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Indexing Iris Biometric Database Using Energy Histogram of DCT Subbands

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Abstract. The key concern of indexing is to retrieve small portion of database for searching the query. In the proposed paper iris database is indexed using energy histogram. The normalised iris image is divided into subbands using multiresolution DCT transformation. Energy based histogram is formed for each subband using all the images in the database. Each histogram is divided into fixed size bins to group the iris images having similar energy value. The bin number for each subband is obtained and all subands are traversed in Morton order to form a global key for each image. During database preparation the key is used to traverse the B tree. The images with same key are stored in the same leaf node. For a given query image, the key is generated and tree is traversed to end up to a leaf node. The templates stored at the leaf node are retrieved and compared with the query template to find the best match. The proposed indexing scheme is showing considerably low penetration rate of 0.63%, 0.06% and 0.20% for CASIA, BATH and IITK iris databases respectively.

Keywords: Indexing, Energy Histogram, DCT, Multiresolution Subband Coding, B Tree, Iris.

1 Introduction

Any identification system suffers from an overhead of more number of comparisons in the large database. As the size of database increases the time required to declare an individual's identity increases significantly [15]. In addition to this the number of false positives also increases with the increase in the database size [16]. Thus there are two ways to improve the performance of a biometric system. First one is by reducing the number of false positives and other is by reducing the search space [2]. The search space can be reduced by using classification, clustering and indexing approaches on the database. Applying some traditional database binning approaches does not yield satisfactory results. The reason behind is that biometrics does not possess any natural or alphabetical order. As a result, any traditional indexing scheme cannot be applied to reduce the search time. Thus the query feature vector is compared sequentially with the all templates in the database. The retrieval efficiency in sequential search depends upon

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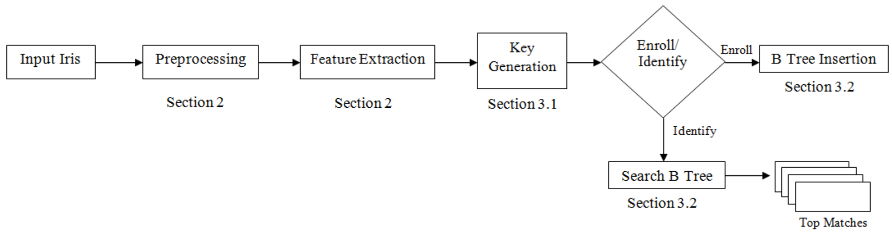

Fig. 1. Block diagram of the proposed indexing scheme

the database size. This leaves behind a challenge to develop a non-traditional indexing scheme that reduces the search space in the large biometric database. The general idea of indexing is to store closely related feature vectors together in the database at the time of enrollment. During identification, the part of the database that has close correspondence with query feature vector is searched to find a probable match.

There already exists some indexing schemes to partition the biometric database. Indexing hand geometry database using pyramid technique has been proposed in [2]. The authors claim to prune the database to 8.86% of original size with 0% FRR. In [1] an efficient indexing scheme for binary feature template using B+ tree has been proposed. In [3] the authors have proposed the modified B+ tree for biometric database indexing. The higher dimensional feature vector is projected to lower dimensional feature. The reduced dimensional feature vector is used to index the database by forming B+ tree. Further, an efficient indexing technique that can be used in an identification system with large multimodal biometric database has been proposed in [4]. This technique is based on Kd-tree with feature level fusion which uses the multi-dimensional feature vector. In [5] two different approaches of iris indexing have been analysed. First one uses the iris code while second one is based on features extracted from iris texture.

In the proposed paper an efficient indexing scheme based on energy histogram on iris database has been studied. The acquired iris image is preprocessed and transformed into a rectangular block. Energy features are extracted from the rectangular block using multiresolution subband coding of DCT coefficients. The energy histogram on extracted features are used to form keys. This key is used to define the B tree and store the iris templates at the leaf that shares similar texture information. The database construction process along with the searching strategy is given in Section 3. The block diagram of system modules along with the section references is given in Fig. 1. The experimental results of the proposed system on three different databases are discussed in Section 4. Conclusions are given in the last section.

2 Preprocessing and Feature Extraction

During preprocessing, the iris circle is localised and transformed into rectangular block known as strip. This transformation makes iris strip invariant to rotation, scaling and illumination. Features are extracted on the strip using Discrete Cosine Transformation (DCT) [11]. A brief description of preprocessing and feature extraction process is discussed in this section. Raw iris image needs to be preprocessed. It involves detection of inner and outer iris boundary using Circular Hough Transform [6]. The annular region lying between the two boundaries is transformed into a rectangular block [7]. The transformed rectangular region is enhanced to improve the texture details and make it illumination invariant [8]. The intensity variation along the whole image is computed by finding the mean of 16×16 block. It helps to estimate the background illumination. The mean image is further expanded to the size of the original image using bi-cubic interpolation. Finally the background illumination is subtracted from the original image. The lightening corrected image is further enhanced using adaptive histogram equalisation approach.

