

Hartley Transform Based Fingerprint Matching

Sangita Bharkad* and Manesh Kokare*

Abstract—The Hartley transform based feature extraction method is proposed for fingerprint matching. Hartley transform is applied on a smaller region that has been cropped around the core point. The performance of this proposed method is evaluated based on the standard database of Bologna University and the database of the FVC2002. We used the city block distance to compute the similarity between the test fingerprint and database fingerprint image. The results obtained are compared with the discrete wavelet transform (DWT) based method. The experimental results show that, the proposed method reduces the false acceptance rate (FAR) from 21.48% to 16.74 % based on the database of Bologna University and from 31.29% to 28.69% based on the FVC2002 database.

Keywords—Biometrics, Feature Extraction, Hartley Transform, Discrete Wavelet Transform, Fingerprint Matching

1. INTRODUCTION

The proliferation of information access terminals and the growing use of applications (such as commerce, e-voting, and e-banking) involving the transfer of personal data make it essential to provide reliable systems that are user-friendly and generally acceptable. With conventional identity verification systems for access control, such as passports and identity cards, passwords and secret codes can easily be falsified. Biometrics seems to provide a way of overcoming some of these systems drawbacks, by using verification that is specific to each individual. For a long time the use of biometrics has remained limited to policing applications, but in view of its potential advantages, this technology is now being considered for many other tasks.

1.1 Motivation

Commercial applications have been developed, based on facial features, fingerprints, the iris, retinal scans, hand and finger geometry; or the behavioral traits of the individual such as voice print, gait, signature, and key stroking with distinct levels of merits. These biometrics identifiers suffer from limitations, which are overcome by using the unique pattern of ridges and valleys in fingerprint images. The two basic ideas scientists believe about permanence and individuality of

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fingerprints are:

1. Fingerprints never change. Small ridges form on a person's hands and feet before they are born and do not change for as long as the person lives.
2. No two fingerprints are alike. The ridges on the hands and feet of all persons have three characteristics (ridge endings, bifurcations, and dots) that appear in combinations that are never repeated on the hands or feet of any two persons. A ridge ending is simply the end of a ridge. A bifurcation is a Y-shaped split of one ridge into two. A dot is a very short ridge that looks like a “.”.

Even the fingerprints of identical twins are different. The maximum global similarity is observed in monozygotic (identical) twins, which is the closest genetic relationship [1-3]. However, the fingerprints of identical twins have different micro details, which can be used for identification purposes. Fingerprint matching techniques are classified into two types: minutiae based and texture based. In the minutiae based technique, minutiae points like ridge ending and ridge bifurcation are extracted from the fingerprint image and are used for comparing the database image and query image. In the texture-based technique, ridge texture information is extracted by using the Gabor filter. Both of the techniques are computationally expensive. Therefore in this paper we proposed a real valued transform based novel feature extraction technique, which has very low computational complexity.

1.2. Related Work

Most of the fingerprint matching algorithms are based on minutiae points of a fingerprint. In 1990, Hrechak *et al.* [4] developed minutiae based structural matching. To extract the quality minutiae features Sherlock *et al.* [5] proposed directional Fourier filtering for fingerprint enhancement. Nalini *et al.* [6] developed a real time minutiae based fingerprint matching system for large database. Binary tree based minutiae matching was carried out by Jain *et al.* [7]. The minutiae based efficient data structure technique called kd-tree is discussed in [8]. A neural network can be used for detecting the various minutiae points of a fingerprint [9]. The above minutiae based matching algorithms do not give a satisfactory matching rate because ridge ending and bifurcation do not give enough information for matching. To enhance the matching rate some non-minutiae points are integrated with minutiae points. This provides additional non-minutiae information for calculating a more reliable degree of similarity between fingerprint impressions and also considerably improves the matching rate [10]. The fingerprint matching technique based on the energy vectors of fingerprints proposed by Nagaty [11] performs better than minutiae based approach.

