IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Iris Classification Based on K-SVD Dictionary Learning Algorithm

[1]Arati Manjaramkar, [2]Atul Pagare

Department of Information Technology,
S.G.G.S. I E&T, Nanded,
Maharashtra, India-431606

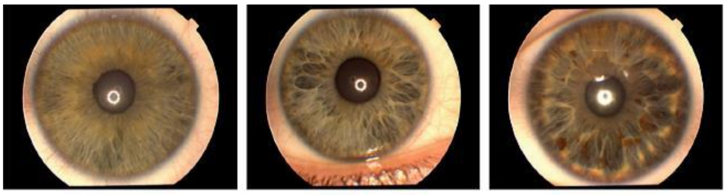
Abstract: Biometric authentication system essentially deals with pattern recognition. All biometric authentication systems must have unique and small error in authentication affect on overall accuracy of system. When any biometric data runs into large scale then classification time complexity increases to deal with time complexity in recent years there has been lots of development in sparse representation of signal. It gives linear combination of image signals. Sparse representation enables feature extraction, regularization of inverted problem and more. Decomposing the image signal to fit into dictionary by using any pursuit algorithm is new emerging activity in signal processing. This paper introduces classification of human iris using iterative K-SVD algorithm. It is flexible with any pursuit method. We analyze K-SVD and demonstrate it with iris dataset. Uniqueness of iris used to create authenticated system where accuracy of classification is very necessary. Predefined iris classes use to for faster retrieval of identities. It's also helpful to identify duplicate entries in data based on unique fiber structures of iris images. UPOL standard iris database is used for experiment.

Index Terms - **Biometrics, Iris fibers, iris classification, K-SVD, Sparse representation, dictionary learning, atom decomposition., image segmentation, image resolution, optimization.**

I. Introduction

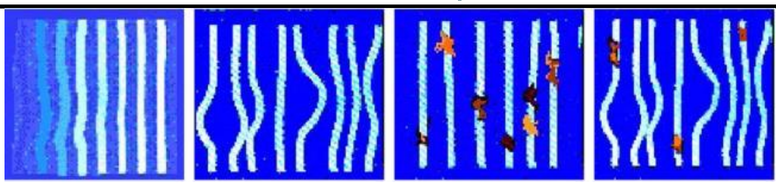
A unique identity enrollment for every citizen of country removes the requirement of multiple documentary evidences for services provided by government and public sectors also cardless design increases security and low cost. Uniqueness of biometric data plays important role when biometric data runs into billions this biometric data mainly facing problem of duplication. De-duplication deals with removing duplicate entries of same object from biometric data also de-duplication is time consuming task.

As compare to other leading biometrics such as face and finger print, iris recognition is simply the most accurate. While many confuses it with retinal scanning, iris recognition mainly ideals with taking a picture of the iris and this image is used for authentication due to properties of iris like stable, unique, flexible, reliable and non-invasive. The unique and complex fiber structure gives importance to iris. First iris recognition system is given Daugman with the iris texture provides help of gabor filter and iris codes [1], [2], [3], [4]. Gradient iris segmentation by using Laplacian pyramid construction is given by Wiles [5]. Also iris classification methodology using hierarchical visual codebook is proposed by Sun and Zang [6], block wise texture survey by Ross and Sunder [7] where color coding proposed by Zhang [8] Iris classification based on predefined iris classes introduced by Nalla and Pattabhi [9].



Stream structure Flower structure jewel-shaker structure

Fig.1: Iris classes [9]



Stream fiber Flower fiber Jewel fiber Shaker fiber

Fig.2: Iris fibers

There are various iris classes based on fiber structure such as; jewel, flower, stream, jewel and shaker are used for superior classification [10] as illustrated in Fig. 1. White fibers arrangement radiating from pupil is used to determine iris structure. The stream iris class structure fibers order in regular manner. Flower iris structure shows irregular fiber structure where jewel fiber structure shows dots on fibers. Shaker iris position shows both characteristic of jewel and flower. Fiber arrangements are shown in Fig. 2

Rest of the paper organized as: Section II explains the details of sparse representation and K-SVD algorithm for dictionary learning. Section III describes proposed iris classification approach. Section IV shows Implementation details and Section V gives our experimental results of proposed classification. Section VI concludes the whole paper.

