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A Novel ANN based Approach for Angle Invariant Face Verification

Basabi Chakraborty
Faculty of Software and Information Science
Iwate Prefectural University
Iwate -20-0193, Japan
basabi@soft.iwate-pu.ac.jp

Abstract—
Face recognition and verification under varying pose and illumination is still a challenging problem. In this work a novel approach for pose invariant face recognition based on aritificial neural network under similar illumination condition is proposed. The neural network is trained to learn the face features with variation of pose and interpolate the face features for any unknown pose, leading to a good matching with the probe image. The simple implementation by simulation experiment with HOIP data base shows promising result.

I. Introduction

Face recognition technologies [1] are gaining importance from academic research to commercial products for past decade as computational power of computers is rapidly increasing. Though comparatively easier for human being, automated face recognition by computers in uncontrolled environment is an extremely complex and highly difficult task. There are variety of approaches reported so far in the literature for recognition of face images. But still the best face identification systems are restricted to frontal face images taken under controlled lighting conditions. Lot of researches are going on to develop unconstrained face recognition system [2], specially for pose and illumination invariant face recognition [3], for a wide variety of real time applications. Person authentication from face verification is considered to be a passive and one of the most nonintrusive modalities of biometrics. For biometric application we need to identify a particular person in real time whose face image is already registered in the system. For proper verification, the input image (probe image) should exactly match to the registered image (gallery image) of that particular person and not with anyone else's face image and at the same time the algorithm should not fail to identify the genuine person. The task becomes difficult when only single image of individual is registered in the data base and the probe image differs considerably in pose.

Face recognition algorithms extract feature vectors from an input (probe) image and search the database (gallery image) for the closest vector. There are two classes of algorithms, model based and appearance based. Model based algorithms use an explicit 2D or 3D models of the face whereas appearance based methods use image pixels or features derived from them. Being computationally simpler, appearance based paradigm is more popular. One of the significant work being the eigenface approach [4] by Turk and Pentland. In this work we have investigated the approaches for pose invariant face recognition and proposed a novel approach based on artificial neural network learning for angle invariant face verification system for biometric application. In the next section we present in very brief the approaches for addressing the problem of pose variation in connection to face recognition. The following section explains our idea and approach to address the problem followed by our simulation experiments and results. The last section contains the conclusion and discussion.

II. Pose Invariant face Recognition

According to FERET and FRVT [5] test reports, performance of face recognition systems drop significantly when large pose variations are present in the input images and it is a major research issue. Approaches to address the pose variation problem are mainly classified into three categories:

1. Single-view approach in which invariant features or 3D model based methods are used to produce a canonical frontal view from various poses. In [6] a Gabor wavelet based feature extraction method is proposed which is robust to small angle variation. This approach did not receive much attention due to complexity and computational cost.
2. Multiview face recognition, a direct extension of appearance based frontal image recognition in which we need gallery images of every subject at every pose. Earlier works on pose invariant appearance based multiview algorithms are reported in [7] [8]. Some of the recent works are reported in [9]. Most algorithms in this category require several images of each subject in the data base, consequently require a lot more computation and storage.
3. Class based hybrid methods in which multiview training images are available during training but only one data base image per person is available during recognition. Numerous algorithms in this category have been proposed. The popular eigenface approach [4] has been extended in [10] in order to achieve pose-invariance. In [11] a robust face recognition scheme based on graph matching has been proposed. More recent methods to address pose and illumination are proposed in [12], [13] [14], [15].

