Modified geometry of ring-wedge detector for sampling Fourier transform of fingerprints for classification using neural networks

Dinesh Ganotra, Joby Joseph, Kehar Singh*

Department of Physics, Indian Institute of Technology, Photonics Group, Delhi, New Delhi 110016, India

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Abstract

Sampling of the Fourier transforms of fingerprints is studied with neural networks to detect regions useful for their classification. Ring-wedge detector (RWD) is modified and simulated to sample such regions. The output of the detector is propagated through a three-layer feedforward-backpropagation neural network for checking the classification performance. Modified detector's performance is also compared with that of RWD. It has been found that fingerprints scanned at 500 dpi resolution and cropped to a size of 200 x 200 contain useful information for their classification in a band of width 20 pixels with inner radius approx. 60 pixels.

Keywords: Ring-wedge detector; Neural networks

1. Introduction

With the advances in electronics there is an increasing interest in the optoelectronic components and techniques in optical information processing. One such device is ring-wedge detector (RWD), a photodetector array especially designed to detect Fourier transform (FT) or diffraction pattern in optics. The principle of the device is described in 1972 US patent by George et al. [1]. It consists of two semicircular regions; one of concentric semicircular rings and the other of radially directed sectors subtending equal angles at the center (Fig. 1). The device is designed

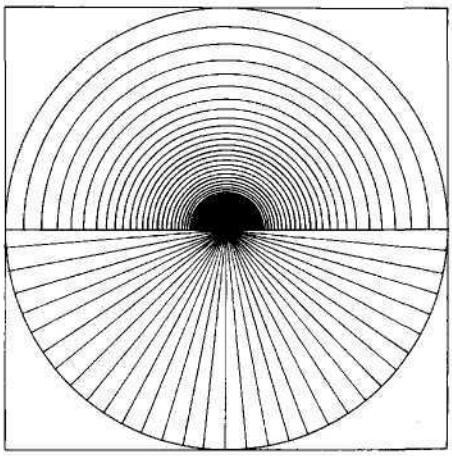

Fig. 1. Sixty-four-elements RWD (32 rings and 32 wedges).

to integrate spatial frequency intensities within specified areas, effectively to reduce the amount of data produced. The frequency regions in the FT intensity pattern are summed up in such a way that the voltages at the output of the detector provides scale and rotational invariant information of the distribution of the spatial frequencies in the input plane. The detector acts as a preprocessor, which reduces the amount of information, the decision-processor has to handle.

FTs have been sampled in the form of rings and wedges by Lendaris and Stanley [2] for automatic pattern recognition. Berfanger and George [3] applied RWD to fingerprint identification. O'Toole and Stark [4] sampled FT in the form of rings for textural pattern recognition. George et al. [5] used RWD and neural networks software to illustrate classification of thumbprints. George and Wang [6] and Berfanger and George [7] applied this to fingerprints sorting. Hexagonal FT of fingerprints was sampled using a RWD by Fitz and Green [8]. Hexagonal sampling lattice is suited to applications that are isotropic in nature, for example, fingerprint, which have no preferred direction. The feature vectors were classified using nearest neighbor classification method. Chen et al. [9] sampled FT of fingerprints using RWD. The feature vectors were subjected to a distance measure for classification. Willis and Myers [10] investigated a fingerprint recognition system for use with low-quality prints and damaged fingertips. In their method, a reference point is located on the image of the fingerprint and a dart-board pattern of wedges and rings is overlaid on the image, with the center of the board at the reference point. The number of minutiae contained in each segment of the grid forms one element of the feature vector.

Another area of application for RWD is particulate analysis and image quality assessment [7,8]. Coston and George [11] applied RWD for recovery of particle size distribution.

Apart from sampling of the FT of fingerprints, features useful for their classification have been extracted using other forms of detectors. Soifer et al. [12]

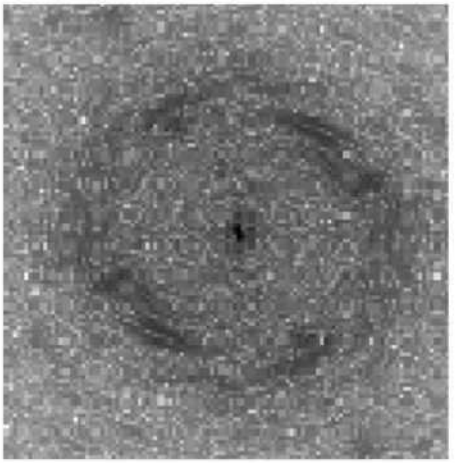

Fig. 2. FT of a fingerprint. (The contrast has been enhanced to differentiate the bands of frequencies from the background.)

discussed an optical-digital method for fingerprint identification using the direction field. Direction field of an image is defined as the angle of tangent to the line image intensity level. Feature vectors corresponding to fingerprints were constructed using such direction fields.

