ISSN 2229-5518

A Comparative Analysis of Histogram Of Gradient (HOG), Gabor Filter Bank and DCT based Feature Extraction Methods used for Fingerprint Recognition

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Abstract— Fingerprint recognition is one of the most reliable and popular biometric methods used for person identification. It plays a very important role in forensic and civilian applications such as criminal identification, access control, and ATM card verification. The two major approaches used for fingerprint recognition are image based and minutiae based. The widely used minutiae based representation does not utilize a significant component of the rich discriminatory information available in the fingerprints and local ridge structures cannot be completely characterized by minutiae. Also, minutiae based matching has difficulty in quickly matching two fingerprint images containing different number of unregistered minutiae points. This paper describes a comparative analysis of image based fingerprint recognition using Histogram of Gradient (HOG), Gabor filter bank and Discrete Cosine Transform (DCT) based feature extraction methods. The image based algorithms are used to capture both local and global details in a fingerprint as a compact fixed length feature vector to overcome the disadvantages of minutiae based finger print recognition. The database is formed by capturing 15 fingerprint images per person using 300 dpi fingerprint scanner from 50 persons. The matching technique such as support vector machine (SVM) is used as classifier. Thirteen images from each person are chosen for training and remaining images are used for testing. The recognition performance is measured in terms of False Acceptance Rate (FAR), False Rejection Rate (FRR) and Equal error rate (EER). According to these performance measures, it is observed that the HOG based method yields better results in contrast to other two methods.

Index Terms— HOG, Gabor filter bank, DCT, GAR, FAR, FRR, and EER.

1 Introduction

Due to its immutability and rareness, fingerprints are far and wide applied in many personal identification systems. In fingerprints, the ridge structures offer both global and local information. Therefore, most of the researchers use global or local ridge orientation of fingerprints for classification. Numerous approaches of automatic fingerprint identification are suggested in the literature. The most prevalent ones are based on the minutiae pattern of the fingerprint and are collectively called minutiae based approaches.

There is one more class of fingerprint identification approaches which do not use minutiae features of the fingerprint. They use directly the fingerprint images or features extracted from the image for matching, hence there name image based methods. For small scale fingerprint identification systems, however, it is not efficient to process all the preprocessing steps and the recognition result will heavily depend on the accuracy of each preprocessing step & also it is time consuming. Apart from this, it has higher computational work and lower recognition rate. So, image based HOG, Gabor filter bank and DCT based fingerprint identification methods are used in this paper to overcome the drawbacks of minutiae based methods.

The rest of the paper is organized as follows. Section 2 discusses HOG based fingerprint recognition. Section 3 presents Gabor filter based fingerprint recognition. Section 4 presents DCT based fingerprint recognition. Section 5 describes fingerprint classification using support vector machine (SVM). Section 6 reports experimental results & section 7 gives the conclusion.

2 HOG Based Finger Print Recognition

The histogram of oriented gradients (HOG) is a feature descriptor used in computer vision and image processing for the purpose of object detection. The technique counts occurrences of gradient orientation in localized portions of an image. This technique is similar to that of edge orientation histograms, scale-invariant feature transform descriptors, and shape contexts, but differs in that it is computed on a dense grid of uniformly spaced cells and uses overlapping local contrast normalization for improved accuracy.

The image is divided into small connected regions called cells and a histogram of gradient directions is compiled for the

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ISSN 2229-5518

pixels within each cell. The descriptor is then the concatenation of these histograms. For better accuracy, the local histograms can be contrast-normalized by manipulating a measure of the intensity across a larger region of the image, called a block, and then using this value to normalize all cells within the block. This normalization results in better invariance to changes in illumination and shadowing.

2.1 Feature extraction

An example of generating HOG representation [3] is depicted in Fig. 3. Given an image I, the main steps of generating HOG representation is presented as follows:

Step 1: Divide the whole image into $n \times n$ non-overlapping cells. Each cell contains $c_1 \times c_2$ pixels.

Step 2: Construct a Block by integrating. $b_1 \times b_2$ Block can overlap with each other.

