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Human Face Recognition Using Modified Hausdorff ARTMAP

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Abstract. This paper proposes a new neural network approach specifically designed for solving two dimensional binary image recognition problems. The proposed neural network is an extension of the Hausdorff ARTMAP introduced by Thammano and Rungruang [1]. The objectives of this research are to improve the accuracy and correct the drawbacks of the original network. The performance of this proposed model has been compared with that of the original Hausdorff ARTMAP. The experimental results on two benchmark databases, the ORL and Yale face databases, show that the proposed network surpasses the original Hausdorff ARTMAP in both performance and processing time.

1 Introduction

Person identification has received increasing attention in recent years. In general, there are three ways to identify an individual: the person knows something (e.g., a PIN, a password); the person possesses something (e.g., an ID card, a passport); or by measuring something about the person's body [2]. The later encompasses the biometric identification. Among all of the biometric identification methods, face recognition is the most natural, non-intrusive, and user-friendly biometric measure because it requires no disturbance to the person being identified. While more intrusive biometric recognition systems (e.g., palm, fingerprint) are presently more accurate, face recognition still has a critical role in certain domains since the person being identified may be at a distance from the sensor, the person does not have to be compliant, and recognition can be performed continuously.

A variety of techniques have been applied to deal with the face recognition problems. The reader should pay attention to Chellappa et al. [3] and the references therein for a more complete survey of previous research works on face recognition. In the early years, many researchers used the structure parameters of faces as the features in the facial image recognition. Kelly [4] used various kinds of facial features, including width of the head and distances between eyes, top of head to eyes, between eyes and nose and the distance from eyes to mouth. During the past decade, researchers have paid much attention to the statistical approaches -- such as eigenfaces [5], KL transform [6], and SVD [7] -- and the neural network approaches [8, 9]. Neural network is very suitable for face recognition systems. It has the ability to automatically learn the rules from the given collection of representative examples, instead of following a set of human-designed rules [10]. Moreover, it is well-known that the neural network is more robust to noise than other methods. Thammano and Rungruang [1] proposed the Hausdorff ARTMAP neural network, which employs the concept of the Hausdorff distance to measure the likeness or similarity between the incoming input pattern and the reference patterns of each subject. The results show that the Hausdorff ARTMAP is very effective in dealing with the face recognition problems. It outperforms many different techniques studied in the past. The research described in this paper concerns a modification of the Hausdorff ARTMAP neural network in order to further improve the accuracy and correct its drawbacks. The ORL and Yale face databases are used in this study to evaluate the performance of the proposed neural network.

Following this introduction, section 2 briefly describes the concept of the Hausdorff distance. The original Hausdorff ARTMAP is introduced in section 3. Section 4 presents the proposed model. In section 5, the experimental results are demonstrated and discussed.

2 Hausdorff Distance

The Hausdorff distance, when used as a measure of similarity between two two-dimensional binary patterns, has shown to agree closely with human performance [11]. The Hausdorff distance measures the extent to which each point of an input pattern lies near some point of a reference pattern. Given two finite sets A = $\{a_1, a_2, \ldots, a_p\}$ and B = $\{b_1, b_2, \ldots, b_q\}$, the Hausdorff distance between sets A and B is defined as:

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

where the function h(A, B) is called the directed Hausdorff distance from set A to set B, which can be computed as follows:

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

where ||a - b|| is the Euclidean distance between point a and point b. The Hausdorff distance exhibits many desirable properties for pattern recognition. However, some modifications of the directed Hausdorff distance are made in this study in order to increase the noise immunity of the measurement.

$$h(A,B) = \frac{\sum_{a \in A} h(a,B)}{|A|}\ . \quad (3)$$

where |A| is the number of points in set A. h(a, B) is the pointwise Hausdorff distance for point a. The pointwise Hausdorff distance is computed as follows:

$$h(a,B) = \min_{b \in B}(\|a - b\|)\ . \tag{4}$$

3 Hausdorff ARTMAP

The architecture of the Hausdorff ARTMAP is a three-layer neural network as shown in Figure 1. The first layer is the input layer, which consists of X×Y nodes. Each node represents a pixel in the input pattern. The second layer is the cluster layer. The nodes in this second layer are constructed during the training phase. The third layer is the output layer. Each node in the output layer represents a class that the Hausdorff ARTMAP has to learn to recognize. During the supervised learning, the binary input pattern I^m is presented to the model, together with its respective target output vector. The input pattern is denoted by

$$I^m_{x,y} = \{1,0\} \quad : x = 1, 2, ..., X; y = 1, 2, ..., Y\ . \tag{5}$$

where m is the m^{th} input pattern. X and Y are the dimensions of the input pattern.