The major limitation of the minutiae based technique is that it only extracts the local features of the fingerprint image. In 1999, Jain *et al.* [12] used the Gabor filter to rectify the lacunae of the minutiae based technique. The filter bank based algorithm proposed by Jain, *et al.* [12, 14] uses a bank of Gabor filters to capture both the local and the global details in a fingerprint and proved that this gives better results as compared with minutiae based matching. In [12, 14], eight even Gabor filters are used, which provide only the even features of the image. Complex Gabor filters, which combine both the even and odd features of the image, are discussed in [13]. If we increase the number of Gabor filters then the matching rate also increases, which is shown in

[15] by using sixteen Gabor filters. The Gabor filter gives good results but it has the following limitations:

1. Gabor basis functions are not orthogonal because a large amount of memory is required.
2. The computational complexity of Gabor algorithm is very high, which limits the speed for matching.

To solve the above limitations of the Gabor filter, Tico *et al.* [16] developed the wavelet-based fingerprint matching technique, which has orthogonal basis functions. Though the wavelet-based algorithms are faster as compared to the Gabor based algorithm the results are not good as the Gabor filter. Bharkad and Kokare [17-19] illustrated the comparison of transform-based features for fingerprint matching.

Hence, in this work we proposed the Hartley transform based feature extraction technique, which is faster than the Gabor filter and approximately same computational complexity as the wavelet transform, and it also provides better discriminative information than a wavelet transform.

1.3. Main Contributions

The main contributions of this paper are summarized as follows:

1. First, this paper introduces the new real valued representation by using the Hartley transform based features for fingerprint matching.
2. Second, the algorithm is evaluated in terms of the Genuine Acceptance Rate (GAR), the False Acceptance Rate (FAR), and the order of computational complexity.
3. Third, experimental results are compared with the DWT based approach based on the standard database of Bologna University and the FVC2002 database. This proposed method performs better in terms of recognition over DWT.

The rest of the paper is organized as follows: the discrete wavelet transform based approach for fingerprint matching is explained in Section 2. Section 3 gives a brief introduction of the Hartley transform. Our proposed feature extraction scheme based on the Hartley transform is elaborated in Section 4. The experimental results are discussed in Section 5 and finally, Section 6 provides the conclusion.

2. DISCRETE WAVELET TRANSFORM BASED APPROACH

To extract features from a fingerprint image using the discrete wavelet transform, a fingerprint image is cropped to the size of 128×128 around the core point called the reference point [20]. The Fig. 1 (a) shows the fingerprint image. The cropped image is then quartered to obtain the four non-overlapping sub images of 64×64 as shown in Fig. 1 (b). Discrete wavelet transform is applied to each sub image separately. Let us consider an image $f(x, y)$ whose forward discrete wavelet transform can be expressed in the form of the following general relation:

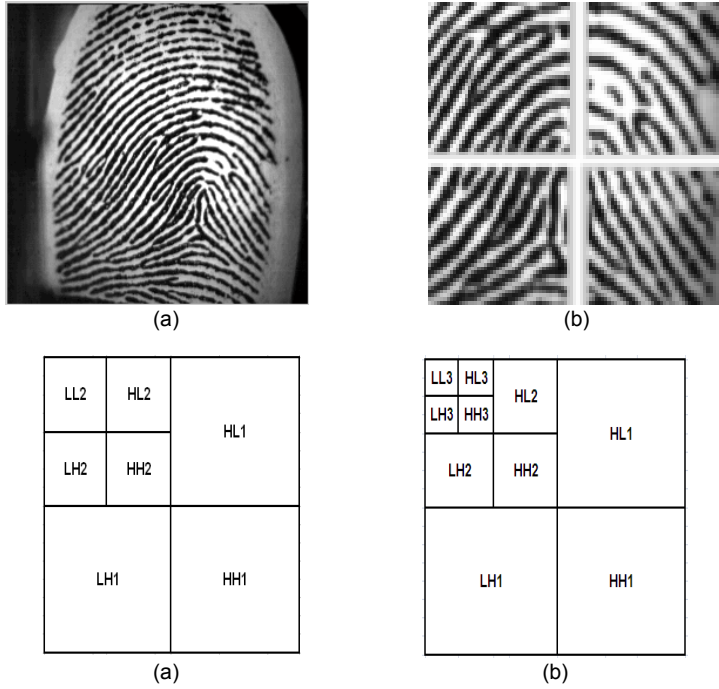


Fig. 1. (a) Fingerprint image (b) Four sub images at the size of 64×64 of a cropped fingerprint image around the core point (c) Two level decomposition of a fingerprint image using DWT (d) Arrangements of the nine regions of DWT coefficients for feature extraction

$$L_j(j_0, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) \varphi_{j_0, m, n}(x, y) \quad (1)$$

$$D_j(j_0, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) \psi_{j_0, m, n}(x, y) \quad (2)$$

Where L_j and D_j gives the approximation and detailed wavelet coefficients of a fingerprint image at level $j-1$.