Step 3: For each pixel, $I(x,y)$ the gradient magnitude, $m(x,y)$ and orientation, $\theta(x,y)$ is computed from

$$dx = I(x+1,y) - I(x-1,y) \tag{1}$$

$$dy = I(x,y+1) - I(x,y-1) \tag{2}$$

$$m(x,y) = \sqrt{dx^2 + dy^2} \tag{3}$$

$$\theta(x,y) = \tan^{-1}\left(\frac{dy}{dx}\right) \tag{4}$$

The gradient orientations and gradient magnitudes are shown in Fig. 2.

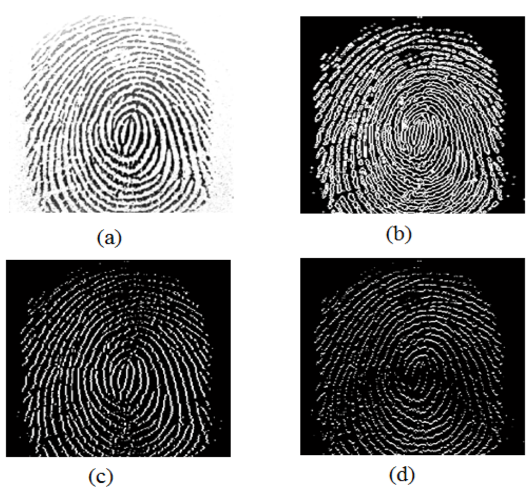

Fig.1. Gradient Orientations and magnitudes: (a) Input image (b) Gradient magnitudes (c) Gradient along x direction (d) Gradient along y direction

Step 4: Divide the orientation range $(0^\circ - 180^\circ)$ into k bins. And then calculate the Histogram within Cell (HC):

$$HC(k)_i = HC(k)_i + m(x,y) \quad \text{if} \quad \theta(x,y) \in bin(k) \quad \text{and} \quad I(x,y) \in Cell_i$$

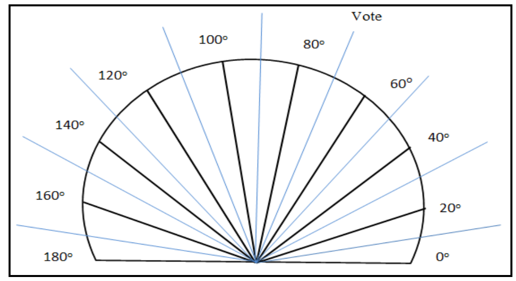

Fig.2. Nine histogram bins spread over 0 to 180 degrees.

Step 5: The Histogram of a block (HB) can be obtained by integrating the HCs within this block:

$$HB_j = \{HC_1, HC_2, \dots, HC_{b_1 \times b_2}\}$$

Then, normalize the vector of HB_j (NHB_j) by L2-norm block normalization

$$NHB_j = \frac{HB_j}{\sqrt{\|HB\|_2^2 + e^2}}$$

Where e is a small constant to avoid the problem of division by zero. If there are N blocks in an image, the last histogram, HOG, can be obtained by integrating all normalized blocks histograms consists of 2×2 cells, and the number of bins,k, is set to 9. As a result, for a fingerprint ROI image with the size of 298×258 there are total 1184 (37×32) cells and 1116 (36×31) blocks, and the dimension of overall HOG is 40,176 $(9 \times 2 \times 2 \times 1116)$ Using principal component analysis dimensionality of the feature vector is reduced from 40,176 to 81.

$$HOG = \{NHB_1, NHB_2, \dots, NHB_j, \dots, NHB_N\}$$

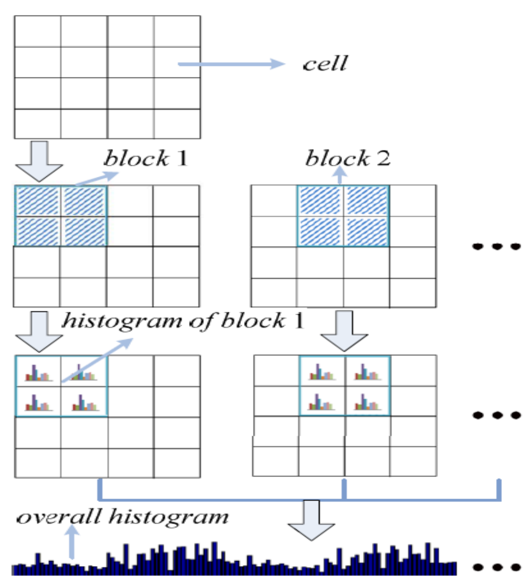

Fig.3. The procedure of generating HOG reprentation from an

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image.

