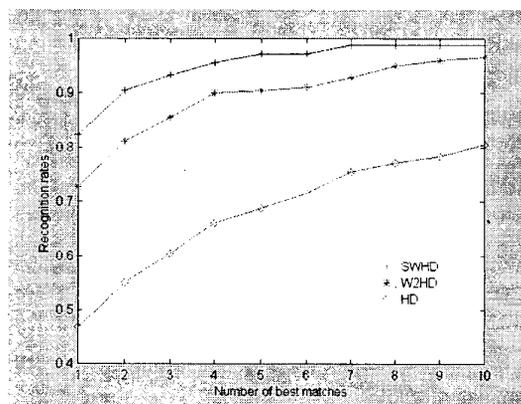


Figure 4. Comparison of the overall recognition rates using 240 testing face images.

##### 4.2 Analysis of the discriminant power

In face recognition, due to variations in illumination, viewing angles, facial expressions, and other factors, an input face image might be somewhat different from the corresponding face in the database. Consequently, the distance between the input face image and its corresponding reference image in the gallery will not be equal to zero although they are two instances of the same subject. Thus, the measured distance can be considered as a random variable, which is affected by the random factors, as mentioned above. The discriminant power of this distance measure can therefore be evaluated by observing the mean and standard deviation of the random variable.

For each input image,  $f_i$ ,  $1 \leq k \leq n$ ,  $m$  distance values can be obtained by measuring the distance between  $f_i$  and  $f_j$ , where  $1 \leq p \leq m$ . All these values are samples of the random distance measure. Using these samples, the probability distribution and some numerical values of the distance measure can be estimated. Given that the random variable  $x$  represents the computed

distance when the recognition result is correct and the random variable  $y$  is the distance when the recognition result is wrong. The approximate probability distribution of the random variables  $x$  and  $y$  can be estimated, as shown in Fig. 5.

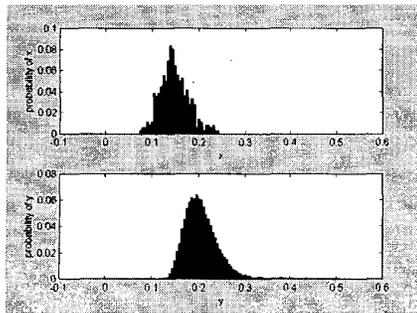


Figure 5. The probability distributions of the random variables  $x$  and  $y$  using the *SWHD* measure.

Given that  $\mu_0$  and  $\mu_1$  are the means,  $\sigma_0$  and  $\sigma_1$  are the standard deviations of the two random variables  $x$  and  $y$ , respectively. The discriminant power of a distance measure is given as follows:

$$D = |\mu_0 - \mu_1| / (\sigma_0^2 + \sigma_1^2) \quad (6)$$

The value of  $|\mu_0 - \mu_1|$  represents the distance or difference between the two classes. The smaller the magnitude of  $|\mu_0 - \mu_1|$ , the more similar these two classes are, and the worse this distance measure would be for distinguishing the two classes. Similarly, the smaller the standard deviations  $\sigma_0$  and  $\sigma_1$ , the less overlapping exists between these two classes at the same  $|\mu_0 - \mu_1|$ . The value of  $D$  is therefore a measure of the separation of two classes, and can be used to indicate the discriminant power of a distance measure to a certain extent. A small value of  $D$  means that the two classes are close and overlap more.

Table 1 tabulates the means and standard derivations of the variables  $x$  and  $y$  and the corresponding values of  $D$ . The *SWHD* measure results in the smallest standard derivations (0.0303 and 0.0368), and the largest  $D$  (1.2301), which implies that this distance measure has the best discriminant power of the three. The discriminant power  $D$  computed for the three methods is consistent with their corresponding recognition rates (Fig. 4).

Table 1 Statistical characteristics of variables  $x$  and  $y$  for methods *SWHD*, *HD* and *M2HD*.

