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Face Recognition using Gabor Filter based Feature Vector for Mobile Phones

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ABSTRACT
Face Recognition Systems are becoming ubiquitous and inevitable in today's world. Being less intrusive and universal face recognition systems serve as good option for access control and surveillance. Here we are proposing a simple biometric system based on face authentication for access control of a handheld device like mobile phone or pocket pc. The propose systems hardware requirements are very low and it uses Gabor Filter based feature vector for face recognition. The proposed system uses simpler matching method and less computational overhead. The proposed systems accuracy is high for lower number of users; hence it is suitable for handheld devices as the accessing population is less. We have successfully tested this method on handheld device and results are presented here.

General Terms
Pattern Recognition, Security

Keywords
Biometrics, Face recognition, Image processing, Gabor Filters, Handheld Devices

1. INTRODUCTION
Biometrics comprises methods for uniquely recognizing humans based upon one or more intrinsic physical or behavioral traits. In computer science, in particular, biometrics is used as a form of identity access management and access control. It is also used to identify individuals in groups that are under surveillance [1]. Biometric characteristics can be divided in two main classes:

- Physiological are related to the shape of the body. Examples include, but are not limited to fingerprint, face recognition, DNA, Palmprint, hand geometry, iris recognition, which has largely replaced retina, and odor/scent.

- Behavioral are related to the behavior of a person. Examples include, but are not limited to typing rhythm, gait, and voice. Some researchers have coined the term behaviometrics for this class of biometrics [2].

By using biometrics it is possible to establish an identity based on who you are, rather than by what you possess, such as an ID card, or what you remember, such as a password. In some applications, biometrics may be used to supplement ID cards and passwords thereby imparting an additional level of security. Such an arrangement is often called a dual-factor authentication scheme [1], [2], [3].

1.1 Face Recognition
Face recognition analyzes facial characteristics. It requires a digital camera to develop a facial image of the user for authentication. Because facial scanning needs an extra peripheral not customarily included with basic PCs, it is more of a niche market for network authentication. With security cameras presents in variety of public places facial recognition is a viable option for biometric identification. Face biometrics is relatively less accurate but requires low user co-operation.

Among all biometrics listed above, face biometric is unique because face is the only biometric belonging to both physiological and behavioral categories. While the physiological part of the face biometric has been widely researched in the literature, the behavioral part is not yet fully investigated. In addition, as reported in [1], [3], [4] face has advantage over other biometrics because it is a natural, non-intrusive, and easy-to-use biometric. For example [5], among the biometrics of face, finger, hand, voice, eye, DNA and signature, the face biometric ranks first in the compatibility evaluation of a machine readable travel document (MRTD) system on the basis of six criteria: enrollment, renewal, machine assisted identity verification requirements, redundancy, public perception, and storage requirements and performance.

Being very popular and used for long time, a lot of research has been done in face recognition. Many face recognition methods have been proposed in the past few decades. A great number of methods are appearance based. Statistical techniques, such as PCA [6], LDA [7], ICA [8], and Bayes [9], etc., are used to extract low dimensional features from the intensity image directly for recognition. A major disadvantage of the appearance based approaches is that they are sensitive to lighting variation and expression changes since they require alignment of uniform-lighted image to take advantage of the correlation among different images. An elastic graph matching (EGM) method is recently developed [10] to alleviate these problems. The EGM method utilizes an attributed relational graph to characterize a face, with facial landmarks (fiducial points) as graph nodes, Gabor wavelet around each fiducial point as node attributes and distances between nodes as edge attributes. In [11] Wang & Tang have integrated Bayesian algorithm and the Gabor to reduce intrapersonal variation.

Gabor filters are also widely used for extracting facial feature vectors. Zhang et al. [12] have used local Gabor binary patterns. They used a reduced set of local histograms based on Local Gabor Binary Patterns (LGBP). In the proposed method, a face image is first represented by the LGBP histograms which are extracted from the LGBP images. Then, the local LGBP histograms with high separability and low relevance are selected to obtain a dimension-reduced face descriptor. This method gave high reduction in dimensionality and about 94% accuracy. In [13] Gonzalez & Castro have proposed another method based on Gabor filter which uses Shape driven Gabor Jets for face description and Authentication.