3 Gabor Filter Based Finger Print Recognition

In this section Gabor-Alter-based method for fingerprint recognition is presented. The method makes use of Gabor filtering technologies and need only to do the core point detection before the feature extraction process without any other pre-processing steps such as smoothing, binarization, thinning, and minutiae detection. The greatest significant advantage of Gabor filters is their invariance to rotation, scale, and translation. Furthermore, they are robust in contradiction of photometric conflicts, such as lighting changes and image noise.

3.1 Feature extraction

In the spatial domain, a two dimensional Gabor filter is a Gaussian kernel function modulated by a complex sinusoidal plane wave, defined as:

$$G(x,y)=\frac{f^2}{\pi\eta\gamma}e^{-\left(\frac{f^2}{\gamma^2}x'^2+\frac{f^2}{\eta^2}y'^2\right)}e^{j2\pi fx'}$$

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

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

Where f, θ, γ and η signify the frequency of the sinusoidal wave, the anti-clockwise rotation of the Gaussian envelope and the sinusoid, and the smoothing parameters of the Gaussian envelope along and orthogonal to the direction of the wave respectively.

In Gabor filter design, the highest frequency f_m, the total number of frequencies n_f and the total number of orientations n_0 of the Gabor filters are first specified, the combination of the frequency, the orientation is then performed to create the Gabor filter bank. here, the relationship between f_m and n_0 can be described as below:

$$f_l=a^{-l}f^m,\ l=0,1,...,n_f-1$$

$$\theta_k=k\frac{2\pi}{n_0},\ k=0,1,...,n_0-1$$

Where f_l and θ_k are the l^{th} frequency and the k^{th} orientation respectively.

The scheme of feature extraction tessellates the region of interest in the given fingerprint image with respect to the point of reference. The five main steps in our feature extraction algorithm are

1. An original image (see Fig. 4a) passes through an enhancement algorithm, followed by a binarization process (see Fig. 4b), in order to intensify the gray-scale level of the image.
2. determine a reference point (point of maximum curvature of the concave ridges in the fingerprint image [1]) and region of interest for the fingerprint image;
3. tessellate the region of interest around the reference point (see Fig. 4c);

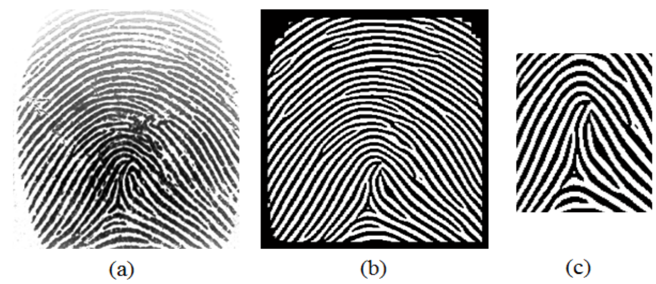

Fig.4. (a) Fingerprint image, (b) Enhanced binary image and (c) Fingerprint ROI.

4. Filter the region of interest in four different directions using a bank of Gabor filters (see Fig. 7).

Fig. 5 shows magnitude Gabor features of two fingerprints belonging to the same person with m=4 $(q=0^\circ,45^\circ,90^\circ,\text{and}\,135^\circ)$ Fig. 6 shows the magnitude Gabor features of two fingerprints belonging to different persons. From Fig. 5 and Fig. 6, we find that the same person's magnitude Gabor features is similar and those of different persons are not. This reveals that magnitude Gabor features can be used as the fingerprint features.