II. SPARSE REPRESENTATION AND K-SVD ALGORITHM

In recent years, a large amount of research has been conducted on sparse representation and their application. Sparsity principle is used to perform model selection also sparse coding used to represent large collection of signal. Some dictionary learning algorithms are on-line dictionary learning [11], Method of Optimal Directions (MOD) [12] have been worked on development of training data. Input query image is match by using sparse representation. Feature extraction method for classification using wavelet features [13]. Huang and Aviyente give methods for simultaneous sparse signal representation [14].

K-SVD (K-mean Singular Value Decomposition) algorithm is proposed by Aharon and M. Elad [15]. It generalizes the K-mean clustering process. K-SVD algorithm is adaptable and works with any coexistence with any sideline algorithm. It is simple and generalization method of the K-means. It work with one atom per signal, vector quantization method is used to training the dictionary for gain-shape.

2.1 Structuring Sparse Representation of Signal

In sparse representation of signal given a dictionary D and a signal y where matrix D $\in R^{n*k}$ that consist of K prototype signal-atoms for each columns, $\{d_j\}^k_{j=1}$,a signal y $\in$ R^n can be represented as a sparse linear combination of this atoms and $x \in R^k$ is vector contains the representation coefficients of the signal y.

$$\min_x x0 \; s.t. \; y= Dx \qquad (1)$$

or

$$\min_x x0 \; s.t. \; y= Dx2\leq \varepsilon \qquad (2)$$

2.2 K-SVD Algorithm in Details

The K-SVD algorithm is flexible and works coexistence with any other algorithm. Generalized K-mean makes it simpler. Start working with one atom to each signal, training of dictionary for gain-shape vector quantization. Steps are coherent with each other both K-mean and SVD works towards the minimization of overall object function. K-SVD is direct extension for K-mean. In generalization of K-mean every input signal to be represented with linear combination fashion of codeword's, which called as dictionary elements then coefficients feature vector is now permissible for more than one nonzero entry with arbitrary values. Representing the sparse signal example set Y

$$\min_{\mathbf{D},\mathbf{X}}\{\|\mathbf{Y}-\mathbf{DX}\|_F^2\} \quad \text{subject to} \quad \forall i, \|\mathbf{x}_i\|_0 \leq T_0. \qquad (3)$$

To calculate similar objective function alternatively by considering eq. (4)

$$\min \sum \|\mathbf{x}_i\|_0 \quad \text{subject to} \quad \|\mathbf{Y}-\mathbf{DX}\|_F^2 \leq \varepsilon \qquad (4)$$

for a fixed value ε.

In K-SVD algorithm minimize the eq. (4) iteratively and fix **D** after that we aim to calculate exact coefficient matrix **X** that should be locate then by using any pursuit method used for approximation, any such algorithm can be used to calculate the coefficients where T_0 is predetermined number of nonzero entries. In second stage searching of better dictionary is done stage to deals with updating single matrix column at a one time, fixing all columns in **D** expect one, $\mathbf{d}_k$, then searching a new column $\mathbf{d}_k$ and new values for the coefficients that good to reduce Mean Square Error(MSE). The process of updating single column in matrix **D** at a time is a problem having solution for that based on Singular Value Decomposition (SVD). It accelerates convergence; as succeeding matrix column upgrades will be depend much more relevant coefficients. Detail description of the K-SVD algorithm is given in Fig.3.

III. PROPOSED IRIS CLASSIFICATION APPROACH

The Following are steps works one by one for the iris classification by using K-SVD.all users.

3.1 Iris Segmentation and Normalization

To remove noise from iris image, limbic boundaries and pupillary of an iris sample is consider as circle using some specifications, the center of circle coordinates (u0, v0) and the radius r, so the integrodiffrential operator [1] is given as:

$$\max_{(r,u0,v0)} G\sigma(r) \times \frac{\delta}{\delta r} \int \frac{I(u,v)}{2\pi r} ds, \qquad (5)$$

Whereas I (u, v) is the sample image of eye and Gσ (r) is a smoothing function. Segmented iris image as shown in Fig.4. Resultant iris image after applying integrodiffrential operator as shown in figure 4. Segmentation task is performed by using the Daugman Rubber Sheet Model [1] by converting it to the dimensionless polar coordinate system as shown in Fig.5.