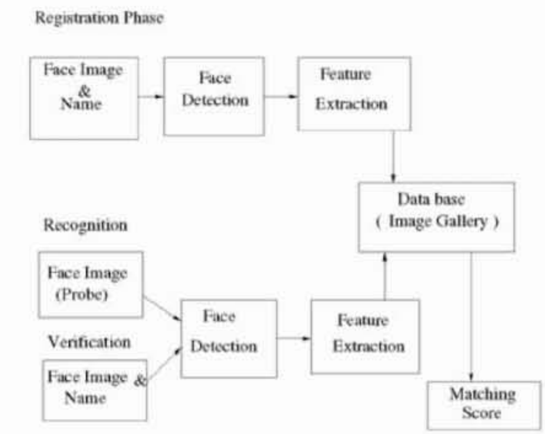

Fig. 1. Block Diagram of Face Recognition/Verification System

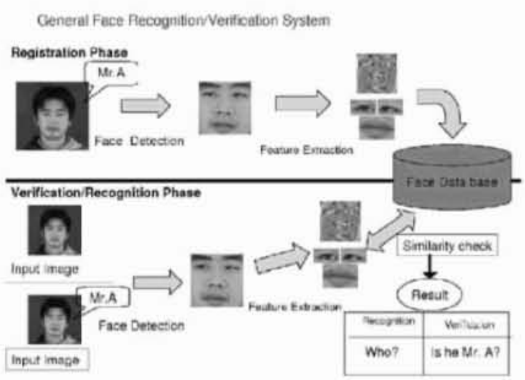

Fig. 2. General Face Recognition/Verification System

The simplest approach to address this problem seems to look for a feature which does not vary with the variation of angles, but in reality, variation of the most features due to pose exceeds variation of features across individuals, jeopardising the recognition process. Prince and Elden [16] presented a heuristic algorithm to construct a single feature which does not vary with pose. Murase and Nayer [17] have used principle component of many views to visualize the change due to pose variation. Graham and Allison [18] sampled input sequences of varying pose to form eigensignature when projected into an eigenspace. A good review of the approaches can be found in [3] [19].

III. Proposed Angle Invariant Face Verification System

In this work we propose an algorithm for angle invariant face verification in which an artificial neural network is trained to capture the variation of features of the face of an individual with angle by using the known face images at different angles of the same individual. The trained network then interpolates the features of a face image at any unknown pose. The registered data base (gallary image) consists of the trained neural networks corresponding to each subject.

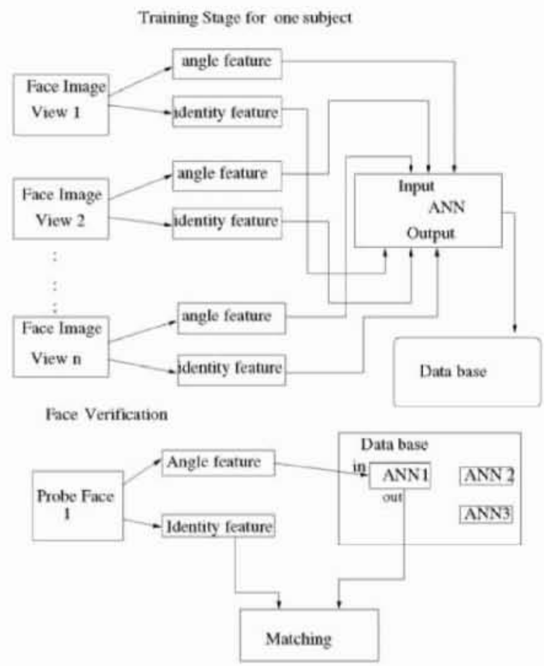

Fig. 3. Block Diagram of Proposed Face Recognition/Verification System

The block diagram of a general face recognition system is shown in Fig.(1). Fig.(reffig:fig1a) represents an example of general face recognition/verification system. In the image registration phase, face image is detected and face features are extracted from the image and the database (gallery image) is constructed to represent the face of a particular face with its feature values. For face recognition/verification system, in recognition/verification phase, features from the probe image are extracted and the feature vector is matched with the data base of all faces to recognize the face or the particular face to be verified. Decision is taken depending on the matching score.

A. Proposed Concept

Now designing face recognition system, several features are reported in the literature. Some features are more dependant on face view and less dependant on face identity whereas some features are less dependant on face view and more dependant on face identity.

