

# Face Recognition Using Gabor Filter And Convolutional Neural Network

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## ABSTRACT

Face recognition involves the extraction of different features of human face and its classification for discriminating it from other persons. Face recognition is quite challenging task because faces are complex, multidimensional visual stimuli and also face recognition rate depends on variations in pose, expression, occlusion, resolution, and illumination. Most of the existing face recognition algorithms give poor performance in the presence of high degree variations in human face images. Hence we propose an approach based on deep learning which uses Gabor filter of feature extraction and Convolution Neural Network for classification in order to improve the performance of face recognition with mentioned variations. The experiments conducted on AT & T database and we attained the efficiency of 89.50%. It is seen that 2.5% improvement in the efficiency as reported in literature. Future work is dedicated to evaluate the performance of proposed algorithm on different dataset with varying illumination and its classification.

## Keywords

Face recognition; Gabor filter; convolution neural network.

## 1. INTRODUCTION

Face Recognition [6] involves recognizing people with their inherent facial characteristics. Humans can easily identify a known face under different conditions and representations. Such an astonishing ability of humans to perceive faces with huge variations has propelled vision researchers to develop automated systems for face recognition based on face images. However, the existing face recognition systems can recognize faces only in a constrained environment and give poor performance in unconstrained environment. A face recognition system [7] [9] can be used in two modes: verification and identification. Face verification involves denying or confirming the identity of a person claimed by him (one-to-one matching). On the other hand, a face identification system involves the comparison of an individual out of a pool of N people (one-to-N matching).

Face recognition is widely used for access control applications such as mobile or computer log-in, video surveillance, information retrieval and human computer interaction [10]. Most of the existing face recognition algorithms [4] provide poor recognition rate in the presence of high degree variations of human face such as,

- (a) Image quality: The essential necessity of face recognition is great quality face image. For choosing the quality of the image we have to consider noise and resolution as they are key factors to decide it. In this manner even the best recognition algorithms fall apart as the quality of the image decreases.
- (b) Variation in illumination: Appearance of the face images varies due to change in illumination and may cause drastic degradation in the face recognition rate.
- (c) Variation in pose and facial expression: Recognition of faces in the wild becomes more difficult due to the variation in pose and facial expression as images are captured in unconstrained settings.
- (d) Variation in occlusion and scale: The face images may have large variation in scale and often contain occlusion which also results in degrading the performance of recognition system.

Therefore recognition of faces in applications like video surveillance, law enforcement, security and multimedia applications has remained unsolved problem as faces are captured or recorded under unconstrained studio settings. By considering the above mentioned challenges, studies in this field have focused much on reducing the effect of changes in illuminations and poses. Therefore, there have been numerous late endeavors to develop algorithms that can perform well with unconstrained face image [11]. In this context, the use of Deep learning models, such as deep belief nets (DBNs), convolutional neural networks (CNNs) [1], and deep auto encoders (AEs), are typically robust to partial occlusions, pose variations, illumination variations and facial expressions.

In our work we will focus on convolutional neural networks [3] [5] as they are Robust against pose and illumination variations and have proved to be highly effective features for face recognition. A convolution neural network, capable of learning local features from input data is used to discriminate facial images. A typical CNN classifier consists of a CNN with alternating sequence of convolution and sub-sampling layers for feature extraction and a softmax layer for classification [13]. To improve the face recognition rate we incorporate Gabor kernels within convolutional neural network. Gabor filters are capable of getting multi orientation information from a face image at few scales, with the inferred data being of local nature.

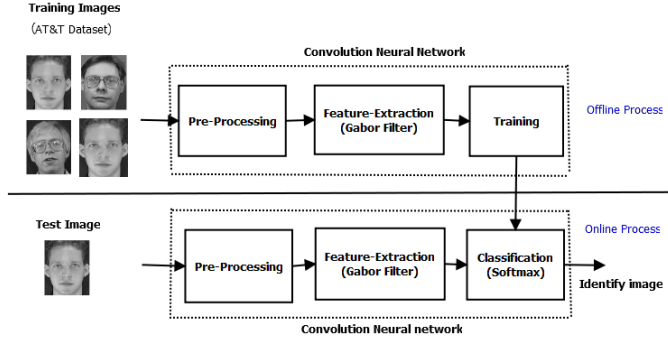
The remaining of this paper is organized as follows: Section 2 presents proposed face recognition algorithm. Section 3 discusses the experimental results and the efficiency of the proposed method, while section 4 concludes the paper and describes the future work.

