Face Recognition using Parallel Associative Memory

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Abstract—This paper proposes a Parallel Associative Memory (PAM) based face recognition system. An image is split into blocks which are processed in parallel by conventional associative memory. The combined output of these are used to discriminate between faces. Further, a parameter termed as run length count has been used to discriminate between similar faces. This approach helps to scale up associative memory to higher resolution images with more detailed features thus improving recognition performance. To analyze the efficiency and goodness of the proposed system the experiments have been performed on ORL face database. The proposed method outperformed most of the existing methods.

Index Terms—Associative memory, Face recognition, Parallel associative memory, Run length count

I. INTRODUCTION

Face verification is the process of one-to-one matching of images where the query face image (i.e., the image whose identity is being claimed) is compared with the template face image. In recent past face recognition has attracted a lot of attention of researchers from pattern recognition, computer vision and biometric communities [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11]. However, most of these algorithms perform poorly in the presence of uncertainties in the face image. Face images inherently contain uncertainties including spectacles, beard and poor lightening condition etc.

To handle these uncertainties face recognition system based on associative memories have been proposed in literature [5], [9], [13], [14]. Associative memory is a neural architecture with human like capacity to recognize pattern in an uncertain environment [13], [12]. Associative memory usually enables a parallel search in a stored data file [12]. The above property may be used to build robust face biometric systems. However, the main drawbacks of associative memories are that they do not scale to large image sizes having high resolution.

As an example the associative memory based ARENA Face Recognition Algorithm [5], [14] reduces the image size to 16 × 16 pixels and as a result, it looses many features of the face which can be used in differentiating the images. In the RCE-based Associative Memory approach to human face recognition [8] the data set is divided in blank, smile, angry and surprised groups. This approach works well for blank faces but performance degrades drastically for other expressions. Moreover, a lot of preprocessing is required on the given data set. In Kernel Autoassociator Approach (KAA) to Pattern classification [11], kernel autoassociator takes a kernel feature space as the nonlinear manifold, and places emphasis on the reconstruction of input patterns from the kernel feature space. The computational complexity of the kernel autoassociator approach is very high even for moderate resolution images.

The concept of sub-images and parallel processing were used in [23] to identify frontal view of human face. In [23] sub-images are referred as decomposition of large image and Fast Neural network is used for parallel processing. Decomposition and parallel processing is used for human face detection in a large image.

This paper proposes parallelization of the auto-associative memory in order to apply it for recognition of high resolution face images. The goal is to retain discriminative feature of the face and thus to improve the recognition performance. Fusion of the output of each component is performed using a novel scheme which considers run lengths of the binary output of the component. The system has been found to be efficient and performed satisfactorily under varying illumination conditions, change in facial expressions, using spectacles etc.

The Olivetti Research Laboratory (ORL) face database [15] has been used to evaluate the performance of the proposed system. Six face images of the same person are used for training the proposed neural network and ten face images of the same person and 390 images of different persons are used for testing. The False Rejection Rate (FRR) and False Acceptance Rate (FAR) are used as performance metrics.

Rest of the paper is organized as follows. Auto-associative memory for face recognition is proposed in Section 2. Next section deals with parallel associative memory for face recognition. Section 4 describes the face similarity measure for recognition. Experimental results are discussed in Section 5. Conclusions are given in the last section.

II. AUTO-ASSOCIATIVE MEMORY FOR FACE RECOGNITION

Associative memories mimic the capacity of human brain to recall information in a robust and associative access mode [12]. The concept of auto-associative memory to store and recall the data has been proposed by Kohonen [16], [17]. Associative memory usually enables a parallel search in a stored data file. The purpose of search is to output either one or all stored data items that match the given search argument, and to retrieve it fully or partially [12]. An associative memory is a distributed memory with human brain like capacity which
learns by association. Kohonen [17] has demonstrated that an auto-associative memory could act as a content addressable memory for face images. An associative memory model [13] is understood as a class of artificial neural networks which stores information as stable attractors. These states are often recorded by Hebbian learning rule [12], [19]. When a perfect, partial, or noisy version of a trained piece of information is presented to the neural network, it responds to the stimulus with the closest of the stored memories [18]. In this section a linear auto-associative memory model has been discussed.