In our approach for angle or pose invariant face recognition conceptually we propose two sets of features as (1) angle features which represents the pose of the face and (2) face features which represent the face identity of the person. Now our algorithm consists of two steps:

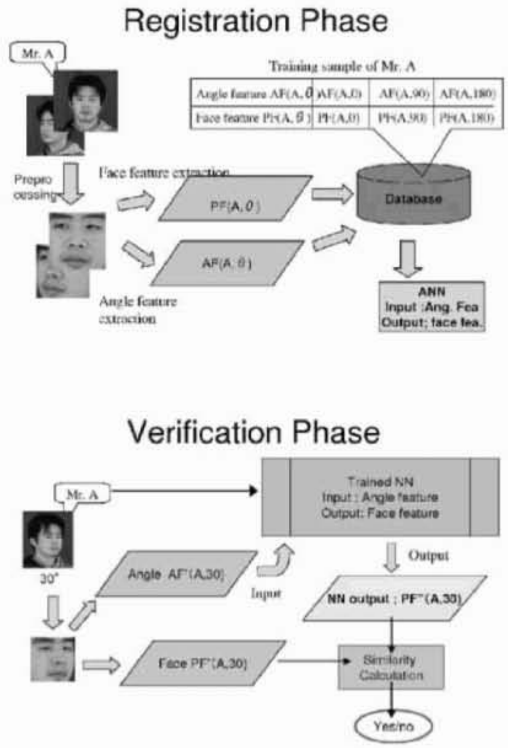

Fig. 4. Proposed Face Recognition/Verification System

1. Training stage: In this stage samples of faces of a particular person for different views are collected. From each face sample, the two sets of features, angle features and face features are extracted. Now a multilayer perceptron is trained with the two sets of features, angle features as input and face features as output. The trained network is supposed to interpolate face features of a particular person's face with any unknown view (not used during training). For each subject, separate neural network is used for training with multiple views of the same person. Trained neural networks for each subject act as the data base.
2. Recognition or verification stage: In the face recognition or face verification stage the two sets of features from the probe image are extracted. Now from angle features, the face features are calculated from trained neural network of the person to be verified (in case of face verification) and from all neural networks (in case of face recognition). The matching is done between the extracted face feature and the calculated face feature from the trained neural network. If the two values match (in case of verification) within a prespecified limit, the verification process is declared to be successful (access allowed). In case of face recognition the closest matching face is recognized.

The block diagram of the proposed system is shown in Fig.(3).

Fig.(reffig:2a represents an example of proposed face recognition/verification system.

B. Implementation

For simple implementation of the proposed approach, in this work we have used the following set of features as the angle feature set and face feature set.

1. Angle features: The location of the eyes and the mouth are detected from the 2D face images. Let the coordinates of the locations are: left eye L (x_1, y_1), right eye R (x_2, y_2) and mouth M (x_3, y_3). Now the features are taken as the distance D_1 = the length of LR, D_2 = the length of RM, D_3 = the length of LM, $m_1 = \frac{y_2 - y_1}{x_2 - x_1}$ (the gradient of line LR), $m_2 = \frac{y_3 - y_2}{x_3 - x_2}$ (the gradient of line RM) and $m_3 = \frac{y_1 - y_3}{x_1 - x_3}$ (the gradient of line LM). Thus the feature set used is $(D_1, D_2, D_3, m_1, m_2, m_3)$. Though these features are to some extent person dependent, not ideal angle features, the variation of these features are more prominent with change in view (pose) than with change of person.
2. Face features: Though there are several set of features known to represent identity of a person, in this work we used the most popular principal component analysis (PCA) for simplicity. Gabor wavelets are also one of the good candidates which are known to be invariant of angles within small change of angles.