The features are extracted from the preprocessed image using multiresolution DCT. DCT has strong energy compaction property and its coefficients represent some dominant gray level variations of the image. Thus it is the most promising approach for texture classification. The input iris strip is divided into non-overlapping 8×8 pixel blocks which are transformed to generate DCT coefficients. The reason behind using block based DCT approach is that it extracts local texture details of an image. It has been observed that multiresolution decomposition provides useful discrimination between texture. Each block of the computed DCT coefficients has to be reordered to form subbands like 3 level wavelet decomposition. The block of size 8×8 is reordered to transform coefficients into multiresolution form. For a coefficient $D(u, v)$ of the block, ordering is done and stored in S_i where i is defined by

$$i = \begin{cases} 0 & \text{for } m = 0 \\ (m-1) \times 3 + (a/m) \times 2 + (b/m) & \text{otherwise} \end{cases} \tag{1}$$

Let $m = max(a, b)$ for $2^{a-1} \leq u \leq 2^a$ and $2^{b-1} \leq v \leq 2^b$, a and b are the integer values and i ranges from 1 to 10. After reordering, the coefficients $D(1, 1), D(1, 2), D(2, 1)$ and $D(2, 2)$ are stored in subband S_1, S_2, S_3 and S_4 respectively. The multiresolution subband ordering for 8 × 8 block is shown in Fig. 2.

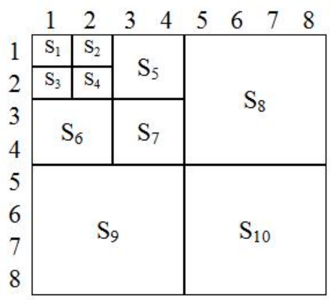

Fig. 2. Multiresolution reordering of 8 × 8 DCT coefficients

After reordering all the DCT blocks, the coefficients from each block belonging to a particular subband are grouped together. Energy value E_i of each subband S_i is obtained by summing up the square of coefficients as

$$E_i = \sum S_i(x, y)^2 \tag{2}$$

Note that the sum of square increases the contribution of significant coefficients and suppresses insignificant coefficients. The feature vector consists of different energy values obtained from 10 subbands.

3 Indexing Scheme

It is expected that the query response time should depend upon the templates similar to the query template and not the total number of templates in the database. Thus the database should be logically partitioned such that images having similar texture patterns are indexed together. To search the large visual databases, content based image indexing and retrieval mechanism based on energy histogram of wavelet coefficients has been proposed in [9]. The scheme provides fast image retrievals. Similar approach has been proposed by considering the energy histogram of reordered DCT coefficients [10]. In the proposed approach biometrics database is indexed using energy histogram of reordered coefficients as given by [10]. The steps involved in indexing are given as follows:

3.1 Key Generation

The feature vector obtained from each image comprises of 10 different energy values one from each subband. The energy histogram (H_i) is build for each subband (S_i) using all the images in the database. This presents the distribution of energy for each subband. Fig. 3 shows the histogram for region S_{10} using all images in the database.

The histogram generated from each subband (H_i) is divided into bins to form logical groups. The texture details of iris strip that have similar energy values (E_i) are placed together in the same bin to have more accurate matches. The size of the bin can be fixed or variable. Here the size of the bin is fixed for experiments. The bins are enumerated in numerical order starting from 1 as shown in Fig. 4. The images falling under each bin are represented on each bar of the histogram. Each image falls under a particular bin of the histogram H_i. This bin number is used to form a global key for indexing. Image key consists of bin number corresponding to each subband. The bin numbers for each subband are combined together using Morton order traversal which places low-frequency coefficients before high-frequency coefficients. The schematic diagram for Morton order traversal is shown in Fig. 5. For example the image I using Morton order forms the key as (3-5-7-8-2-1-4-5-6-7). Similarly all the images in the database obtains keys.