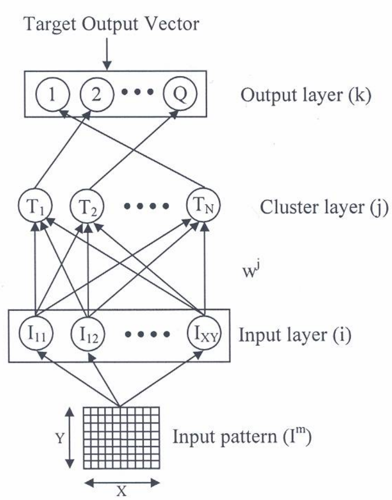


Fig. 1. Architecture of the Hausdorff ARTMAP

Each node in the cluster layer is fully connected to the nodes in the input layer via the connections w^j. The weight w^j, which has the same dimension as the input pattern, represents the reference pattern of the j^{th} node in the cluster layer. Once the input pattern is transmitted to the cluster layer, the choice function of each j^{th} node in the cluster layer is evaluated as follows:

$$T_j(I^m) = H(I^m, w^j) \ . \tag{6}$$

where $H(I^m, w^j)$ is the Hausdorff distance between the input pattern I^m and the reference pattern of the j^{th} node (w^j). The system then makes a cluster choice by selecting the winning node J with minimum choice function value, among all the nodes j in the cluster layer. The cluster choice is indexed by J, where

$$T_J(I^m) = \min \{ T_j(I^m) \} \quad : j = 1, 2, ..., N. \tag{7}$$

where N is the number of nodes in the cluster layer. In case of a tie, the node with the smallest index is chosen. Next, the vigilance criterion is evaluated to check whether the degree of mismatch between the input pattern and the reference pattern of the chosen cluster is within an acceptable level.

$$T_J(I^m) \leq \rho \ . \tag{8}$$

where ρ is the vigilance parameter, which has the value between 0 and the length of the diagonal line. Resonance will occur if the chosen cluster meets the above criterion. However, if the condition in (8) is not satisfied, a new cluster node J is recruited to code the input pattern. The weight of this new node is initialized to be equal to the input pattern and this new node will automatically satisfy (8).

$$w^J = I^m \ . \tag{9}$$

Next, the system associates the winning node J in the cluster layer with the target output vector. If the winning node J does not belong to the correct class defined by the target output vector, a new cluster node J is recruited and its weight is initialized using equation (9). Then the connection between a new cluster node and the target output is created. However, if the winning node represents the class to which I^m belongs, the weight vector w^J is then updated according to

$$b^J_{x,y} = \sum_{u=-S}^{S} \sum_{v=-S}^{S} I^m_{x+u,y+v} \ . \tag{10}$$

$$w^{J^{new}}_{x,y} = \begin{cases} w^{J^{old}}_{x,y}, & \text{if } b^J_{x,y} > 0 \\ 0, & \text{otherwise} \end{cases} \tag{11}$$

where S is a positive integer value; it tells the model how many pixels surrounding the current x, y position should be considered during the weight adjustment.

During testing, each test pattern is applied in turn and its class is predicted. The class whose cluster node returns the minimum output value is the result of the prediction.

Results of the experiment conducted by Thammano and Rungruang [1] show that the Hausdorff ARTMAP is very effective in dealing with the face recognition problems. It outperforms many different techniques studied in the past. However, the Hausdorff ARTMAP suffers from the following problems. First, the performance of the Hausdorff ARTMAP depends directly on the order in which the training images are examined. Second, the time used for recognizing the subject is long due to its large reference pattern size. The above drawbacks motivate the development of the proposed model presented in the next section.