An associative memory model is classified, according to nature of memorized associations, as auto-associative or heteroassociative [12]. The input-output relationship in a linear associative memory is described by

$$v = W u$$

(1)

where the vector $u$ denotes the key pattern or input applied to an associative memory and the vector $v$ denotes a memorized pattern or output of associative memory. The matrix $W$ is called the weight matrix which describes the network connectivity in the associative memory. In an associative memory if input vector $u$ is equal to the response vector $v$ the associative memory is referred to an auto-associative memory; otherwise, it is a heteroassociative memory. In this paper the inputs to the auto-associative memory are $M \times N$ gray scale images. The $j^{th}$ image is represented by a column vector $u_j$ of size $(M \times N) \times 1$ which consists of pixel brightness values of the image taken in row major fashion.

To train the auto-associative memory simple Hebbian learning rule [12], [19] may be used for auto-associating each image vector, $u_j$, and summing the resultant product response matrices, given by,

$$W = \sum_{j=1}^{k} u_j u_j^T$$

(2)

where $k$ is the number of patterns in the network; $W$ is an $(MN)\times(MN)$ matrix and the vectors are assumed normalized so that $u_j^T u_j = 1$. When an input vector $u_i$ is given to the auto-associative memory then the response or memorized pattern of the auto-associative memory is computed using (1) and is given by:

$$v = W u_i$$

Now substituting $W$ from (2) we have

$$v = \sum_{j=1}^{k} u_j u_j^T u_i = \sum_{j+i} u_j u_i^T u_i + u_i$$

(3)

When all the input vectors are mutually orthogonal, the summation in (3) vanishes and one gets $v = u_i$. This is the case of perfect recall from auto-associative memory. If the input vectors are not orthogonal then the summation term in (3) represents a noise vector. Associative memory algorithm given in [19] is applicable to binary images and is not directly applicable to gray scale images. Here the basic auto-associative memory algorithm has been modified to develop an efficient recognition system for gray scale images. Therefore, a system has been developed based on the concept of auto-associative memory to gray scale images. The proposed system exhibits the better performance of face recognition in gray scale images.

III. PARALLEL ASSOCIATIVE MEMORY FOR FACE RECOGNITION

This section describes the proposed system, Parallel Associative Memory (PAM) for face recognition using auto-associative memory as a basic block. Here a set of auto-associative memories is used in parallel to process the sub-images of the size $16 \times 16$ which are obtained by splitting the given image. The system mainly performs three tasks: (i) Information storage, (ii) information retrieval based on some input pattern and (iii) matching of the information. These three tasks are described through three algorithms namely STORAGE, RETRIEVAL and PARALLEL_AM_FACE_MATCH. First two algorithms are described in this section while the last one is given in the next section. In STORAGE Algorithm the images are given to the input of different associative memory blocks and are stored as weight matrix $W$. The storage process works as follows. First the input image of size $N \times N$ pixels is divided into smaller sub-images of fixed size (i.e., $n \times n$ pixels). These sub-images are represented as 8-bit binary vectors. Then Hebbian Learning Rule [19] is applied on these binary vectors to store the information as weight matrix.

Now the general auto-associative memory retrieval algorithm for binary images given in [19] is modified to retrieve the gray scale image information. The information of each sub-image stored by STORAGE ALGORITHM in the corresponding associative memory block is retrieved using the test images. In retrieval process also the query image is divided into 8-bit binary vectors and then processed in parallel by the auto-associative memory blocks to output the best match. The schematic diagram of parallel associative memory is shown in Fig. 1 and the process of image retrieval is given in RETRIEVAL ALGORITHM. In Fig. 1 the small black square represent the portion of training/test image processed by the corresponding associative memory block.

STORAGE Algorithm

Step 1: Split the given image into the smaller sub-images of size $n \times n$ pixels. Hence, we get $L = N^2/n^2$ such sub-images.

Step 2: Convert these $n \times n$ sub-image matrices into corresponding $n^2 \times 1$ vectors (say $P_k^{(n)}$), where $m = 1, 2, ..., T_r$.