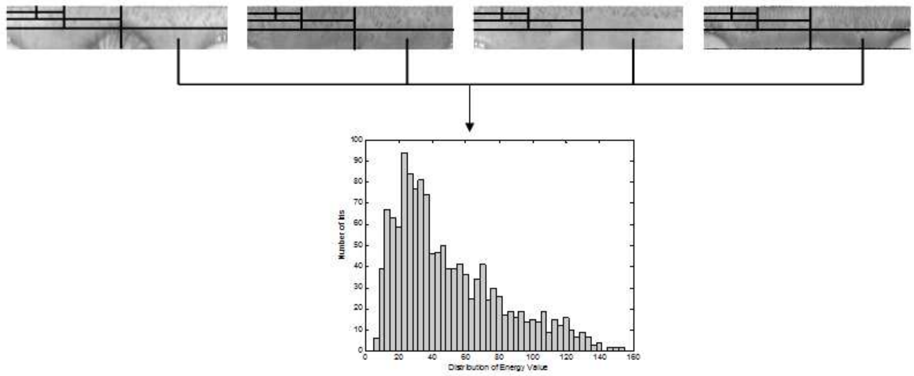

Fig. 3. Energy Histogram of S_{10} region

3.2 Database Creation and Searching

The key is used for inserting an image in the database during enrollment. To store an iris template B tree data structure is used. The degree of the tree is total number of bins that has been constructed for each subband. The height of tree is the number of subbands i that has been taken into consideration. The root node of the tree represents subband S_0 with bins as children that are formed using energy histogram. The leftmost branch represents the first bin and then the next branch represents the second bin and so on. Each node in the second level of the tree corresponds to the immediate following subband. To insert a template in the database, B tree is traversed using the image key generated in Section 3.1. After reaching at the leaf node the template is inserted in the database. Each leaf node in the tree is denoted as a class that contains iris templates. The tree structure used for indexing is given in Fig. 9. Thus more the number of classes lesser will be the retrieval time. The algorithm for inserting an image in the database is given below:

Algorithm 1. database_indexing(n: total number of iris strips)

1. For each image I in the database
2. Find DCT for each 8×8 block
3. Reorder the coefficients using subband coding
4. Find total energy value of each subband (S_i)
5. Construct energy histogram (H_i) for each subband using n images
6. Divide each histogram into bins and enumerate them
7. Obtain a key for I using bin numbers of each (H_i)
8. Traverse the tree using key
9. Store the image at the leaf node

The best match for query strip is obtained by searching the database using the key. Each block of the image is divided into subbands using multiresolution reordering of coefficients. The coefficients of each subband is used to compute

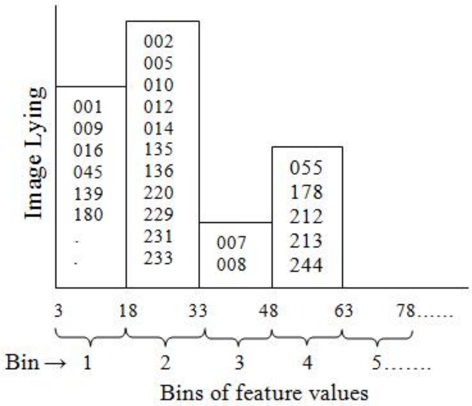

Fig. 4. Logical Grouping of Energy Histogram

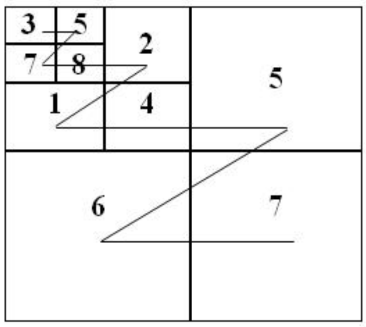

Fig. 5. Global key formation using Morton order traversal

Algorithm 2. searching(q: query strip)

1. Find blockwise DCT coefficient of q
2. Reorder the coefficients using subband coding
3. Find energy value of each subband (S_i)
4. Construct query image key using histogram bins
5. Traverse the tree using complete/partial key
6. Retrieve all K images stored in a class
7. Perform comparisons of q with K
8. Find the probable match

the energy values. The key for query image is calculated by finding bin number of each subband using bin allocation scheme given in Section 3.1. This key is used for traversing the tree to arrive at the leaf node and retrieve the images stored in a particular class. The query image is compared with the retrieved images to find a suitable match. However if the complete key is used for traversing the tree then the probability of finding exact match becomes less. Thus partial key is used that is constructed from first B subbands where B is less than total number of subbands i. The images that fall in the same bin for the first B subbands are retrieved and compared with the query template. The step-wise process for finding a query is given in Algorithm 2.