In Fig. 1 (c) L and H are the low pass filter and the high filter that are used for the decomposition of the fingerprint image. $LL1$ gives the approximation of the original image at Level 1 of the 2D wavelet decomposition. $LH1$, $HL1$, and $HH1$ sub bands give the details of the original image at Level 1 of the 2D wavelet decomposition. Fig. 1 (c) shows the decomposition process by applying the 2D wavelet transform on a fingerprint image up to Levels 1 and 2. For Level 2 decomposition, the wavelet transform is applied to the low-frequency information image (i.e., $LL1$ sub band). Equation (3) gives the representation of two-dimensional wavelet decomposition on the j octaves of a discrete image $f(x, y)$ as 3^{j+1} sub-images.

$$\left(L_j, \{D_j^1, D_j^2, D_j^3\}_{j=1, \dots, j} \right) \quad (3)$$

Where L_j is a low-resolution approximation of the original image, and D_j^k are the wavelet sub images containing the image details at different scales 2^j and orientations k (i.e., at the horizontal, vertical, and diagonal). Each sub image is decomposed for $j=3$ as shown in Fig.1 (d). The standard deviation and energy of the DWT coefficients from each level of wavelet decomposition of each sub image could be computed to create a feature vector of the length $3j$. Decomposition beyond three levels does not give significant contribution in recognition rate; rather it increases the computational complexity. The standard deviation and energy are represented by equations (4) and (5) respectively.

$$S = \sqrt{\frac{1}{N \times N} \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (b(i, j) - M)^2} \quad (4)$$

$$\text{energy}(E) = \frac{1}{N \times N} \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} |b(i, j)| \quad (5)$$

Where $b(i, j)$ represents the pixel values of the decomposed sub images, $N \times N$ is the size of the decomposed sub image, M is the mean of the sub image, S is the standard deviation of the sub image, and E is the energy of the sub image respectively. Both the standard deviation and energy features are used to form a feature vector. Thus the length of feature vector is 72.

3. DISCRETE HARTLEY TRANSFORM

Images are expanded in terms of a discrete set of basis arrays called basis images [21]. Energy conservation, energy compaction, and decorrelation are the important properties of these transforms. The Hartley transform jointly utilizes both the sine and cosine basis functions. Its coefficients are real numbers as contrasted with the Fourier transform whose coefficients are in general, complex numbers. The two dimensional discrete Hartley transform of an $N \times N$ image $f(x, y)$ is defined using equation (6).

$$H(u, v) = \frac{1}{N} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x, y) \left[\cos\left(\frac{2\pi(ux + vy)}{N}\right) + \sin\left(\frac{2\pi(ux + vy)}{N}\right) \right] \quad (6)$$

The inverse discrete Hartley transform is represented by equation (7).

$$f(x, y) = \frac{1}{N} \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} H(u, v) \left[\cos\left(\frac{2\pi(ux + vy)}{N}\right) + \sin\left(\frac{2\pi(ux + vy)}{N}\right) \right] \quad (7)$$

where $0 \leq x, u \leq N-1, 0 \leq y, v \leq N-1$. The Hartley transform is the real, orthogonal, and computationally fast transform. To observe the impacts of the types of transformation on the informative features within a fingerprint image, the fingerprint shown in Fig. 1 (a) is transformed by the DWT and the Hartley transform. The coefficients distribution in frequency domain obtained from both transforms are illustrated in Fig. 2. In Fig. 2 (a) and (b), we can observe that the Hartley transform coefficients have more variation than the DWT ones, which