Step 3: for $k = 1$ to $L$

for $m = 1$ to $T_r$

Convert $P_k^{(n)}$ into 8-bit binary code and store in $P_k^{(m)}$

end

end
/* The binary code matrix $P$ becomes of size $n^2 \times 8 */$

**Step 4:** Process one by one the corresponding columns from each of the $m$ matrices constructed in Step 3 and store them sequentially in the new matrix (say $R$) of the size $n^2 \times m$ to compute the weight matrix $W$ of size $n^2 \times n^2$ as follows

$$W = R \ast R^T - I$$

where $I$ is an $n^2 \times n^2$ unit matrix and $R^T$ is the transposed matrix of $R$.

**Step 5:** Output the weight matrix $W$.

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**Fig. 1.** Schematic Diagram of Parallel Associative Memory

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**IV. FACE SIMILARITY MEASURE FOR RECOGNITION**

Based on the best match information of **RETRIEVAL ALGORITHM** the two criteria to decide the similarity between images are proposed. The first criterion is the **number of matched sub-images** and the other is **matching run length count**. To calculate matching run length we observe the output of each associative memory block which processes a sub-image. It outputs ‘1’ if the sub-image is matched and ‘0’ otherwise. The outputs from $L$ memory blocks corresponding to $L$ sub-images, are put in a square matrix then the number of ‘1’s in a stretch are counted row wise as well as column wise and average is taken over rows and columns. This average quantify the run length count. The detailed process to identify the face image is presented in **PARALLEL_AM_FACE_MATCH ALGORITHM** algorithm which recognizes the query face in the given face database. In this algorithm the threshold is initially taken randomly which is modified later by calculating the **False Rejection Rate** (FRR) and **False Acceptance Rate** (FAR) to get the more accurate value. By experimenting with large number of images from ORL face database and other data sets it is observed that 44% is a good approximation for initial value of threshold.

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**RETRIEVAL ALGORITHM**

**Step 1:** Initialize the vector $K = \Phi$ and assign the integer values between 1 and $N$ randomly to $a_i$ for $i = 1, 2, ..., N$.

**Step 2:** For a given test image compute the binary code using **Step 1** through **Step 3** of **STORAGE ALGORITHM** and store it in a binary vector $V$.

**Step 3:** Retrieve the output ($V'$) of auto-associative memory for the vector $V$ using weight matrix $W$ as computed in **Step 5** of **STORAGE ALGORITHM** as follows,

$$K_{i_k} = \sum_{j=0}^{N} W_{a_i,j} V_j$$

$$V'_{a_i} = \text{sgn}(K_{a_i})$$

where $\text{sgn}()$, $V_j$, $W_{a_i,j}$, $K_{a_i}$ represent the signum function, the $j^{th}$ element of vector $V$, the elements of weight matrix $W$ and the $a_i^{th}$ element of vector $K$ respectively.

**Role of Threshold:** There are two steps where threshold is needed. Threshold is decided on the basis of the experimental results. There are two criterion, used in order to recognize a face, first is referred as number of matched sub-images and the other is matching run length count, where threshold is applied. In the first criterion, number of matched sub-images, threshold is applied on the sum of the output vector to get number of sub-images matched.

In the second criterion, matching run length count, threshold is applied on the run length as defined in **PARALLEL_AM_FACE_MATCH ALGORITHM**. This is used on the concept that for the matched cases maximum number of ‘1’s will be in the center as exhibited by the grid shown in Fig.2.

**Fig. 2.** A grid structure to explain the concept of run length count

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**V. EXPERIMENTAL RESULTS**

An extensive testing methodology has been used to evaluate the performance of proposed parallel associative memory (PAM) based face recognition system. The details of the experimental setup and results are given below.

**A. Face Database**

The results reported in this paper are based on the performance of the system using face images from Olivetti Research
Laboratory (ORL) face database [15]. The ORL database contains total 400 images of 40 individuals from various ethnicity and sex under various pose, light, scale and expression as shown in Fig. 3 for two different galleries.