4 Modified Hausdorff ARTMAP

The architecture of the modified Hausdorff ARTMAP is exactly the same as the Hausdorff ARTMAP. The modifications are done to the training algorithm. The details of the training algorithm are presented as follows:

1. The closest similarity between the input pattern m and other input patterns within the same output class K is located.

$$d_m = \min_{\forall n, n \in K, n \neq m} \left[\min_{o=1}^{c} \left[H(I^n, w^m) \right] \right]. \quad \textbf{(12)}$$

   where I^n represents the input pattern n which belongs to the same class as the input pattern m. w^m is the small area on the input pattern m; it is used to represent the whole I^m image. c is the number of locations on the input pattern n, which w^m is compared to.

   Next, d_m is compared to the similarity threshold ($\rho_{similar}$). $\rho_{similar}$ is a predetermined value between 0 and the length of the diagonal line. If d_m is less than or equal to $\rho_{similar}$, the process will continue to the next step. However, if d_m exceeds $\rho_{similar}$, w^m size will be increased by predefined pixels and this step will be repeated.

2. After w^m is identified, its similarities with other input patterns outside the output class K are determined. The minimum of the above similarities is compared to the dissimilarity threshold ($\rho_{dissimilar}$) based on equation 14.

$$do_m = \min_{\forall p, p \notin K} \left[\min_{o=1}^{c} \left[H(I^p, w^m) \right] \right]. \quad \textbf{(13)}$$

$$do_m > \rho_{dissimilar}. \quad \textbf{(14)}$$

where I^p represents the input pattern p which does not belong to the same class as the input pattern m. $\rho_{dissimilar}$ is a predetermined value between 0 and the length of the diagonal line. However, it must be greater than or equal to $\rho_{similar}$. If the condition in (14) is satisfied, the process will continue to the next step. If not, w^m size will be increased by predefined pixels and then go back to step 1.

3. This third step determines the capability of w^m in representing the input patterns within the same output class.

$$R_{mn} = \begin{cases} 1, & \text{if } d_{mn} \le \rho_{similar} \\ 0, & \text{otherwise} \end{cases} \quad (15)$$

$$d_{mn} = \min_{o=1}^{c}\left[H(I^n, w^m)\right]. \quad (16)$$

where m = 1, 2, 3,   , e and n = 1, 2, 3,   , e. e is the number of input patterns in class K. "$R_{mn} = 1$ means that w^m is capable of representing the input pattern n. On the contrary, "$R_{mn} = 0$ means that w^m is incapable of representing the input pattern n.

4. In this step, the nodes in the cluster layer are created and a select group of w^m is used to be their reference weights. w^m which is capable of representing the maximum number of input patterns in the class is the first to be chosen. The next most capable w^m are subsequently picked until all input patterns in the class are represented. In case of a tie, the averages of the similarities between each w^m in question and the rest of the input patterns in the same class are calculated; the one with the smallest average is selected.

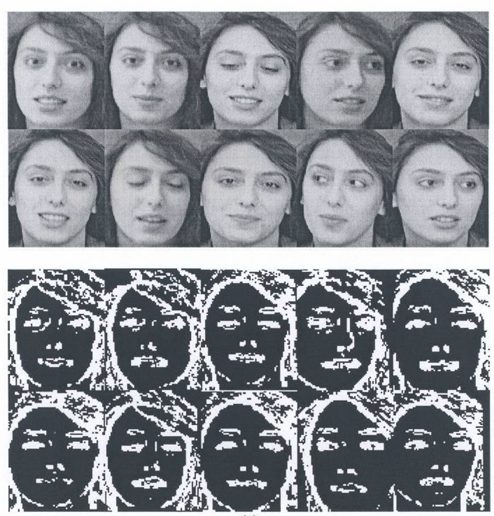
5 Experimental Results

To test the performance of the modified Hausdorff ARTMAP for face recognition, the experiments have been conducted on 2 databases: the ORL face database [12][13] and the Yale face database [14][15]. The results of the experiments are then compared to those of the original Hausdorff ARTMAP. In order to be comparable, the preprocessing step of this study replicates that of Thammano and Rungruang's study. First, the gray-level edge image E(x, y) is obtained by applying morphological operations [16] on the original face image f(x, y). Then, the gray-level edge image is converted to a binary edge image using the adaptive threshold method.