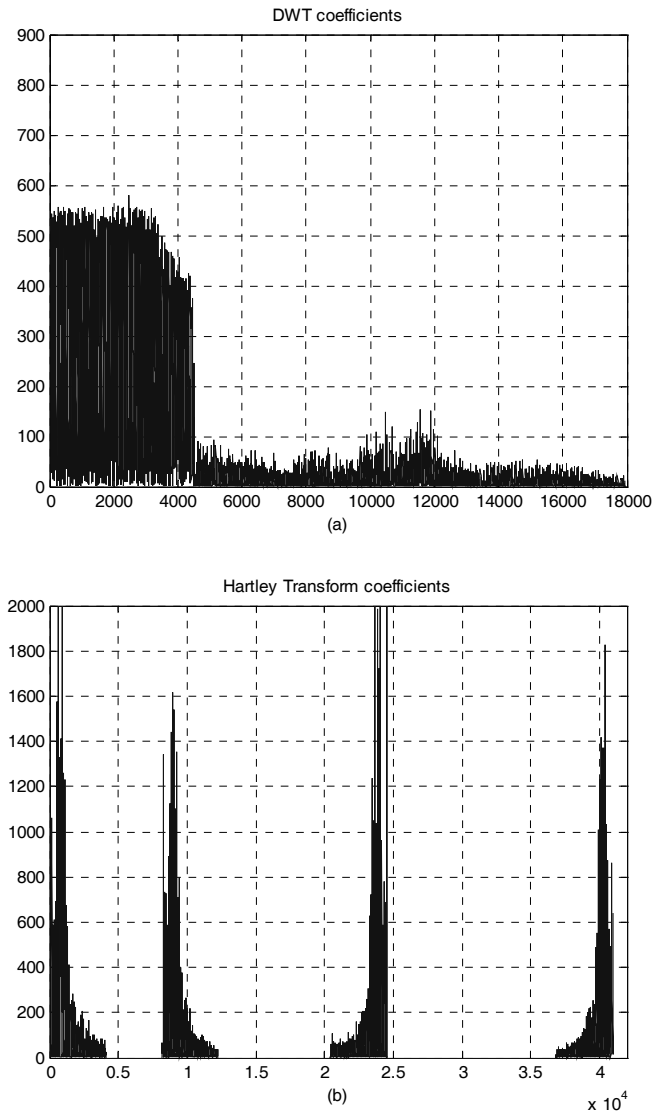


Fig. 2. Comparison of (a) DWT coefficients. (b) Hartley transform coefficients

provide a higher resolution for the fingerprint matching features. In other words, informative features derived from the Hartley transform coefficients are more distinguishable than those from the DWT coefficients. Theoretically, it should provide a higher recognition rate in fingerprint matching.

4. PROPOSED METHOD

The proposed feature extraction method is based on a real valued Hartley transform. A Hart-

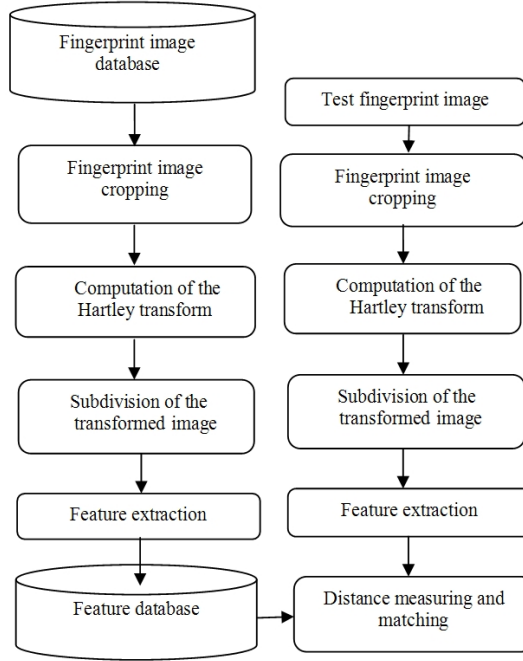


Fig. 3. System Architecture

ley transform of a small portion of fingerprint images is computed and the transformed image is quartered. Each sub image is decomposed according to the energy distribution like DWT. The energy and standard deviation of each sub band is computed to form a feature vector. The system architecture of the proposed method is shown in Fig.3. It consists of functional blocks such as a fingerprint image database, fingerprint image cropping, computation of the Hartley transform, subdivision of the transformed image, feature extraction, feature database, and distance measuring and matching.

4.1 Fingerprint image database

We used the two standard databases DB1 [22] and DB2 to evaluate the performance of the proposed method. DB1 is the database that is available from the University of Bologna. DB2 is the database used that was used in the fingerprint verification competition 2002 (FVC2002 db1_a).