In this implementation other assumptions are as follows
:

- The multiple images with different angles of each subject are taken with the same distance between the camera and the subject.
- All the images are taken with similar illumination condition. The effect for the change of illumination is not studied here.
- The rotation plane is parallel across the eye level.
- The range of rotation considered here is from -60 degree to + 60 degree.
- The face images are normalized and of same size (from chin to forehead)
- The size of all the images used are 40×40 pixel.
- 12 principal components are used to represent the features of the face (dimension reduction from 40x40 =1600 to 12).
- Euclidean distance is used as the similarity measure for matching of the probe image with gallery images (between the extracted face feature vector and the calculated face feature vector from neural network output). The smaller values represent better match.

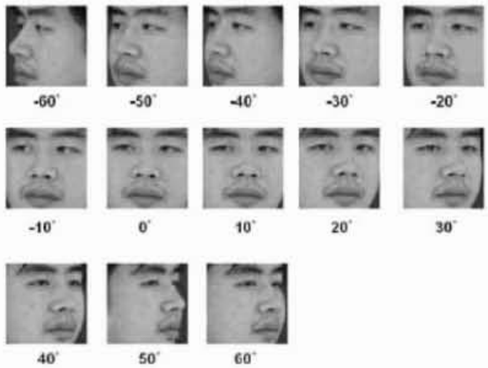

Fig. 5. Sample faces in HOIP data base

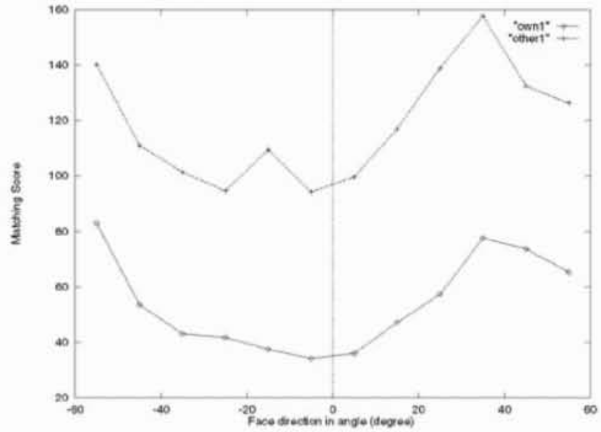

Fig. 6. Simulation Results for Case 1

IV. Simulation Experiments and Results

Simulation experiments have been done using HOIP data base available from [20]. HOIP data base contains face images of 300 subjects (150 male and 150 female) of various age (from 15 to 64) with 73 different poses (change of every 5°). An example of faces in HOIP data base is shown in Fig.(5). We selected a subset of the data for 50 subjects (25 male and 25 female) in the range of -60° to +60° for our simulation experiment as beyond that our algorithms will not work and for practical face verification system the changes in face views generally occurs in this region. Three sets of simulation experiments have been done.

A. Case 1

Here we used data of faces with views of 10° apart for training. We used faces of each subject with angles -60, -50, -40, -30,-20,-10, 0, 10, 20, 30, 40, 50, 60 degrees respectively for training and used faces with angles -55, -45, -35, -35, -15, -5, 5, 15, 25, 35, 45, 55 randomly for probe images. For neural network training 6 dimensional angle features are used as input and 12 dimensional identity features (principal component) are used as output. The number of neurons in the input, output and hidden layer of 3 layer feed forward network have been used as 6, 12 and 16 respectively. The neural network was trained to lower the error to .001 by back propagation algorithm.

Fig.(6) represents the matching score (distance values) of the probe image with the gallery image of same person and the average score of probe image with gallery images of other persons with various pose angles. The experiment has been repeated for 100 times with randomly chosen faces. The lower curve reprents the mathcing score for same person and the upper curve represents the average of other persons. For training data with multiview faces with 10 degrees apart the results are quite promising. Selecting proper threshold for matching score, false acceptance rate is achieved as 0%. The recognition rate on the average is achieved as 92.7%.