	$\mu_0$	$\mu_1$	$\sigma_0$	$\sigma_1$	$D$
HD	5.783	7.874	1.471	1.648	0.9462
M2HD	0.857	1.063	0.142	0.111	1.1383
SWHD	0.147	0.206	0.030	0.036	1.2301

## 5. CONCLUSION

A new Hausdorff distance measure based on a spatially weighted function is proposed in this paper for human face recognition. Since different facial regions have different amounts of importance for face recognition, this new distance measure incorporates the *a priori* structure of a human face by emphasizing the importance of facial regions. This can reduce

the effect of outliers on the image. Experimental results show that this method has a better discriminant power and can achieve a higher recognition rate than the *HD* and *M2HD* methods. Moreover, this method is also more robust than the other two methods in a noisy environment. This new Hausdorff distance measure is tailor-made for human face recognition. It can be extended to recognize other objects by modifying the spatially weighted function accordingly if the *a priori* knowledge of the required subject is available. Experimental results based on the *ORL* database show that this new Hausdorff distance measure can achieve recognition rates of 82%, 93%, and 97% for the first three, and the first five likely matched faces, respectively.

## 6. REFERENCES

- [1] R. Chellappa, C. L. Wilson and S. Sirohey, "Human and Machine Recognition of Faces: A Survey", *Proceedings of IEEE*, vol. 83, no. 5, pp. 705-740, May, 1995.
- [2] Samal and P.A. Iyengar, "Automatic recognition and analysis of human faces and facial expressions: A survey", *Pattern Recognition*, vol. 25, no. 1, pp. 65-77, 1992.
- [3] D. Valentin, H. Abdi, A. J. O'Toole and G. W. Cottrell, "Connectionist models of face processing: a survey", *Pattern Recognition*, vol. 27, no. 9, pp. 1209-1230, 1994.
- [4] M. Turk and A. Pentlan, "Eigenfaces for Recognition", *J. of Cognitive Neuroscience*, vol. 3, no. 1, pp. 81-86, 1991.
- [5] L. Wiskott, J. Fellous, N. Kruger and C. Malsburg, "Face recognition by elastic bunch graph matching", *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol.19, no.7, pp. 775-779, 1997.
- [6] M. Lades, J. Vorbruggen, J. Lange, C. Malsburg, R. Wurtz, and W. Konen, "Distortion invariant object recognition in the dynamic link architecture", *IEEE Trans. on Computers*, vol.42, no.3, pp. 300-311, 1993.
- [7] S. Lawrence, C. Giles, A. Tsoi, A. Back, "Face recognition: a convolutional neural-network approach", *IEEE Trans. on Neural Networks*, vol. 8, no.1, pp. 98-113, 1997.
- [8] J. Zhang, Y. Yan and M. Lades, "Face recognition: eigenface, elastic matching, and neural nets", *Proceedings of the IEEE*, vol. 85, no. 9, pp. 1423-1435, Sept. 1997.
- [9] R. Brunelli and T. Poggio, "Face recognition: features versus templates", *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 15, no. 10, pp.1042-1052, Oct. 1993.
- [10] P. Belhumeur, J. Hespanha, and D. Kriegman, "Eigenfaces vs. fisherfaces: recognition using class specific linear projection", *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol.19, no.7, pp. 711-720, 1997.
- [11] K.M. Lam and H. Yan, "An analytic-to-holistic approach for face recognition based on a single front view", *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol.20, no.7, pp. 673-686, 1998.
- [12] S. Ma and Z. Zhang, "Computer vision: computing theory and algorithm" *Academic Press*, Beijing, 1998.
- [13] Takács, "Comparing Face Images Using the Modified Hausdorff Distance", *Pattern Recognition*, vol. 31, no. 12, pp. 1873-1880, 1998.
- [14] D.P. Huttenlocher, G. A. Klanderman, and W. J. Rucklidge, "Comparing Images Using the Hausdorff distance", *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 15, no. 9, pp. 850-863, Sept. 1993.