In [14] Arivazhagan, Mumtaj & Ganesan Used Multi-resolution Transform such as, Gabor Wavelet Transform. Gabor Wavelet was used to extract the spatial frequency, spatial locality and orientation selectivity from faces irrespective of the variations in the expressions, illumination and pose & then Normalization was done. Then by considering each Eigen faces as each co-ordinate, a co-ordinate system was formed called Face space. In this Face space, each face was considered as a point. By projecting each faces, its co-ordinate values were determined, which were later used for distance measures in discrimination analysis. Achieved accuracy varied from 84 to 94% on various databases considered.

Kotani and Quiu [15] have used vector Quantization of face to generate a codevector histogram, the codebook is defined as a 33 different variation in grey levels. They generated a codevector histogram and matched them. This method is robust towards grey level intensity variations. Average recognition rate was 97%.

DCT was also used for face recognition in [16] Ekenel Stiefelhagen utilized local information by using block-based discrete-cosine transform (DCT). The main idea is to mitigate the effects of expression, illumination and occlusion variations by performing local analysis and by fusing the outputs of extracted local features at the feature and at the decision level. In this algorithm local information is extracted using block-based discrete cosine transform. Obtained local features are combined both at the feature level and at the decision level.

2. GABOR FILTER

Gabor filters are band-pass filters which have both orientation-selective and frequency-selective properties and have optimal joint resolution in both spatial and frequency domains [17], [18], [19]. By applying properly tuned Gabor filters to an image, the true texture pattern information can be greatly accentuated. An even symmetric Gabor filter has the following general form in the spatial domain [20].

$$h(x,y,\theta, f) = \exp\{-\frac{1}{2}\left[\frac{x_\theta^2}{\sigma_x^2}+\frac{y_\theta^2}{\sigma_y^2}\right]\}\cos(2\pi f x_\theta)$$

Where $x_\theta = x\cos\theta + y\sin\theta$, and

$$y_\theta = -x\sin\theta + y\cos\theta \quad (1)$$

This filter consist of a Gaussian envelope (of parameters σ_x and σ_y) modulated by a sinusoid of frequency *f* along the direction of the x_θ axis. The angle θ allows rotating the direction of the response. Example of 2D Gabor filter is shown in Fig. 1. The frequency *f* can be set as the inverse of the average inter-ridge distance. The value of θ is given by

$$\theta_k = \frac{\pi(k-1)}{m} \qquad k = 1...m, \quad (2)$$

Where m denotes the number of orientations (currently m = 8). For each image block of size W ×W centered at (*X*,*Y*), with W even, we extract the *Gabor Magnitude* [207] as follows for k = 1, . . . ,m:

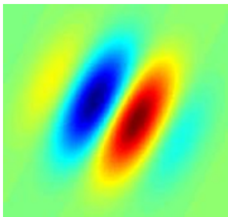


Fig. 1. 2D Gabor Filter Response in Spatial Domain

$$g(X,Y,\theta_k,f,\sigma_x,\sigma_y) =$$

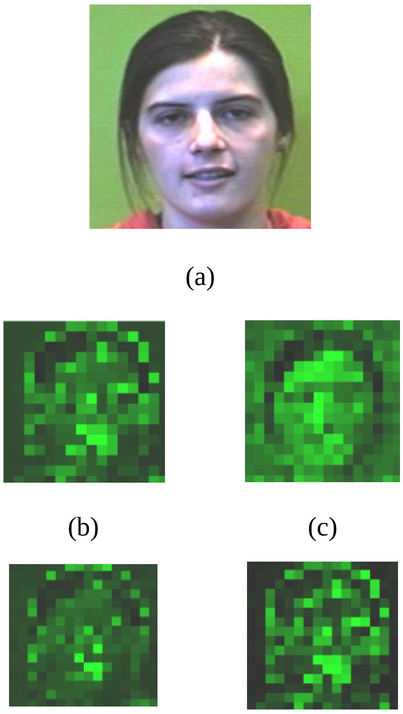
$$|\sum_{x_0=-W/2}^{(W/2)-1}\sum_{y_0=-W/2}^{(W/2)-1} I(X+x_0, Y+y_0)h(x_0,y_0,\theta_k,f,\sigma \quad (3)$$