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## 2. METHODOLOGY

In this section, we look into convolution neural network (CNN) architecture and Gabor filter.

### 2.1 Proposed face recognition algorithm:



**Figure.1 Training and testing process of face recognition algorithm**

The proposed method for face recognition as shown in Figure. 1 consists of two processes: online process and offline process. In online process the images in the database are trained using convolution neural network (CNN). Here we extract edge features using Gabor filters from face and these features are stored into single feature vector. In offline process the feature of a test image is extracted and it is compared with the features which are stored, for recognition. The recognition is done using softmax classifier.

### 2.2 Gabor filter

Gabor filters [2] [8] have turned out to be an effective tool for facial feature extraction. Their utilization in face recognition task is motivated by two main considerations: computational properties and biological importance.

Gabor channel is a Gaussian kernel multiplied by a sinusoidal plane wave and generally used for edge detection. Frequency and orientation of Gabor kernel resemble those of the human visual system, and they have been seen to be most suitable for texture analysis. The filter has a real (eq.2) and imaginary (eq.3) component representing orthogonal directions. The two components might be formed into a complex number (eq.1) or utilized exclusively. Complex:

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) \exp\left(i\left(2\pi\frac{x'}{\lambda} + \psi\right)\right) \quad (\text{eq.1})$$

Real:

$$\left| g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) \cos\left(2\pi\frac{x'}{\lambda} + \psi\right) \right| \quad (\text{eq.2})$$

Imaginary:

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) \sin\left(2\pi\frac{x'}{\lambda} + \psi\right) \quad (\text{eq.3})$$

Where

$$x' = x \cos \theta + y \sin \theta$$

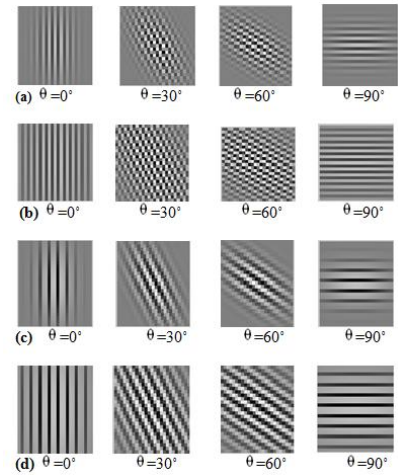
And

$$y' = -x \sin \theta + y \cos \theta$$

The parameters  $\lambda$ ,  $\theta$ ,  $\psi$  are parameters for the sinusoidal part.  $\lambda$  controls the wavelength of this sinusoid.  $\theta$  controls the rotation of pattern see in the image above. A value of  $\theta = 0^\circ$  indicates no rotation and would make the pattern vertical as shown in Figure.2.  $\psi$  is the phase shift of the sinusoid i.e., how much the pattern need to be shifted with respect to the centre.  $\sigma$  is the standard deviation of the Gaussian part.  $\gamma$  controls the aspect ratio of the pattern. The parameters specified above are the inputs. The output value of the calculation is simply the weight of the filter at the (x, y) location.

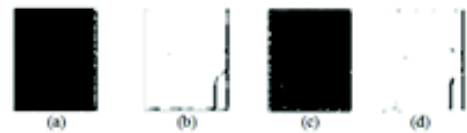
Gabor filters [2] [12] are self-comparative and all filters can be created from one mother wavelet by using different scales and orientations. A filter bank comprising of different scales and orientations of Gabor filters is created. As a result of this Gabor space is obtained by convolving these filters with the face image.

By specifically changing each of the Gabor function parameters [6] [14], we can tune the filter to specific patterns emerging in the images. In Figure.2 we outline the variation of parameters in the shape of the Gabor function. When convolving these Gabor filters with a sample face image, we obtain the filter responses as in Figure.3 and Figure.4.