Task: Find the best dictionary to represent the data samples $\{\mathbf{y}_i\}_{i=1}^N$ as sparse compositions, by solving

$$\min_{\mathbf{D},\mathbf{X}} \{\|\mathbf{Y} - \mathbf{D}\mathbf{X}\|_F^2\} \quad \text{subject to} \quad \forall i, \ \|\mathbf{x}_i\|_0 \le T_0.$$

Initialization : Set the dictionary matrix $\mathbf{D}^{(0)} \in \mathbb{R}^{n \times K}$ with ℓ^2 normalized columns. Set $J = 1$.

Repeat until convergence (stopping rule):

- *Sparse Coding Stage*: Use any pursuit algorithm to compute the representation vectors $\mathbf{x}_i$ for each example $\mathbf{y}_i$, by approximating the solution of

$$i = 1, 2, \ldots, N, \quad \min_{\mathbf{x}_i} \{\|\mathbf{y}_i - \mathbf{D}\mathbf{x}_i\|_2^2\} \quad \text{subject to} \quad \|\mathbf{x}_i\|_0 \le T_0.$$

- *Codebook Update Stage*: For each column $k = 1, 2, \ldots, K$ in $\mathbf{D}^{(J-1)}$, update it by
  - Define the group of examples that use this atom, $\omega_k = \{i \mid 1 \le i \le N, \ \mathbf{x}_T^k(i) \ne 0\}$.
  - Compute the overall representation error matrix, $\mathbf{E}_k$, by

$$\mathbf{E}_k = \mathbf{Y} - \sum_{j \ne k} \mathbf{d}_j \mathbf{x}_T^j.$$

  - Restrict $\mathbf{E}_k$ by choosing only the columns corresponding to ω_k, and obtain $\mathbf{E}_k^R$.
  - Apply SVD decomposition $\mathbf{E}_k^R = \mathbf{U}\Delta\mathbf{V}^T$. Choose the updated dictionary column $\tilde{\mathbf{d}}_k$ to be the first column of $\mathbf{U}$. Update the coefficient vector $\mathbf{x}_R^k$ to be the first column of $\mathbf{V}$ multiplied by $\Delta(1,1)$.
- Set $J = J + 1$.

Fig.3: K-SVD algorithm [15].

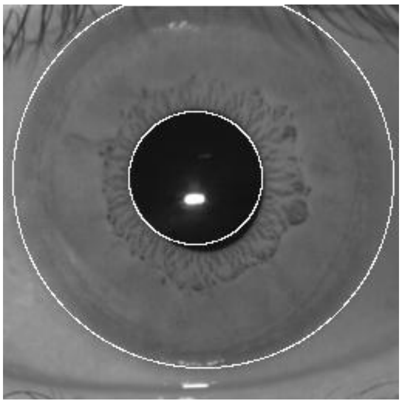


Fig.4: Iris segmentation

Fig.5: Normalization of iris

3.2 Feature Extraction from Iris Template

Considering the output of normalization step we extract 720×40 size feature vector from 360 × 40 size iris data image by using log gabor wavelet. Now we translated feature vector in single column vector with the help of column majoring ordering [16]. From predefined iris classes, some of the iris images are taken for representation of it in a linearly weighted sum of the feature vectors in a respective class dictionary of three different classes of iris.

Iris template is generated with encoding the fiber textural feature. The 2D log Gabor filter is used for iris texture template polar coordinates but unlike the frequency dependence on a linear graduation the dependency is realized by log frequency scale. Log-Gabor filter shown below:

$$G(x, y) = \exp\left\{\frac{-[\log(x1/x0)]^2}{2[\log(k/x0)]^2}\right\}\exp\left\{\frac{-y1^2}{2\sigma_y^2}\right\} \quad (6)$$

Where x1 = x cos (θ) + y sin (θ), y1 = -sin(θ) + y cos(θ), k determines the bandwidth of the filter in the x1 direction, θ is the orientation of 2D Log-Gabor filter, x0 is the center frequency & σy determine the filter bandwidth in y1 direction. For a template generation polar iris image is deteriorate into a number of 2D signals where each matrix row corresponds to an iris image. We used angular direction rather than radial one, which related to columns for the pattern. Complex output signals are encoded to generate iris template which is bitwise and corresponding noisy area given by noise mask. With the help of Hamming Distance similarity between two bits is analyze. Template matching is based on Hamming Distance.