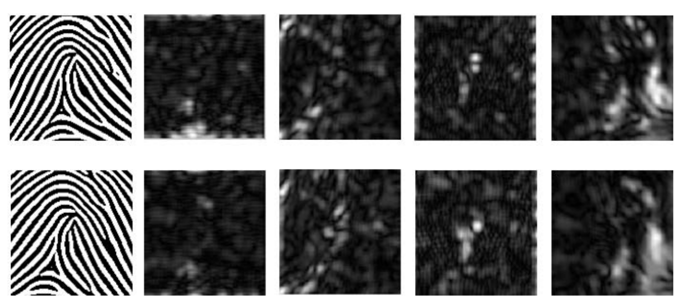

Fig.5. Magnitude Gabor features of two fingerprints belonging to same person with m = 4 $(q=0^\circ,45^\circ,90^\circ,\text{and}\,135^\circ)$

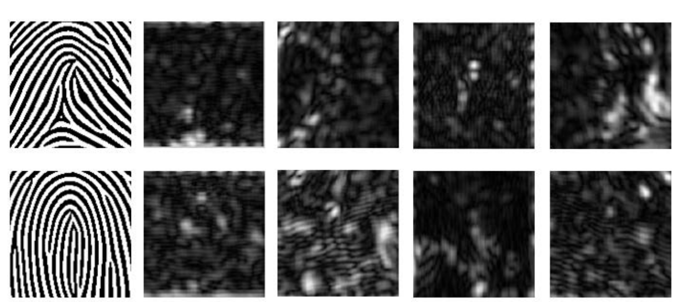

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Fig.6. Magnitude Gabor features of two fingerprints belonging to different person with m = 4 $\left(q = 0^{\circ}, 45^{\circ}, 90^{\circ}, \text{and } 135^{\circ}\right)$

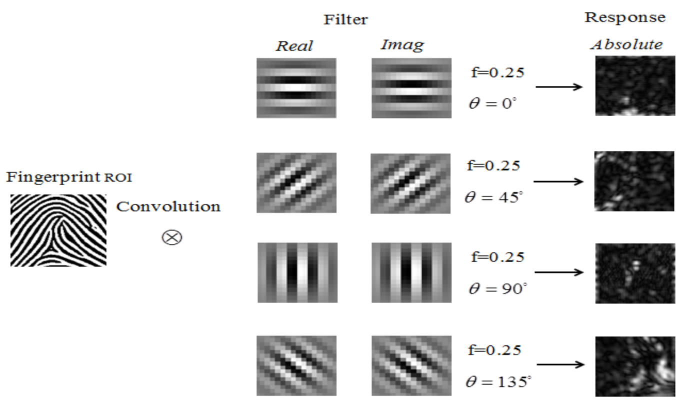

Fig.7. Feature extraction using a bank of Gabor filters.

5. Compute the average absolute deviation from the mean (AAD) of gray values in individual sectors in filtered images to define the feature vector.

The size of the fingerprint images used in our experiments is 298×258 pixels (shown in Fig. 4 a). Fingerprint region of interest (ROI) around the core point is of size 128×128. Using 16 Gabor filters, the dimensionality of the feature vector is $128 \times 128 \times 4 \times 4 = 2{,}62{,}144$.

Since the adjacent pixels in an image are usually highly correlated, we can reduce the information redundancy by down-sampling the feature images by a factor of four, which means that the feature vector will have a size of $2{,}62{,}144/(4\times4)$=16,384. These vectors are then normalized to zero mean and unit variance. In addition to down-sampling; we need to use dimensionality reduction methods to further reduce the size of the feature vectors. Using principal component analysis dimensionality of the feature vector is reduced from 16,384 to 64.

4 DCT Based Finger Print Recognition

In this section, third image based approach called discrete cosine transform (DCT) is considered to fingerprint identification. Fingerprint image is considered as collection of black and white lines, which typically causes oscillatory patterns in the mid-frequency band. The energy distribution over the middle scales in the frequency domain can hence be considered informative features and used for fingerprint identification.

To extract the informative features from a fingerprint image, the image is first cropped to a pixel region, Centered at the reference point, and then quartered to obtain four non-overlapping sub-images of size pixels. Next, the DCT is applied to each sub-image to a block of 64×64 DCT coefficients. Next, the DCT is applied to each sub-image to obtain a block of 64×64 DCT coefficients. Finally, the standard deviations of the DCT coefficients located in six predefined areas, as shown in Fig. 9, are calculated and used as a feature vector of length 6 (24 in total from four sub-images) for fingerprint identification.

Fig.8. (a) Fingerprint image, and (b) four 64×64 pixel sub-images, cropped and quartered at its center.