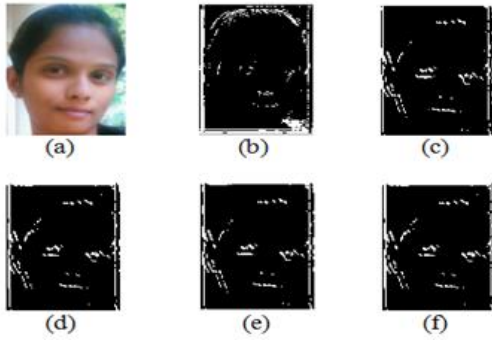


**Figure 2.Examples of Gabor functions for different values of  $\theta$ ,  $\sigma$ ,  $\lambda$ . (a)  $\theta=\{0^\circ, 30^\circ, 60^\circ, 90^\circ\}, \lambda=2, \sigma=4$ . (b)  $\theta=\{0^\circ, 30^\circ, 60^\circ, 90^\circ\}, \lambda=2, \sigma=8$ . (c)  $\theta=\{0^\circ, 30^\circ, 60^\circ, 90^\circ\}, \lambda=3, \sigma=4$ . (d)  $\theta=\{0^\circ, 30^\circ, 60^\circ, 90^\circ\}, \lambda=3, \sigma=8$ .**

By comparing Figure.3 and Figure.4 we can conclude that by integrating Gabor filter with CNN we can extract efficient features from face image hence our proposed algorithm gives better recognition rate than basic CNN.



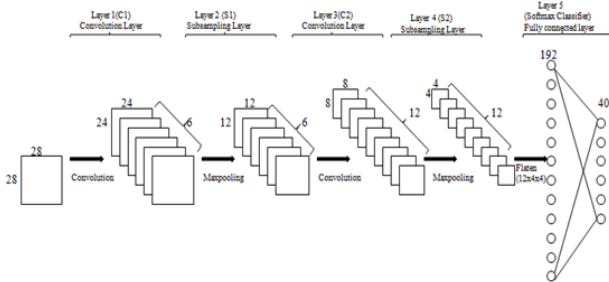
**Figure. 3 (a), (b), (c) and (d) are the responses of simple edge detection filter used in CNN.**



**Figure. 4** (a) sample face image and (b),(c),(d),(e) and (f) are the Gabor filter responses.

### 2.3. CNN Architecture

The convolution neural network we proposed as shown in Figure.5 consists of 5 layers namely, Convolution layer (C1), Sub sampling layer (S1), Convolution layer (C2), Sub sampling layer (S2) and Output layer. The filter size that are used in convolution layers (C1, C2) and sub-sampling layers (S1, S2) are 5x5 and 2x2, respectively. The input to the convolution neural network is 28x28 raw images. The output of the convolution layers (C1) and (C2) gives the feature map sets 6 and 12, respectively. The output of the sub-sampling layers (S1) and (S2) will have the same number of feature map sets as (C1) and (C2), respectively. The output of the CNN is traversed in a row major order to obtain a column vector of dimension 192x1 which is used by the softmax classifier to classify the input images into one of the 40 output classes. The last two layers of the CNN classifier i.e., (S2) and the output layer (softmax) are fully-connected. The CNN classifier is trained using back-propagation algorithm in batch mode, to learn the convolution masks used in C1, C2 and the connection weights between last two layers of classifier.



**Figure.5** CNN Architecture

### 2.4 CNN architecture in detail

- **Input Layer :**  
The 28x28 pixel grayscale image is input to the CNN. It is likewise considered as yield of layer 1.
- **Convolution Layer (C1) :**  
It is used to carry out some convolutions over the image. Here we used the Gabor kernel as the convolution filter of size 5x5. When 28x28 pixel image convolved with this filter results a 24x24 filtered image. This layer has six different filters and these six convolutions will create six separate output feature maps. Thus output of layer 2 is a 24x24x6 matrix.
- **Sub-sampling Layer (S1) :**

In this layer in order to reduce the feature map obtained from the previous layer, we apply the sub sampling operation on the output of the layer 2. Here we are taking the maximum pixel value among the given pixels, those pixels will be replaced by maximum value and the size of mask used is 2x2. It results in reducing the output feature map by factor of 2 in both dimensions, so we obtain a 12x12x6 matrix.

- **Convolution Layer (C2):**  
Layer 3 is another convolution layer with a filter size of 5x5. In Layer 3, we have 12 different filters that will be applied. when we perform the convolutions in layer 1 (C1) input image had a depth of 1 (since it's grayscale), but the input of Layer 3 has a depth of 6. Thus a single filter in layer 3 will be associated to each of the 6 maps in layer 2. So Layer 3 filters will be of size 5x5x6. For a single filter six convolutions (one for every output map in Layer 2) are performed. At this point all the subsequent maps are summed up to make a single 8x8x1 output map. This is accomplished for all 12 filters which give the 8x8x12 as output of the Layer 3.
- **Sub-sampling Layer (S2):** At last, we perform one final sub-sampling operation which is same as that in Layer 3. The subsequent output feature maps are loosened up into final feature vector consisting of 192 values (4x4x12 = 192).
- **Output Layer:** Here softmax classifier is used to classify the above obtained feature vector (one per category) on the output.