Where, I(x, y) denotes the gray level of the pixel (x, y). As a result, we obtain *m* Gabor features for each W ×W block of the image. In blocks with texture pattern, the values of one or several Gabor features will be higher than the others (those values whose filter angle is similar to the texture pattern angle of the block). If the block is noisy or having non-oriented background, the m values of the Gabor features will be similar. Therefore, the standard deviation 'Sd' of the m Gabor features allows segmenting foreground and background or identifying specific texture pattern. We use this capacity of Gabor Filters to extract facial information in a feature vector. We calculate the Standard Deviation of the Gabor response of the face image at eight different angle and four different frequencies. In the next section we discuss this technique in detail.

3. GABOR FILTER BASED FEATURE VECTOR GENERATION

We are using 8 Directions of the Gabor Filters (K=0 to 7), the angle values are {θ = 0, 22.5, 45, 67.5, 90, 112.5, 135,157.5}. We have selected the frequency by empirical study. The frequency values are selected so as to capture maximum texture information and give maximum matching. We are using 4, 8, 10, 12 pixel/cycle as the frequency values. Input Face image is selected and scaled to 256x256 pixels or the Face is selected through a 256x256 window. Gaussian envelope (of parameters σ_x and σ_y) are taken as σ_x = 4 and σ_y= 4. The block size is 16X16 pixels (W x W).

For each frequency values we get 8 Gabor Filter Response arrays of size 16 X 16, for each block 8 values of filter response are available, we calculate standard deviations of these values as discussed previously. For four different frequency values we get four different arrays for standard deviation of Gabor filter response.



(a) (b) (c) (d) (e)

RowID	ColumnID	Frequency	Std. Deviation Value
0	0	F1	20
0	1	F1	23
0	2	F1	17
0	3	F1	27
0	4	F1	37
0	5	F1	29
0	6	F1	25
0	7	F1	29
0	8	F1	26
0	9	F1	17
0	10	F1	21
0	11	F1	32
0	12	F1	24
0	13	F1	24
0	14	F1	26
0	15	F1	33

(f)

Fig. 2. Gabor Filter Standard Deviation Maps of an Input face Image (a) Input face Image (b) f=4 Pixel/Cycle (c) f=8 Pixel/Cycle (d) f=10 Pixel/Cycle (e) f=12 Pixel/Cycle (f) Snapshot of Gabor Filter SD Values for one Row (frequency = 4 Pixel/cycle).

Fig. 4.1 shows a typical face image and its corresponding Gabor Filter Standard Deviation maps for four frequency values (4, 8, 10, and 12). This four standard deviation arrays are used as a feature vectors for face. The steps for feature extraction are as listed below.

1. Read the face image, select the ROI. Scale the selected part to 256X256 pixels size.
2. Divide the selected face into 16X16 pixels size blocks.
3. For each block find Gabor Filter response for four different scales (frequency) of 4, 8, 10, 12 pixels/cycle and eight different values of filter angle {θ = 0, 22.5, 45, 67.5, 90, 112.5, 135,157.5}. Store this response in a Multi-dimensional array of size [Angle, Scale, Width/16, Height/W] (Width=Height=256, W=16).
4. For each Scale find Standard Deviation S_d for Gabor Filter response of 8 angles, We will get four different set of values for four different scales. Store these values in a 3-D array of size [Scale, Width/W, Height/W].
5. For each user account read 'N' training faces with different poses or expressions. Repeat steps 1 to 5 for calculating feature vector. Save this data on disk.