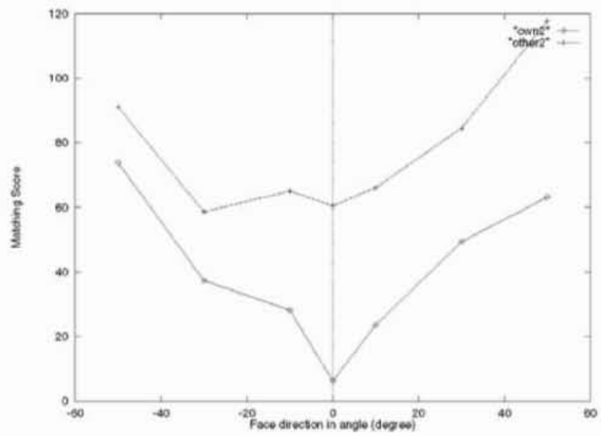

Fig. 7. Simulation Results for Case 2

B. Case 2

Here we used data of faces with 20° apart for training i,e we used faces of each subject with angles -60, -40, -20, 0, 20, 40, 60 degrees respectively for training the neural network and used other faces randomly for probe images. Neural network with same structure and parameters as in case 1 has been used for learning.

Fig.(7) represents the matching score (distance values) of the probe image with the gallery image of same person and the average score of probe image with gallery images of other persons with various pose angles for case 2 of the simulation experiment. The experiment has been repeated for 100 times with randomly chosen faces. In this case the two graphs are not as separated as in case 1. Selecting different thresholds the false accetance rate could be acheived as 0% but genuine persons are denied (false rejection rate) on an average 5% of trials. Average recognition rate is achieved as 88.5%.

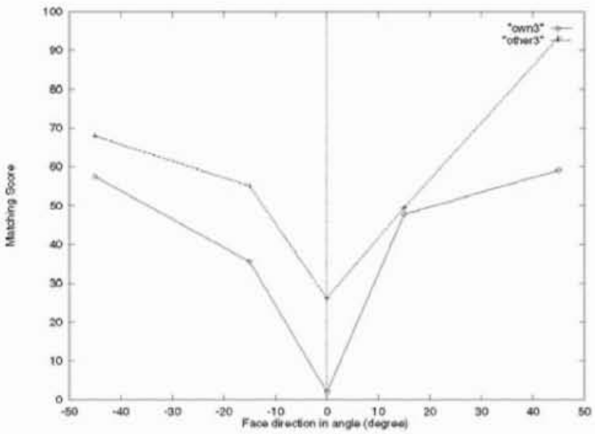

Fig. 8. Simulation Results for Case 3

C. Case 3

Here we used data of faces with 30° apart for training i,e we used faces of each subject with angles -60, -30, 0, 30, and 60 degrees respectively for training the neural network and used other faces randomly for probe images. Neural network with same structure and parameters as in case 1 has been used for learning.

Fig.(8) represents the matching score (distance values) of the probe image with the gallery image of same person and the average score of probe image with gallery images of other persons with various pose angles for case 3 of the simulation experiment. The experiment has been repeated for 100 times with randomly chosen faces. In this case two graphs are not separated much. Proper selection of threshold for matching score has been difficult. False acceptance rate and false rejection rate have been on the avarage more than 10%. The results were not very stable also. This has happened may be due to poor training of the neural network.

V. Conclusion and Discussion

In this work we have presented a simple concept of addressing view invariant face verification problem using learning of feedforward neural network. The concept is based on the assumption of two sets of features, one being view dependant and the other being view independant. In practice such features are difficult to extract. We used some simple implementation and found promising results when number of training data is large i,e, many views are presented, which is ,of course, self explanatory. But with simple features and few training samples with few views the verification rate is not too bad. For the identity features, other features like Gabor wavelets can be used instead of principle component analysis. In fact a transformation or mapping of features to angle invariant and angle dependant feature space could be a good solution for this approach to become successful. The learning and proper tuning of neural network is also important for the success of this approach. Though there are several points to be improved, the initial simulation results with a subset of HOIP data base seem quite promising. Various extension and modification of the proposed approach is currently under investigation.

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