4 Experimental Results

The proposed indexing algorithm has been tested on CASIA [13], BATH [14] and Indian Institute of Technology Kanpur (IITK) iris databases. CASIA iris database comprises of 2655 images from 249 individuals. The camera for acquiring images is self designed by the university with NIR illumination scheme. Most of the images were captured in two sessions, with at least one month interval. The acquired image is of high quality with very rich texture details. The resolution of the acquired image is 320×280 pixels. Database available from BATH university comprises of 2000 iris images of 50 subjects each from left and right eye. Within each folder there are two subfolders - L (left) and R (right), each containing 20 images of the respective eyes. The images are in grayscale format with 1280×960 resolution. The database collected at IITK consists of over 1800 iris images taken from 600 subjects (roughly 3 images per person) from left eye. The images are acquired using CCD based iris camera along with uniform light source. The image resolution is 640×480 pixels.

The performance of an identification system is measured in terms of bin miss rate and penetration rate. Bin miss rate is obtained by counting the number of genuine biometric samples that has been mis-placed in a wrong class [12]. Penetration rate is defined as the percentage of total database to be scanned on an average for each search. The lower the penetration rate, more efficient the system. In estimating penetration rate it is assumed that the search does not stop on finding the match but continues through the entire partition.

A comparative study on performance rates is done by changing the number of subbands. The number of subbands determines the length of the key. To find

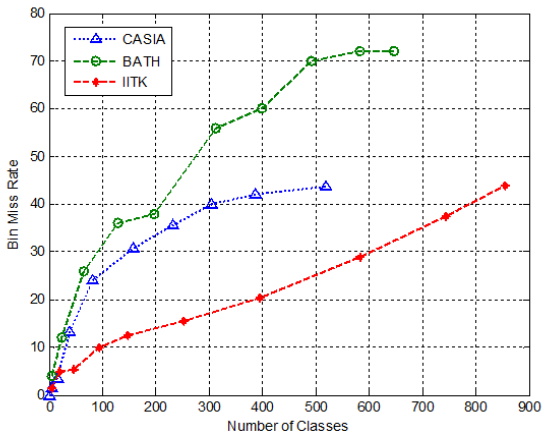

Fig. 6. Bin miss rate for change in number of classes

Table 1. Performance rates for change in the number of classes for CASIA, BATH and IITK datasets. BM: Bin Miss Rate in (%), PR: Penetration Rate in (%), #: Number.

	CASIA			BATH			IITK		
Subband(#)	**Class(#)**	**BM%**	**PR%**	**Class(#)**	**BM%**	**PR%**	**Class(#)**	**BM%**	**PR%**
1	2	0.00	99.69	5	04	26.14	5	1.5	41.44
2	5	1.60	35.96	23	12	7.69	19	5.0	17.21
3	16	3.60	22.70	66	26	3.04	46	5.5	9.24
4	39	13.2	10.23	130	36	1.42	93	10.0	4.77
5	82	24.0	6.12	197	38	0.92	148	12.5	3.25
6	158	30.8	3.46	313	56	0.49	252	15.5	1.56
7	233	35.6	2.63	399	60	0.30	396	20.5	0.92
8	304	40.0	1.77	492	70	0.16	584	29.0	0.50
9	387	42.0	1.22	583	72	0.09	744	37.5	0.27
10	519	43.6	0.63	648	72	0.06	856	44.0	0.20

an exact match the tree is traversed using all the subbands. However to obtain similar matches the tree traversal will stop before reaching the leaf and images having the same partial key is retrieved to find a match. The large set of images will be obtained using partial match which in turn increases the penetration rate. For database construction, an input image is divided into 10 subbands using 8×8 block. Further energy histogram of each subband is divided into 5 bins. Thus every node in B tree is of degree 5. For the sake of convenience fixed number of bins are taken into consideration.

The bin miss rate and penetration rate is obtained by varying the number of subbands. With the change in the number of subbands the number of classes formed at leaf node also changes. Table 1 shows the number of classes, penetration rate and bin miss rate by varying the number of subbands for CASIA, BATH and IITK databases. From the table it has been observed that with increase in the number

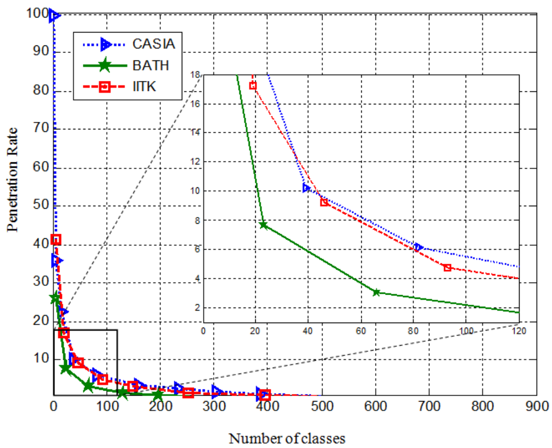

Fig. 7. Penetration rate for change in number of classes with enlarged view of the selected portion