In the case of fingerprints, the distance between the successive ridges lies within a limited range with a characteristic period of 0.5-0.7 mm [11]. The importance of ridge spacing and ridge orientation in fingerprints suggests the utility of spatial-frequency information such as FT features. The spatial spectrum of such images is mainly located (Fig. 2) in a narrow range of frequencies in the vicinity of the carrier spatial frequency. Thus the corresponding FT has only a band of frequencies to be examined.

We sampled the FT of fingerprints by simulating a band form of RWD for various radii. The detector is in the form of a ring of width 20 pixels, with the inner radius varying from 10 to 80 pixels. The detector has 52 sensors arranged as described in Section 2. We carried out the computer simulation by sampling eight scanned thumbprints with each of such detector designs. The simulated detector output for each detector array geometry was propagated through a three-layer backpropagation neural network (BPNN). With this, we determined the specific detector geometry, which samples useful information for fingerprint detection/classification.

2. The modified detector

Sampling of the FT is done to reduce the amount of information the decision-processor has to handle, as it leads to fewer computations in neural networks. The two-dimensional distribution of light is reduced to relatively small set of

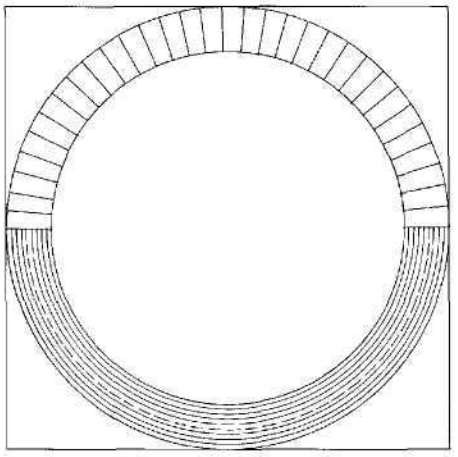

Fig. 3. Fifty-two-elements modified RWD.

numbers—called a sample signature. The detector acts as a preprocessor, which reduces the amount of information, the decision-processor has to handle. The reduction in dimensionality is quite important but should be done with caution so that it contains sufficient information for the subsequent classification to be effective. Mostly the RWDs have been designed with 32 rings and 32 wedges [1,3,6]. The rings make the output rotational invariant and the wedges make them scale invariant. The accuracy of the detector is affected or fine tuned by varying the number and size of the segments used. Ten rings and 12 wedges were found to be optimum in the case of Willis and Myers [10] in their minutiae detector. Our modified form of RWD has 32 wedges and 20 rings (Fig. 3). Thirty-two wedges have been chosen to keep conformity with the literature for comparison in future and 20 rings have been chosen because the ring, which has a width of 20 pixels, was found to contain sufficient information about the reconstruction of the fingerprint as mentioned in Section 2. The FT (modulus square) was sampled using the modified form of the RWD to generate a 52-element vector. For each element of an array, the simulated FT intensity was sampled by integration over the corresponding area of the transform. A trade-off between the dimension of the feature vector and the accuracy of the detector exists and thus the number of wedges and rings have to be suitably determined. An estimate was made of the optimum dimensions of digital RWD for sampling FT of matrices having random numbers as elements by Ganotra et al. [13]. Many of the classifiers have variables or parameters, which require optimization, e.g. number of neurons, etc.

3. Fingerprints used

Fingerprints were scanned at a resolution of 500 dpi. It was found that when the FT of fingerprints is filtered, the fingerprint is reconstructed when the radius of the

low pass filter is about 100 pixels. The images of the reconstructed fingerprints for different low pass filtering radii are shown in Fig. 4. The actual image of the fingerprint is shown in Fig. 4(a). The reconstructed fingerprints when its Fourier spectrum is filtered in a radial area of 5 pixels from the center is shown in Fig. 4(b). Similarly, the reconstructed fingerprints for Fourier spectrum is filtered at 40, 80 and 100 pixel radii are shown in Fig. 4(c)-(e), respectively. Thus a choice of 200 x 200 pixels image for FT of fingerprints was found to be sufficient. Fig. 5 shows the plot of the mean square error (mse) between the actual and reconstructed fingerprint vs.