4.2 Fingerprint image cropping

Significant information is present around the core point in a fingerprint image. Instead of using the whole image for feature extraction we used a small portion around the core point. To crop the small portion around the core point, first the core point is detected [20]. An area of 128×128 is then cropped around the core point. Fig. 4 (a) shows the original image and (b) is the cropped image size of 128×128 around the core point.

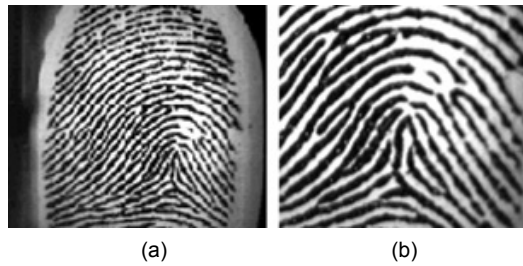


Fig. 4. (a) Original image (b) 128×128 image size that has been cropped around the core point

4.3 Computation of the Hartley transform and subdivision

The Hartley transform of the cropped image is computed using equation (6). Fig. 5 (a) shows the Hartley transform of the cropped image. This image shows that the energy distribution is more at the four corners of the Hartley transformed image as compared to the middle portion. In the Hartley transformed image four corners are brighter than the centre portion. All the frequency domain coefficients of the Hartley transformed image are quartered into equal sub image sizes of 64×64 as shown in Fig. 5 (b).

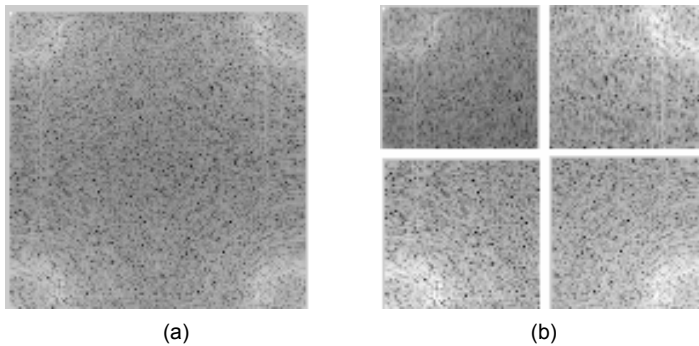


Fig. 5. (a) Hartley transform of a 128×128 cropped image around the core point (b) Decomposition of a Hartley transformed image into four 64×64 sub images

4.4 Feature extraction and feature database

According to the frequency domain characteristics of the Hartley transform, features can be extracted from the fingerprint image, in the same way as the DWT features, by using a new arrangement as illustrated in Fig. 6. Each sub image is decomposed up to three levels as shown in Fig. 6 (a), (b), (c), and (d). Decomposition beyond three levels does not give significant contribution in recognition rate; rather it increases the computational complexity. Extracting features using the standard deviation and energy of each sub band forms the feature vectors of the test and database images. The combination of the standard deviation and energy feature improves the system performance as compared to the individual feature. The energy and standard deviation are computed using equations (4) and (5) respectively. F_i and F_t are the feature vectors for the database image and the test image respectively. Equation (8) gives the representation of