We are using K-Nearest Neighborhood classifier to find classifying faces & Euclidian Distance between to feature vectors FV_1(s, i, j) & FV_2(s, i, j) is used for calculating matching distance.

$$\text{Matching Distance} = \sqrt{\sum_{s=0}^{3}\sum_{i=0}^{w-1}\sum_{j=0}^{w-1}(FV_1(s,i,j)-(FV_2(s,i,j))^2} \quad (4)$$

Fig. 3. Enrolled Faces for a User Account in the Database

4. RESULTS

We have tested this method on Faces94 database given by Computer Vision Research Project [20]. We have enrolled 19 persons in the database, for each person we have enrolled 5

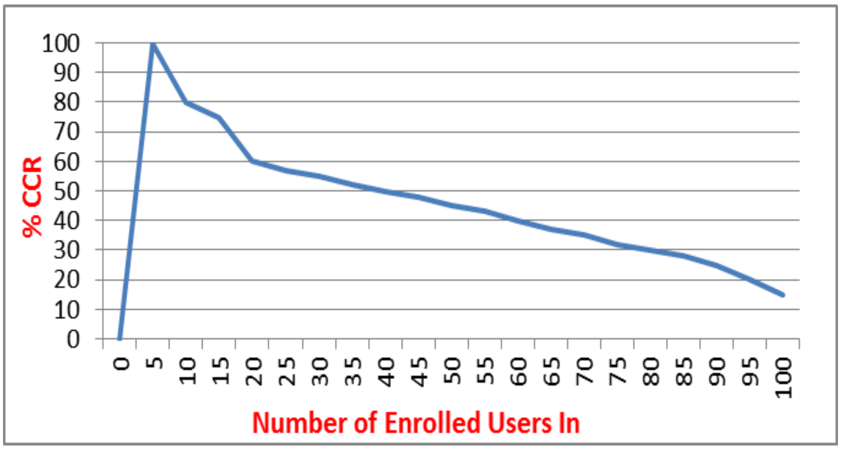


Fig. 4. Correct Classification Rate (CCR) Vs Number of Enrolled Users. Graph Showing Decrease in Accuracy as Enrolled Users Increase.

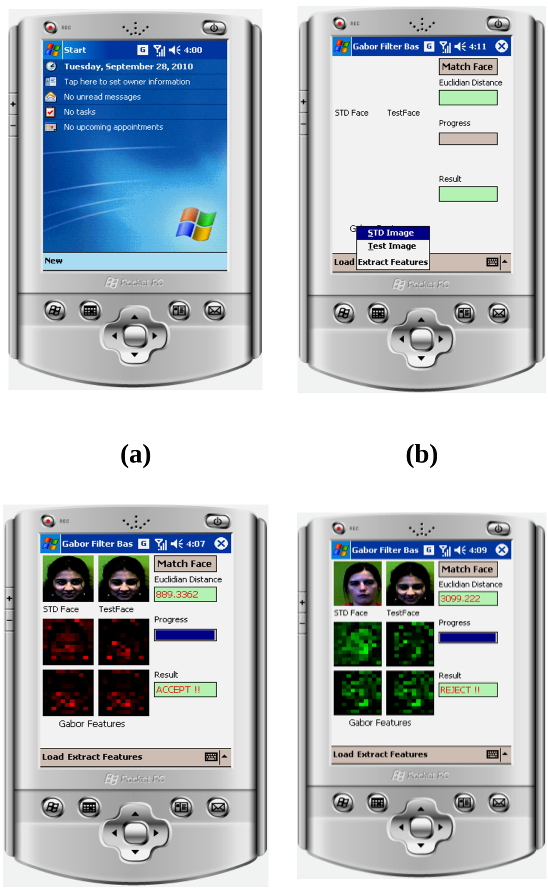
images for training. Another important point is that the feature vector has only integer numbers making computation faster. K-NN Classifier using Euclidian distance between Gabor Filter based feature vector as a classifying metric was implemented. The method is tested on 250 different images from the database. It was observed that the accuracy of algorithm goes on reducing as number of enrolled users increased. For a set of 5 users the accuracy is 97% and for set of 21 users it is 61%.