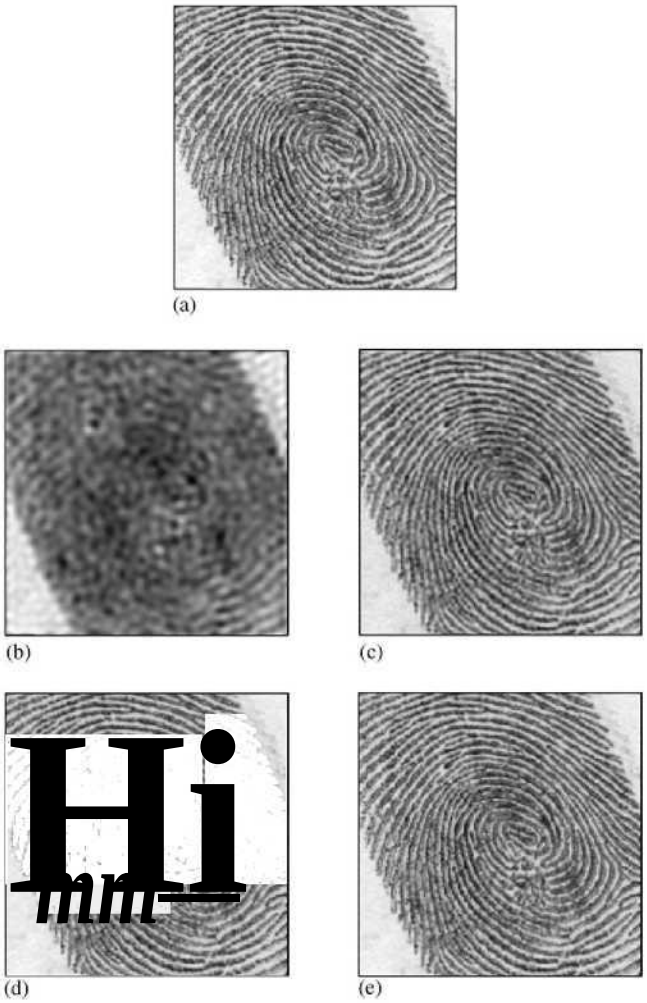

Fig. 4. Reconstructed fingerprints after filtering at the Fourier plane: (a) Original fingerprint; (b) 5 pixels radius; (c) 40 pixel radius; (d) 80 pixels radius; and (e) 100 pixels radius. Note that 100-pixel radius does not have much difference from 40-pixel radius. (With the pixel radius we mean that the FT was filtered in the form of a circle with a radius of x pixels from their centers.)

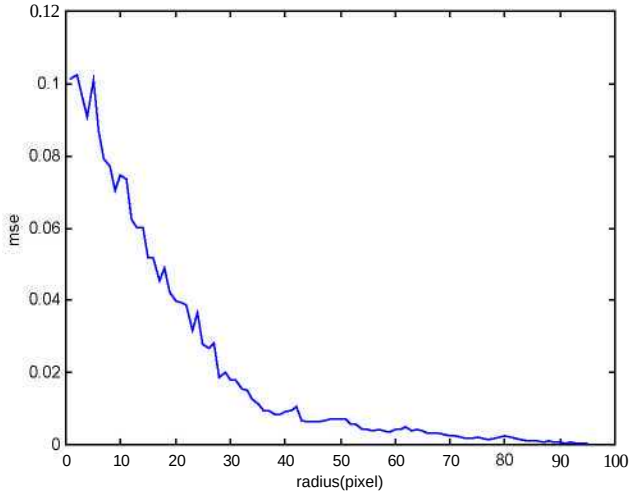

Fig. 5. Plot of the mse between the actual and reconstructed fingerprint vs. the radius of the low pass filter used in their FT filtering.

the radius of the low pass filter used in their FT filtering. From the plot it can be seen that the mse reaches almost zero for a radius of 100 pixels for the low pass filter.

Similar simulations were carried out by filtering the FT of the fingerprint using a band pass filter for estimating the width of the band. It was found that the fingerprint was reconstructed only when along with the band the central dc component of the FT is included during inverse FT. Fig. 6(a) shows the reconstructed fingerprint without the central dc part and Fig. 6(b) shows the reconstructed fingerprints with central dc part. The central dc part was a window of size 3 x 3 pixels. It was found that approximately a band of 20 pixels was sufficient to reconstruct the fingerprint. Our aim in using the modified RWD detector geometry and neural network was to identify the area within the FT of a fingerprint, which distinguishes one fingerprint from another. Note that we have ignored the central dc part during training the neural network as it provides only a background illumination to the fingerprint, which may be necessary to observe it as an image but not for distinguishing one from another.