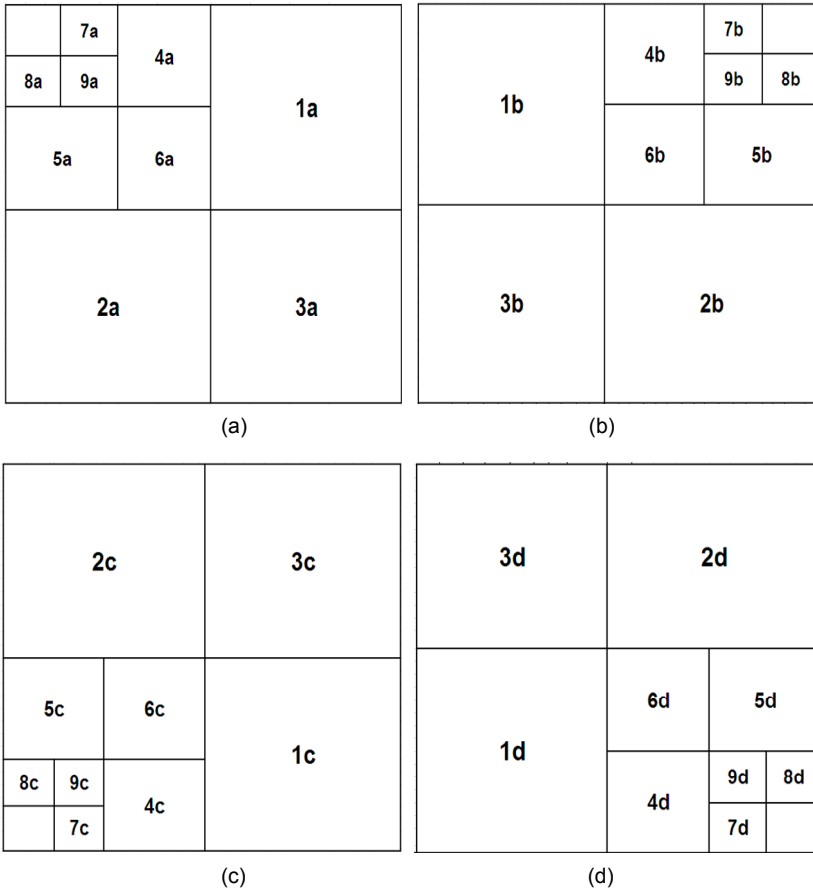


Fig. 6. Arrangements of the nine regions of Hartley transform coefficients for features extraction (a) For the first sub image (b) Second sub image (c) Third sub image (d) Fourth sub image

feature vectors for the database image and the test image.

$$F_i, F_t = [S_1, S_2, S_3, \dots, S_{36}, E_1, E_2, E_3, \dots, E_{36}] \quad (8)$$

The length of the feature vector is equal to the (4 × No. of sub bands × the No. of combined feature parameters) elements. The features of each database image are stored to form a feature database.

4.5 Distance measuring and matching

The distances between the features of the test and database images are computed to find the similarities between them. The test image will be more similar to the database image if the distance between them is small. The standard Euclidean distance between the features of database image F_i and test image F_t is given in equation (9).

$$d_E = \sqrt{\sum_{j=1}^N (F_i - F_i)^2} \quad (9)$$

The Euclidean distance is not always the best metric. The fact that the distances in each dimension are squared before summation places a great emphasis on those features, for which the dissimilarity is large. Hence, we have used the moderate approach by computing the sum of the absolute difference in each dimension rather than their squares, as the overall measure of dissimilarity. This sum of the absolute difference for each dimension is sometimes called the City Block or the Manhattan distance. The Manhattan distance or L_1 distance metric is defined by equation (10).

$$d_M = \sum_{j=1}^N |F_i - F_i| \quad (10)$$

The Manhattan distance performs better than Euclidean distance [23]. These distances are stored in an ascending order. The mean of the top seven greatest distances are computed to calculate the threshold. The threshold value is chosen as being slightly greater than the mean value.

5. EXPERIMENTAL RESULTS

We performed the experiments on the Pentium IV machine using MATLAB 7.0. The results of the proposed method were then compared with the standard DWT based approach. The performance of the proposed approach is measured in terms of GAR, FAR, false rejection rate (FRR), ROC and computational complexity in terms $O(n)$.

5.1 Fingerprint image database

DB1 is the fingerprint database that is available from Bologna University Cesena-Italy [22]. It consists of 140 fingerprint 256×256 images from 20 persons with 7 impressions from each person. DB2 is the FVC2002 db1_a database. We used the 400 fingerprint images of size 388×374 from 100 persons with 4 impressions from each person of DB2 database.

5.2. Performance measurement based on GAR, FAR, and FRR

The performance of the proposed method is evaluated in terms of GAR, FAR, and FRR. Each sub image is decomposed up to five levels using the Hartley transform and DWT. Analyzing the results of each level in terms of GAR, FAR, and FRR finds the optimum level of decomposition. The FRR, FAR, and GAR are given in equations (11), (12), and (13) respectively.

$$FRR = (\text{true claims rejected}/\text{total true claims}) \times 100 \quad (11)$$

$$FAR = (\text{imposter claims accepted}/\text{total imposter claims}) \times 100 \quad (12)$$

$$GAR = (100 - FRR) \times 100 \quad (13)$$

Table 1. Comparison of the GAR, FAR, and FRR of the Hartley transform and DWT with energy + the standard deviation feature measure at different levels of decomposition using the City Block distance metric on the DB1 database