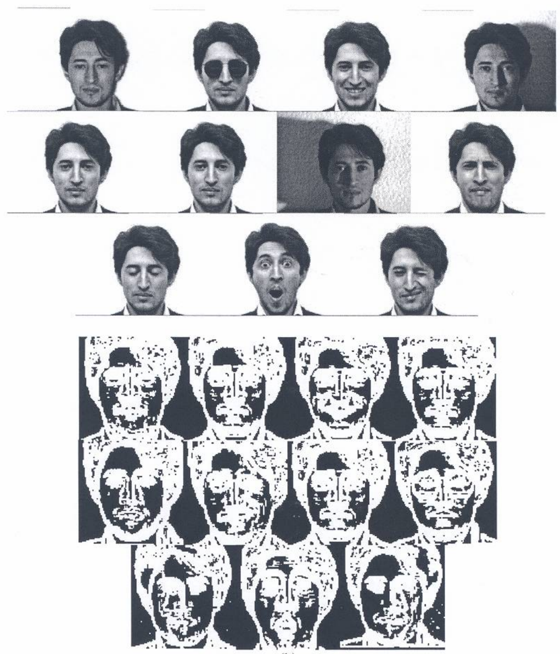
$$n(x, y) = \frac{E(x, y)}{f(x, y)}. \quad (17)$$

The values of the function n(x, y) are then sorted in descending order, and the threshold is set so that 30% of the points with the largest magnitudes in n(x, y) are selected.

For the ORL database, there are 10 different images of each of 40 distinct subjects; therefore, the total of 400 different face images are used in this experiment. The images of each subject were taken at different times with different lighting, facial expressions (open/closed eyes, smiling/non-smiling), and facial details (glasses/no-glasses) as shown in Figure 2(a). Four images of each subject are randomly chosen for training and the remaining six images are used for testing. Previously, Lin et al. [17] carried out a comparison study of many different techniques – the principal component analysis (PCA), the conventional Hausdorff distance (HD), the doubly modified Hausdorff distance (M2HD), the spatially weighted Hausdorff distance (SWHD), the spatially weighted doubly Hausdorff distance (SW2HD), the spatially eigen-weighted Hausdorff distance (SEWHD), and the spatially eigen-weighted doubly Hausdorff distance (SEW2HD) – on this ORL face database. The reported recognition rates varied from 46 – 91%. The best recognition rate (91%) was achieved from the SEW2HD. Table 1 shows the recognition results of both the Hausdorff ARTMAP and the modified Hausdorff ARTMAP on the ORL database. The best performance of the Hausdorff ARTMAP is obtained when the vigilance parameter (ρ) is set at 0.8 and S is 2. However, the performance of the model might be lower if the sequence of the training images is changed. For the modified Hausdorff ARTMAP, the best recognition rate of 95.83% is achieved when $\rho_{similar}$ and $\rho_{dissimilar}$ are 0.35 and 0.9 respectively.



(a)



(b)

Fig. 2. Examples of the original face images and the binary edge images of the ORL (a) and Yale (b) face databases

The Yale database (Figure 2(b)) contains 165 different face images of 15 distinct subjects. There are 11 images per subject, one per different facial expression or configuration: center-light, w/glasses, happy, left-light, w/no glasses, normal, right-light, sad, sleepy, surprised, and wink. In this experiment, randomly picked 90 images (6 images per subject) are included in the training set. The remaining 75 images (5 images per subject) are included in the testing set. The recognition results of the Hausdorff ARTMAP vary from 89.33 – 96.00% depending on the order in which the training images are examined. On the other hand, the recognition results of the modified Hausdorff ARTMAP are always 96.00%, whatever the order of the training images is.

Table 1. Experimental results on ORL database

	Number of Cluster Nodes	Size of Reference Patterns	% Correct
Hausdorff ARTMAP	152-153	100×100	94.58-95.42
Modified Hausdorff ARTMAP	159	85×85, 59×59	95.83

Table 2. Experimental results on Yale database

	Number of Cluster Nodes	Size of Reference Patterns	% Correct
Hausdorff ARTMAP	83-88	100×100	89.33-96
Modified Hausdorff ARTMAP	63	93×93, 61×61	96

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