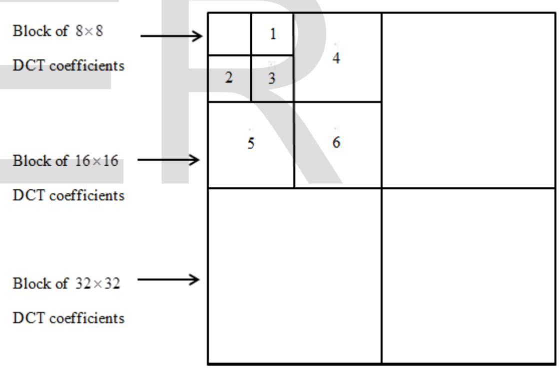

Fig.9. Arrangement in block of 64×64 DCT coefficients used to extract six informative features.

5 Classification Using SVM

LIBSVM is most widely used tool for SVM classification. In SVM approach, the main aim of an SVM classifier is obtaining a function $f(x)$, which determines the decision boundary or hyper plane. This hyper-plane optimally separates two classes of input data points. SVM performs a non-linear mapping from an input space to a high-dimensional space through a kernel, which is an important component for SVM learning. A classification task usually involves separating data into training and testing sets. Each instance in the training set contains one target value (i.e. the class labels) and several attribute (i.e. the features). The goal of SVM is to produce a model (based on the training data) which predicts the target values of the test data given only the test data attributes.

128×128

64×64

Given a training set of instance-label pairs $(X_i, Y_i), i = 1,2,...,l$ Where, $X_i \in R^n$ and $Y_i \in [-1,+1]^l$, the SVM require the solution of the following optimization problem:

$$\min_{w,b,\xi} \frac{1}{2} W^T W + C \sum_{i=1}^{l} \xi_i$$

Subject to, $Y_i\left(W^T (X_i) + b\right) \geq 1 - \xi_i, \ \ \xi_i \geq 0$

Here, training vectors X_i are mapped into a higher dimensional space by the function. SVM finds a linear separating hyperplane with the maximal margin in this higher dimensional space. C>0 is the penalty parameter of the error term. Furthermore, $K(X_i, Y_i) = (X_i)^T (X_i)$ is called the kernel function. The four basic kernels are:

- Linear: $K(X_i, Y_i) = X_i^{\ T} X_j$
- Polynomial: $K(X_i, Y_i) = \left(\gamma X_i^{\ T} X_j + r\right)^d, \ \lambda > 0$
- Radial Basis Function (RBF):

$$K(X_i, Y_i) = e^{\left(-\gamma \|X_i - X_j\|\right)^2}, \gamma > 0$$

6 Results

Three fingerprint identification methods in this paper are implemented by collecting 750 fingerprints (i.e. 15 fingerprints each from 50 persons) from local database. The first 650 fingerprints (13 of each person) are used as training set & remaining 100 fingerprints (2 of each person) are used as test set to demonstrate the performance of the recognition system.

Further comparative analysis of the results from fingerprint identification methods (HOG, Gabor filter bank & DCT) were performed by calculating the standard error rates (false acceptance rate (FAR), false rejection rate (FRR) and equal error rate (EER)). The FRR is the percent error of a system that rejects genuine users as imposters while FAR is the percent error of a system that accepts imposters as genuine users. The point where the FAR and FRR curve intersect is known as the ERR.

The FRR is computed by equation as follows:

$$FRR = \frac{\sum_{i=1}^{N} f(x_i)}{N}$$

$$f(x_i) = \begin{cases} 1, D_x\left(F_i, Y_{C_i}\right) > T \\ 0, Otherwise \end{cases}$$

Where F_i is the feature vector of the test image of the i^{th} user. Y_{C_i} is the feature vector template of the claimed identity that, in this case, the same person as the claimer. T is a predefined threshold. $f(x_i)$ is the function that equals one when the distance is higher than the threshold. $D_x\left(F_i, Y_{C_i}\right)$ is the distance measured from matching the feature vector with the template Y_{C_i} N is the total number of test claimer's images.