Levels of Decomposition	Hartley Transform			DWT		
	GAR	FAR	FRR	GAR	FAR	FRR
1	85	33.46	15	85.81	30.37	14.18
2	91.53	29.36	8.46	90.51	24.04	9.48
3	95.10	16.74	4.89	95.40	21.48	4.59
4	95.51	16.45	4.48	95	23.22	5
5	95.30	16.14	4.69	93.36	32.86	6.63
Average	92.9567	22.4300	7.5040	92.0160	26.3940	7.9760

Table 2. Comparison of the GAR, FAR, and FRR of the Hartley transform, DWT, and Gabor filter with energy + the standard deviation feature measure at the third level of decomposition using the City Block distance metric on the DB1 database

Method	GAR	FAR	FRR
Hartley Transform	95.10	16.74	4.89
DWT (db4)	95.40	21.48	4.59
DWT (db5)	95.40	22.08	4.59
DWT (db6)	94.79	19.96	5.20
DWT (sym4)	93.36	20.45	6.63
DWT (sym5)	94.28	20.07	5.71
DWT (sym6)	93.46	21.70	6.53
Gabor Filter	95.10	17.29	4.89

Table 1 shows the comparison of the performance of the Hartley transform and DWT (db4) at five levels of decomposition in terms of GAR, FAR, and FRR. The db4 is the Daubechies wavelet, which has four vanishing moments. The results in Table I indicate that the Level 3 decomposition results are better than the Level 1 and Level 2 decomposition results. Beyond the third level of decomposition there is no significant increase in GAR or decrease in FAR. However, it increases the length of the feature vector and hence, the matching time as well. Therefore, we found the third level of decomposition as being the optimum level of decomposition. The average performance of the five levels of decomposition of this proposed method is better than the DWT as shown in Table 1. Table 2 shows the comparison of the performance of the proposed method, the DWT, and the Gabor filter based feature extraction method. The db4, db5, db6, sym4, sym5, and sym6 are Daubechies and Symlet wavelets with four, five, and six vanishing moments respectively. The results of the proposed method are compared with the results of the Daubechies wavelets, Symlet wavelets, and the Gabor filter based method. The proposed method gives 95.10% GAR at 16.74 % FAR, DWT(db4) 95.40% GAR at 21.48% FAR, and the Gabor filter based method 95.10% GAR at 17.29 % FAR . The results in Table II show the good performance of the proposed method over the DWT and Gabor filter.

5.3. Performance measurement based on the receiver operating curve (ROC)

The receiver operating curve is the plot FAR versus GAR. Fig. 7 shows the comparison of the

Hartley transform, the DWT, and Gabor filter in terms of the receiver operating curve on database DB1. The top most curve in Fig. 7 shows the superior performance of the proposed method. Fig. 8 shows the comparison of the Hartley Transform and DWT in terms of the receiver operating curve on database DB2. Fig. 7 and Fig. 8 show the better performance of the proposed method over the DWT and Gabor filter.

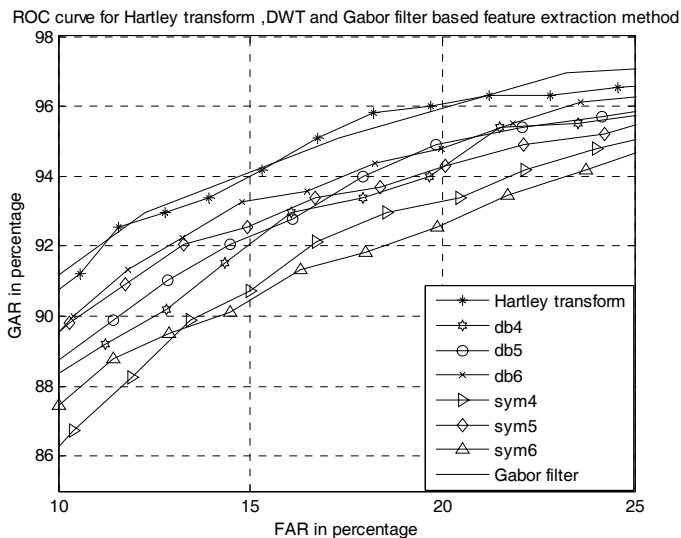


Fig. 7. Comparison of the receiver operating curve of the Hartley transform, DWT, and Gabor filter based on DB1 database