The face database used in this experiment has 10 images per person and all the 40 persons are used in our experiment. One set is considered as training set and the remaining 39 sets are used as testing set. In some cases there are images of same individual with spectacles and/or without spectacles. These variations in face images indicates the improved efficiency of the proposed PAM based face recognition system. All the results are the average of 5 trials where for each gallery the database is randomly divided into 6 images for training and 4 images for testing. The performance is observed for exact match (i.e., match for rank=1). The images considered in this experiment are gray scale images with 256 gray-levels and $N \times N$ pixel resolution. The size of sub-images is taken as $n \times n$. The threshold is decided by the system itself adaptively using the training images. It is found that the best suitable value of $T_{h1}$ and $T_{h2}$ are 40 (i.e, 65 % portion of input image) and 25 (i.e, 40 % portion of input image) respectively. In this experiment values of $N, n$ and $T_r$ are set to 128, 16 and 6 respectively. The value of $N$ and $n$ will change with change in input image resolution.

B. Correct Recognition Experiments

In this experiment the query test face is taken from the database and is known to be present in database. All the results are the average of 5 trials where for each gallery the database is randomly divided into 6 images for training and 4 images for testing. The performance is observed for exact match (i.e., match for rank=1). The performance of the system is encouraging and False Rejection Ratio (FRR) for frontal images for testing. The performance is observed for exact match (i.e., match for rank=1). The images considered in this experiment are gray scale images with 256 gray-levels and $N \times N$ pixel resolution. The size of sub-images is taken as $n \times n$. The threshold is decided by the system itself adaptively using the training images. It is found that the best suitable value of $T_{h1}$ and $T_{h2}$ are 40 (i.e, 65 % portion of input image) and 25 (i.e, 40 % portion of input image) respectively. In this experiment values of $N, n$ and $T_r$ are set to 128, 16 and 6 respectively. The value of $N$ and $n$ will change with change in input image resolution.

C. False Accept Experiments

For false accept experiments the system was tested with 40 randomly chosen face images which are not present in database. This experiment was carried out 40 times and the resultant FAR value is the average of the 40 values. The observed FAR is 3.1%.

D. Comparison with other Methods

The ORL database provided us a chance to compare the proposed system with other system such as Eigenfaces [20], [21], Principal Component Analysis (PCA) [7], [6], PCA + Moment Invariant [22], Kernel Associator Approach (KAA)[11] and ARENA [5]. ARENA is a memory based algorithm that employs reduced-resolution images $16 \times 16$ pixels and compute the similarity measure with and without synthetic images. The results by ARENA compared here are without synthetic images [5] as the proposed system do not use any synthetic image.
Here only those results are considered which have used 5 or more images for training. The comparison of recognition accuracies is shown in Table 1. The first column gives the name of method and the second column gives the corresponding accuracy for the benchmark face database. The last row of the table represents the result obtained with parallel associative memory system.

It is evident from Table 1 that parallel associative memory (PAM) based face recognition system has achieved favorably competitive accuracy with other popular recognition approaches. Because of the associative nature, the proposed recognition system is tolerant to noise and distortion such as blurring, and presence of artifacts like beards and glasses. Parallelization is implied to reduce the high space requirement of conventional associative memories, making it suitable for recognition of high resolution face images.

VI. CONCLUSION

In this paper a parallel associative memory based efficient face recognition system has been proposed. The system has been implemented using auto-associative memory blocks in parallel. The goal is to scale the associative memories to high resolution images so that discriminative features are retained and benefits of associative memory are applied to face recognition. A novel run length count based measure of face similarity suited for parallel associative memory is also proposed. The proposed face recognition system efficiently identifies and differentiates the face images of the person from various ethnicity and variable poses. The efficiency is justified by its best performance on ORL face database which also contains some scale and rotation variations.

Experiments and simulation on benchmark face data set have proved that the parallel associative memory system for face recognition performed better than many methods reported in literature also system does not have any human intervention.

As a future work we are testing the proposed face recognition system on other face data sets such as AR and FERET and trying to build a hardware for the same.

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Table 1

<table>
<thead>
<tr>
<th>Method</th>
<th>% Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eigenface</td>
<td>89.5</td>
</tr>
<tr>
<td>PCA</td>
<td>92.0</td>
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<tr>
<td>PCA + Moment Invariant</td>
<td>94.3</td>
</tr>
<tr>
<td>KAA-1</td>
<td>94.5</td>
</tr>
<tr>
<td>KAA-2</td>
<td>95.5</td>
</tr>
<tr>
<td>ARENA</td>
<td>96.0</td>
</tr>
<tr>
<td>PAM</td>
<td>96.9</td>
</tr>
</tbody>
</table>

REFERENCES