## 3. EXPERIMENTAL RESULTS

Here, we estimate the performance of the proposed algorithm for face recognition task. The database AT and T is used to test the proposed method under varying facial expressions, pose and illumination conditions.

For our experiments we used a machine with following specifications: Intel i7 processors with 3.4GHz speed, 24GB RAM, 512GB hard disk and 64 bit- windows 8 operating system.

### 3.1 Results

The AT and T database contains 400 images of 40 individuals. 10 different images are taken for each person under various lighting conditions (center-light, left- light, right-light), facial expressions (happy, normal, sad, sleepy, and surprised, wink) and wearing glasses (glasses, no-glasses). All the images in database are pre-processed.

Here we measure the performance of the proposed algorithm by the parameter efficiency and it is defined as the ratio of number of images classified correctly to the total number of images trained.

We conducted experiment on this database using basic convolutional neural network, proposed CNN with 6/12 neurons and CNN with 12/24 neurons to test the efficiency and we attained efficiency of 85.75%, 87.75% and 89.50% respectively.

### 3.2 Parameter selection:

- 1) Convolutional neural network:
  - Learning rate- 0.5
  - Batch size- 40

- Number of trained images- 400.

For all three models parameter used for CNN are same.

2) Gabor Filter: Basic CNN: It is the basic convolution neural network with adaptive filter.

Proposed CNN with 6/12 neurons: It consist of 6 and 12 filters (neurons) in first convolution layer (C1) and second convolution layer (C2) respectively. Parameters used are:

- Orientation- 30°, 60°, 90°.
- Wavelength- 3 pixel/cycle.
- Sigma- 4, 8, 12, 16.

Proposed CNN with 12/24 neurons: It consist of 12 and 24 filters (neurons) in first convolution layer (C1) and second convolution layer (C2) respectively. Parameters used are:

- Orientation- 30°, 60°, 90°.
- Wavelength- 2 pixel/cycle, 3 pixel/cycle.
- Sigma- 4, 8, 12, 16.

We can observe from the tables 1, 2 and 3 is that, as we increase number of epochs by 10 times; we find increase in the efficiency of 3.75%.

**Table 1. Efficiency for basic CNN**

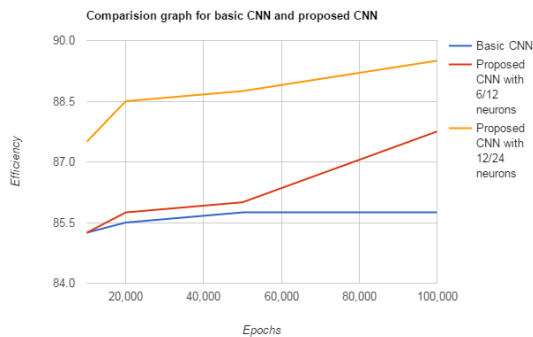
Sl. No	No. of epochs	Efficiency
1	10000	85.25
2	20000	85.50
3	50000	85.75
4	100000	85.75

**Table 2. Efficiency for proposed CNN with 6/12 neurons**

Sl. No	No. of epochs	Efficiency
1	10000	85.25
2	20000	85.75
3	50000	86
4	100000	87.75

**Table 3. Efficiency for proposed CNN with 12/24 neurons**

Sl. No	No. of epochs	Efficiency
1	10000	87.50
2	20000	88.5
3	50000	88.75
4	100000	89.50



**Figure.6 Comparison graph for basic CNN and proposed CNN**

The Figure.6 shows the comparison between basic CNN and our proposed CNN in terms of efficiency. By this graph we can conclude

that as number of epoch's increases the efficiency also increases and the basic CNN gives us 85.75%, while proposed CNN gives 89.50%. Thus overall we achieved 3.75% increase in efficiency.

## 4. CONCLUSION

In this paper, we proposed an algorithm for face recognition under varying pose and illumination conditions using deep convolutional neural networks. The algorithm is tested for AT and T database, which provides the accuracy of 89.5%. Experiments prove that there is a significant improvement (3.75%) in the performance of CNN classifier by incorporating Gabor filter within CNN. Future work includes the use of data-set with varying illumination conditions for improving the efficiency of CNN classifier.

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