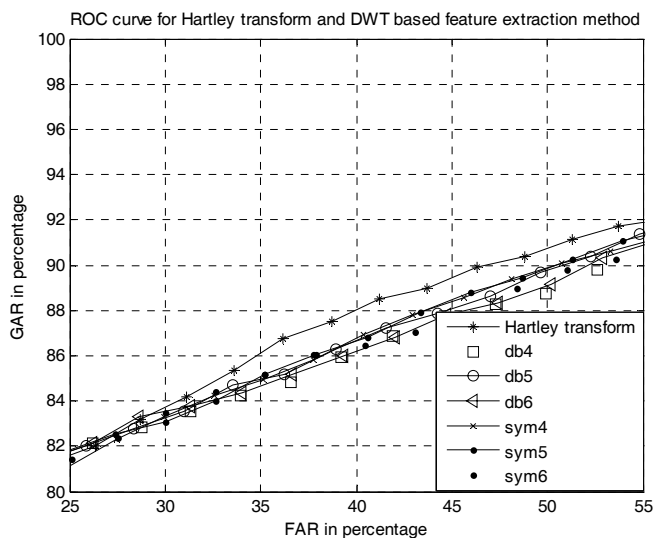


Fig. 8. Comparison of the receiver operating curve of the Hartley transform and DWT on the DB2 database

5.4. Performance measurement based on computational complexity

Computational complexity is measured in terms of the time complexity of the algorithm. Time complexity is measured by the number of elementary operations carried out during the execution of the algorithm. The worst case time complexity can be described using the big O notation. Table 3 shows the time complexity for the Hartley transform, the DWT, and the Gabor filter. The Hartley transform can be implemented using the standard fast Fourier transform (FFT) algorithm. The Hartley transform requires $O(N \log_2 N)$ real operations, unlike the Discrete Fourier transform [24]. The computational time complexity of Hartley transform for a one-dimensional signal of length N is $O(N \log_2 N)$. The time complexity of the DWT and Gabor filter for a one-dimensional signal of length N is $O(N)$. However, to extract the features of an image using a Gabor filter, a set of Gabor filters need to be tuned to several different frequencies and orientations. The computational complexity of these features, because of their non-orthogonality, is more.

The most straightforward technique to conduct the filtering operation is by performing the convolution in the spatial domain. The complexity of the convolution depends directly on the size of the convolution mask. The mask in this case is the Gabor filter. The complexity of calculating the filter response for one point is $O(M^2)$, where M is the width and height of the mask. If the filtering is done on the entire image of size $N \times N$, the complexity becomes $O(M^2 N^2)$. The frequency domain implementation of the Gabor filter requires $O(N^2 \log_2 N)$ operations [25, 26]. DWT gives the orthogonal features, which reduces the redundancy. Hence the DWT is faster than the Hartley transform and Gabor filter. Guo and Burrus [27] proposed the fast approximate Fourier transform via a wavelet transform algorithm to reduce the complexity of the FFT algorithm. Hence, the Hartley transform can be implemented with the fast approximate Fourier transform via a wavelet transform algorithm to approximately obtain the same computational complexity of the DWT.

Table 3. Time Complexity for the Hartley Transform, DWT, and Gabor filter

Method	Time complexity $O(N)$
Hartley transform	$O(N \log_2 N)$
DWT	$O(N)$
Gabor filter	$O(N)$

6. CONCLUSION

In this paper we have shown that the Hartley transform can be efficiently used to extract the informative and discriminative features from the fingerprint image for the fingerprint matching purpose. The experimental results have shown that the proposed method reduces the false acceptance rate (FAR) from 21.48% to 16.74 % based on the database from Bologna University and from 31.29% to 28.69% based on the FVC2002 database over existing methods that use wavelet features. The Hartley transform can be computed with approximately the same computational complexity of DWT using the Guo and Burrus algorithm [27]. It is faster than the Gabor filter, which requires a set of filters oriented at different angles and frequencies. The Hartley transform

is a real valued transform, unlike the discrete Fourier transform. Hence, the Hartley transform requires real additions and multiplications, unlike the discrete Fourier transform, which requires complex additions and multiplications.

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