The analysis shows that the accuracy of the system is poor for high number of users, but at less number of users the system provides good accuracy. This system is suitable for access control of handheld devices and laptops where operating users are very less in number. We have implemented this algorithm for Pocket PC running Windows CE 2003 using Visual C# 2005. Fig.5. Show this program running on a Pocket PC. A sample test for successful and a failure matching is also shown. This program is successfully tested on With a good classifier and database interface this algorithm can be implemented in smart phones and Pocket PC's.

Fig. 5. HTC P3400 Running Developed Application for Face Recognition

5. CONCLUSION

In this paper we have proposed a simpler method for face recognition based on Gabor Filter response. This algorithm gives high accuracy for less number of users and can be used for handheld devices for access control. The proposed method is successfully tested on handheld device HTC P3400 running Windows CE 3.0 as well as desktop computer with Windows XP as operating system. With a good classifier the accuracy can be further increased.



(a) (b) (c) (d)

Fig. 6. Face Recognition Application on Windows CE (a) Pocket PC Emulator (b) Running Application (c) Sample Test for Successful Match (d) Sample Test for Rejected Face Matching

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Appendix: Gabor Filtering Code (C# 2.0)

The code for calculating Gabor filter based feature vector is given below.

```
private void Gabor(int freq)
{
    double f, sigmax, sigmay, xt, yt,
h_gabor, sum;
    int m, k, l, i, j, x0, y0;
    w = width / 16;
    h = height / 16;
    float[, ,] gaborkernel = new float[8,
16, 16];
    // Initializing gabor feaure mean var
SD array
    gaborfeature = new float[8, w, h];
    gaborsdfeature = new float[3, w, h];
    m = 8;      // Number of Gabor Filter
    sigmax = 4; // Gausian Envelope
Parameters
    sigmay = 4;

f = (float)1 / freq;  // 4,8,10,12 Pixels
Per Cycle
for (l = 0; l <= 7; l++) // Loop for
angle thetak
 {
     k = l + 1;
  for (x0 = -8; x0 <= 7; x0++)
   for (y0 = -8; y0 <= 7; y0++)
    {
      i = x0 + 8;
      j = y0 + 8;
      //Finding Gabor envelop
      xt = x0 * Math.Cos(3.14159 * (k -
1) / m) + y0 *
           Math.Sin(3.14159 * (k - 1) /
m);
      yt = -x0 * Math.Sin(3.14159 * (k -
1) / m) + y0 *
```

```
           Math.Cos(3.14159 * (k - 1) /
m);
      h_gabor = Math.Exp(-0.5 * (((xt *
xt) / (sigmax * sigmax))
                + ((yt * yt) / (sigmay *
sigmay)))) *
                Math.Cos(2 * 3.14159 * f
* xt);
      gaborkernel[l, i, j] =
(float)h_gabor;
     }
}
int cx, cy;  //Current X and Y
coordinates- Center of the block;
// Loop Covering Image Blocks of 16 x 16
i,j
for (i = 0; i <= w - 1; i++)
  for (j = 0; j <= h - 1; j++)
   {
      // Loop for Finding magnitude Gabor
feature for each
      // 16 x 16 Block
       cx = i * 16 + 8;  //X
       cy = j * 16 + 8;  //Y
       for (l = 0; l <= 7; l++) // Loop
for angle theta is k
         {
           sum = 0;
           k = l + 1;
               for (x0 = -8; x0 <= 7;
x0++)
                 for (y0 = -8; y0 <= 7;
y0++)
                  {
                   sum = sum +
gaborkernel[l, x0 + 8, y0 + 8] *
                        objimage[cx +
x0, cy + y0];
                  }
          gaborfeature[l, i, j] =
(float)sum;
         }
      }
     return;
}
```