The FAR is calculated by equation as follows:

$$FAR = \frac{\sum_{i=1}^{N} f(x_i)}{N}$$

$$f(x_i) = \begin{cases} 1, D_x\left(F_i, Y_{C_i}\right) < T; i \neq j \\ 0, Otherwise \end{cases}$$

Y_{C_i} is the feature vector template of a different user. In general, EER is used to compare the system's optimal performance. lower EER has better performance than the system with higher EER. Fig. 10, Fig.11 and Fig.12 illustrates the results from our experiments in graphs of FAR and FRR versus thresholds for HOG, Gabor filter bank & DCT based finger print recognition respectively.

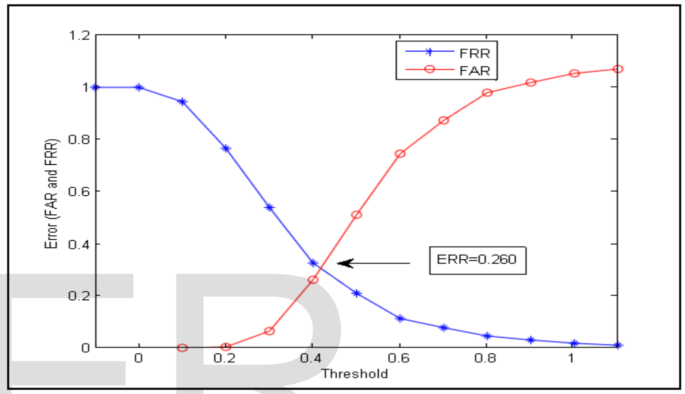

Fig.10. Graph FAR and FRR with vary threshold for HOG based fingerprint recognition.

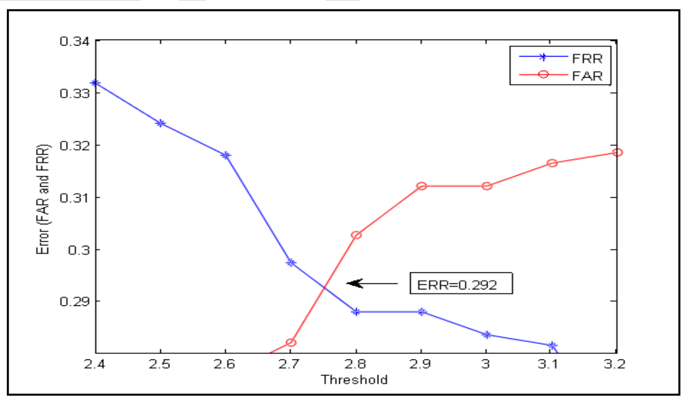

Fig.11. Graph FAR and FRR with vary threshold for Gabor filter based fingerprint recognition.

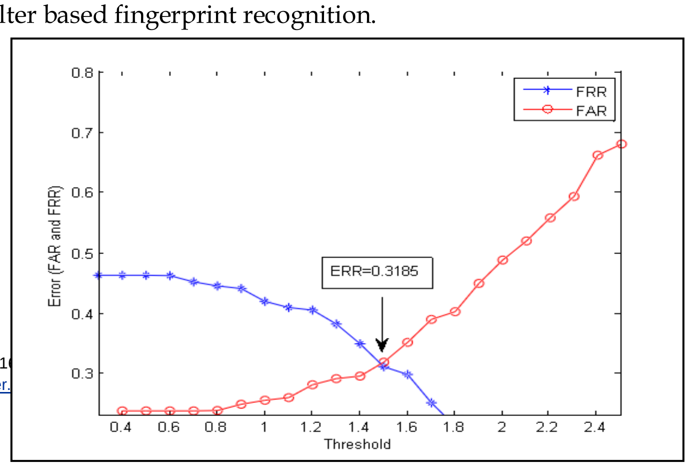

Fig.12. Graph FAR and FRR with vary threshold for DCT based fingerprint recognition.

7 Conclusion

In this paper, comparative analysis of image based fingerprint recognition using Histogram of Gradient (HOG), Gabor filter bank and Discrete Cosine Transform (DCT) based feature extraction methods is described. The recognition performance is measured in terms of False Acceptance Rate (FAR), False Rejection Rate (FRR) and Equal error rate (EER). HOG based method gives ERR value of 0.26, Gabor filter bank based method gives ERR value of 0.292 where as DCT based method gives 0.3185. HOG gives best recognition performance compared to other two methods, Gabor filter bank comes second & lastly DCT.

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