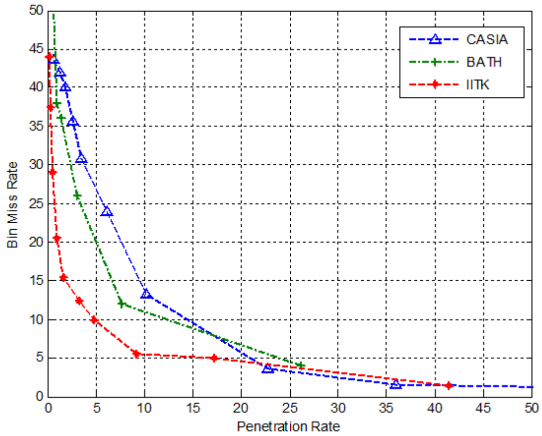

Fig. 8. Graph showing relationship between Penetration Rate versus Bin Miss Rate

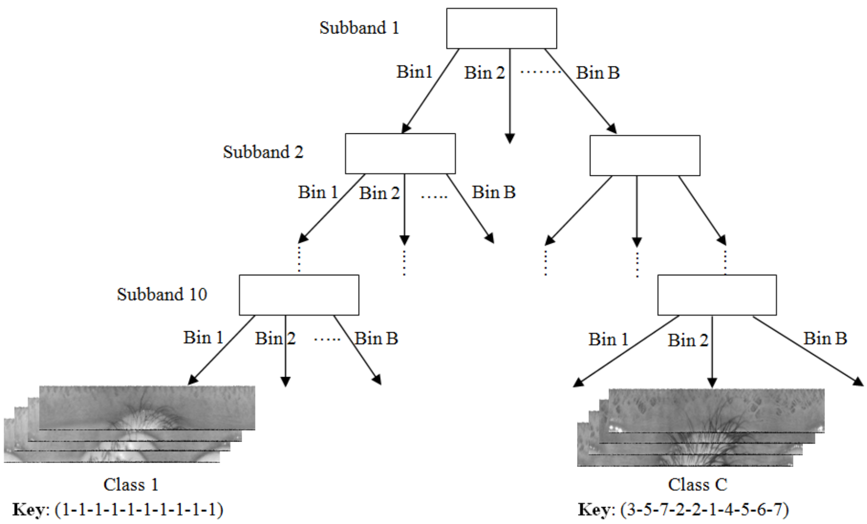

Fig. 9. B tree data structure for storing iris templates

of subbands the number of classes (#) also increases. This is because with less number of subbands the length of global key reduces. The tree is not traversed completely till the leaf node and the images that have same partial key are used to find the match. Hence probability of finding an image is higher in partial traversal compared to complete traversal. The bin miss rate reduces for partial traversal. However, partial traversal gives higher penetration rate due to increase in the number of templates stored in each class. If number of subbands is 2, CASIA database shows bin miss rate of 1.60% and penetration rate of 35.96%. However if number of subbands is 10, the penetration rate reduces significantly to 0.63%. Similar results are obtained for BATH and IITK databases (Table 1). Thus there exists a trade off between the two evaluation rates. The number of subbands used for traversal should be chosen carefully so that both bin miss rate and penetration rate are optimal. Fig. 6 shows change in bin miss rate for change in number of classes. The graph is plotted for all the three databases. Similarly penetration rate is plotted for different number classes as shown in Fig. 7. Fig. 8 represents the relationship between the penetration rate and bin miss rate.

5 Conclusion and Future Work

In the proposed paper, an effort has been made to reduce the search time of iris identification system. A non-traditional indexing scheme has been applied using energy histogram of DCT coefficients. The results are obtained on three available databases. The databases are collected taking various important factors into consideration like difference in time, transformations etc. The number of classes varies depending upon the length of the key. For partial key, the bin miss rate is 1.5% with penetration rate of 41%. For complete key, the bin miss rate increases to 44% while the penetration rate reduces significantly to 0.20%. The two error rates have inverse relationship to each other and is greatly dependent on the number of subbands that are taken into consideration for forming the key. The length of key has to be chosen depending upon the application context and level of security. From the results it can be inferred that the system can be deployed for filtering the database using partial keys. This reduces the penetration rate of the system by grouping the irides with similar texture information. Further, an efficient matching strategy can be applied on the filtered database for finding the exact match. In future the performance of proposed indexing scheme can be extended in the context of invariance to scale and rotation.

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