Variation in the fingerprints from the same person can be due to contrast adjustment, rotation, translation, pressure angle, orientation and various dry and wet pressure levels, etc. Some of the variations can be taken care of but some cannot be avoided for example variations caused due to plasticity of the skin. To generate filters, which make their classifications/identifications invariant to such distortion, a large number of training images are required. If the fingerprints are limited then different impressions of the same fingerprint need to be generated using software. The generated images can be varied in scale, rotation and intensity but these variations introduce digital artifacts due to pixelation.

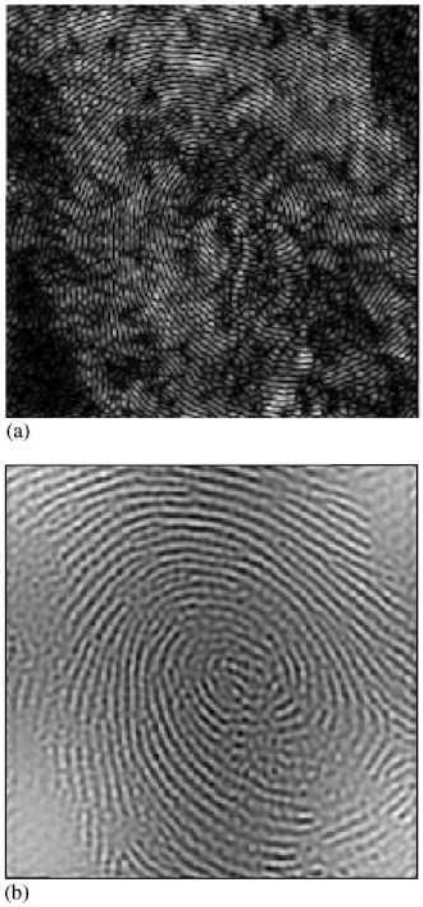

Fig. 6. Reconstructed fingerprints after filtering at the Fourier plane: (a) without central dc part; and (b) with central dc part.

We used four rotated images of the same fingerprint to be recognized. The rotations were of 0°, 90°, 180°, and 270°. Such rotations seem quite unnatural for training, as the fingerprints can be oriented correctly during scanning even with visual examination, but if rotations other than above are brought about using software, then they produce their own digital artifacts. Rotations by these angles do not produce any digital artifacts and thus serve our purpose of training the neural network to extract only the features, which remain invariant in a particular fingerprint.

For fingerprints' identification from a database, computers of crime records bureaus use location of minutiae and angles between them. This vector matching technique finally results in identifying 10-15 fingerprints. Thus, with the help of computers, matching from 1:10,000,00 (say) is reduced to 1:10 within minutes.

However, the decision to select one of these becomes very difficult and requires human intervention. The fingerprints look so similar that even by looking visually at the positions of the minutiae, it becomes difficult to come to a conclusion. Our aim in the present paper is to supplement this human intervention with neural networks.

Correlators are a natural choice when identification is to be made of one fingerprint out of many nearly similar fingerprints. However, to generate a correlation filter, a large number of the prints with different variations of the fingerprint (the one to be identified) are required. If collected from scene of the crime, it is normally difficult to get more than one version of the fingerprint. We have made an attempt to overcome this problem by rotating the same fingerprint by 90°, 180° and 270° and training the neural network with these images. Though the rings in the modified RWD carry redundant information, we have retained them as they help in identifying variations caused due to plasticity of the skin.

A symbolical representation of the data set used for training the neural network is given in Table 1 and for testing the generalization is given in Table 2. Eight thumbprints chosen to train the network were such that, four were supposed to be recognized and belonged to the same subject and four were supposed to be rejected and belonged to different subjects. Since the four rotated version are from the same

Table 1

Set of fingerprints used for training

Fingerprint	Desired output
A	+1
90° rotated A	+ 1
180° rotated A	+1
270° rotated A	+ 1
B	-1
C	-1
D	-1

A, B, etc., belong to different subjects.

Table 2

Set of fingerprints used for testing the generalization

Fingerprint	Desired output
A^0	+1
90° rotated A^0	+ 1
180° rotated A^0	+1
270° rotated A^0	+ 1
E	-1
F	-1
G	-1

A^0 and A belong to the same finger of the same subject but differ in there manner of grabbing. One is flat and the other is rolled.

fingerprint, we have essentially trained the network with only single fingerprint, which is closer to a practical situation. Note that our aim here is to detect one fingerprint out of many fingerprints. The scanned images of the fingerprints used for training were flat and the ones used for testing for generalization were rolled.

4. Algorithm

Fingerprints which were initially on paper were scanned at 500 dpi to 256 gray level images. A two-dimensional FT of each image was calculated on Matlab (Ver. 5.2). As it was shown that useful information about the fingerprints in their FT for the above resolution of images of fingerprints is contained within a radial area of 100 pixels, we cropped the FT of fingerprints to 200 x 200 pixels from the center. The modified RWD was then used to sample these FTs, which generates a vector with 52 elements. Such 52 element vectors for various fingerprints are propagated through a feedforward-backpropagation neural network for training. A three-layer BPNN with 52 input-, and 15 hidden neurons, and 1 output neuron was simulated on neural network toolbox Ver. 3.0 in Matlab Ver 5.2. The transfer function from input neurons to hidden layer was tansigmoidal and from hidden layer to output layer was purelinear. The desired outputs were chosen as + 1 for the class to be accepted and — 1 for the class to be rejected. The learning rate used was 0.05 and the network was trained for 200 epochs. Vectors from eight thumbprints were used for training. Out of these, four vectors are derived from same fingerprint and vary only in rotation. The corresponding desired outputs are chosen to be +1 and —1 (Tables 1 and 2). After the network has been trained, the FT of a generalization-set of fingerprints which is mutually exclusive from the training set, is sampled by the detector and propagated through the network and mse is chosen as the criterion for identification.

5. Results

Fig. 7 shows the plot of the mse of the output of the neural network for generalization set, as a function of the inner radius (in terms of pixels) of the band of the modified form of RWD. It can be seen that the mse reaches below 0.5 when the inner radius of the detector is between 50 and 70 pixels. Thus the FT of fingerprints contains relatively more useful information about their classification when sampled within a ring of width 20 pixels and inner radius between above range. The reason for the local minima observed between the inner radii of 1-20 pixels is discussed in the Section 6. The same data set was sampled with a complete RWD and propagated through a neural network having 64 input neurons The horizontal line shows the mse when a complete RWD of 32 wedges and 32 rings was used. Note the drop in the mse with modified RWD. This clearly suggests that the neural network gets trained better when the FT is sampled for the radii between 50 and 70 pixels.

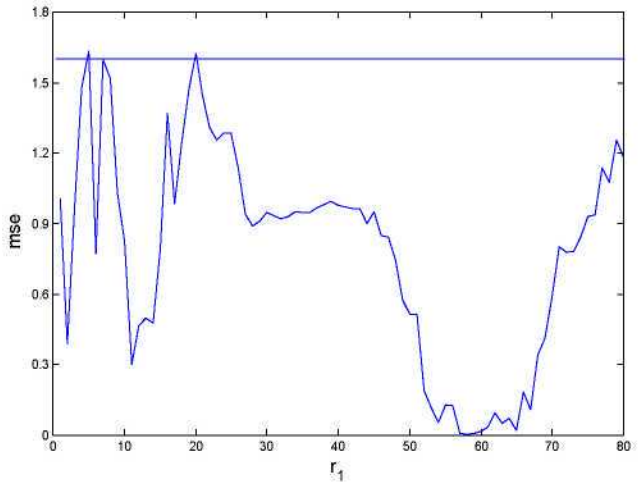

Fig. 7. Plot of the mse of recognition using neural network vs. inner radius *(r1)* of the detector (in pixels).

6. Conclusion

To detect regions of the fingerprint's FT which contain relevant information about their identification/classification, the RWD was simulated in a band form and the radii of the detector were varied keeping the difference between the radii same. This study has determined the specific combination of detectors within the constraints of conventional personnel computer processing performance. It has been found that fingerprints scanned at 500 dpi resolution contain useful information for their classification in a band of width 20 pixels with inner radius approx. 60 pixels.

The reason for the local minima of mse near lower frequencies (Fig. 7) can be that these frequencies might be containing information about the coarse classification of the fingerprints like arches, loops, etc. It may be interesting to study what features can be classified from this region of frequencies.

Acknowledgements

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