3.3 Iris Classification using K-SVD

The K-SVD algorithm is used as a dictionary learning it classifies the iris images into three different classes to reduce the searching time complexity. Associated weights of vectors in dictionary are calculated with K-SVD algorithm. Feature vectors which are related with respective iris classes carry significantly more vector weights values which are non-zero maximum values.

Consider class L = [L1 . . . . , L N] consist of training set samples selected from iris dataset. By K-SVD working dictionary model, iris images representing by the same class are assumed to lie roughly in a low dimensional subspace. Model takes N training sample classes; the pth class has KP training images { y_i^N } i = 1,…, K P. Let x be an iris image belonging to the pth class, it is represented as a linear combination of these training samples:

$$x = DP\ \ \Phi P, \quad (7)$$

DP is a dictionary with size n×KP , where columns are the training samples in the pth class and ΦP is a sparse feature vector.

1. Steps for the K-SVD classification method: Dictionary Construction Step: Dictionary constructed for each class of training images using K-SVD sparsity model.
2. Classification Step: classification step deals with, the sparse vector Φ for given test image is found in the test dataset X=[x1, ...,x2] Using dictionaries of training samples D = [D1, ... ,DN], the sparse representation Φ satisfying D Φ=X is obtained by solving the following optimization problem:

Ep. (7) is adequately addressed by any pursuit algorithm if T0 is small enough, their solution is good .

$$\max_{Xi}\left\{ Yi - DX_i\ {}_2^2 \right\} \text{ subject to } x_i \leq T0$$

For i=1,2, . . . , N. (8)

IV. K-SVD Implementation Details

Variations in K-SVD algorithm during iris classification.

I. With the help of approximation technique with fixed number of coefficients then the Focal Underdetermined System Solver (FOCCUS) [17] result to be consider good in terms of get the considerable iteration.
II. When elements in dictionary not being used it shall be changed with least represented signal elements.
III. To avoid unpopular elements from dictionary then it is efficient to prune the dictionary from having too close signal elements.
IV. Applying the K-SVD involved initialized data signal by Orthogonal Matching Pursuit (OMP) [18] and Matching Pursuit (MP) [19] gives coefficients according to respective iris class. Maximum iterations are set to 80.

4 Experimental results

To test classification of iris using K-SVD algorithm, UPOL iris database [20] is used. It is collection of three image samples of right and left eyes from each 64 subjects. Overall total number of iris images are 384, each object sample consist resolution 768 × 576 and 24 bit RGB color space. Optical devices used to capture sample is TOPCON TRC50IA with connection of Sony 3CCD camera. Iris classification approaches:

SVM-3 Class-IrisFibers [9]
K-SVD-3Class-IrisFibers

Efficiency of proposed K-SVD-3 Class approach is compared with SVM-3Class-IrisFibers.The details are as follow:

4.1 SVM-3Class-IrisFibers [9]

SVM-3Class-IrisFibers uses SVM as a classifier. To construct classes of iris by using fiber structure is define with manual labeling.SVM-3Class-IrisFibers used UPOL iris database is used for training and testing purpose [9].

In support of SVM also hamming distance approach is used to further classification. Depends on need SVM models are increases. For calculating performance of SVM with consideration of acceptance rate. False Acceptance Rate (FAR) and False Rejection Rate (FRR) used. With consideration of SVM with log gabor methodology FAR = 0% and FRR=27.33% where accuracy with current setup is 72.11 %.

4.2 K-SVD-3Class-IrisFibers

By using UPOL database experimental results as shown in fig.6 Comparison for both approaches shows classification accuracy is better in the K-SVD-3Class-IrisFibers. K-SVD dictionary learning algorithm is used to in this approach. This classification used to reduce the search space as well as time complexity. To construct classes of iris based on fiber structure is define by manual labeling.

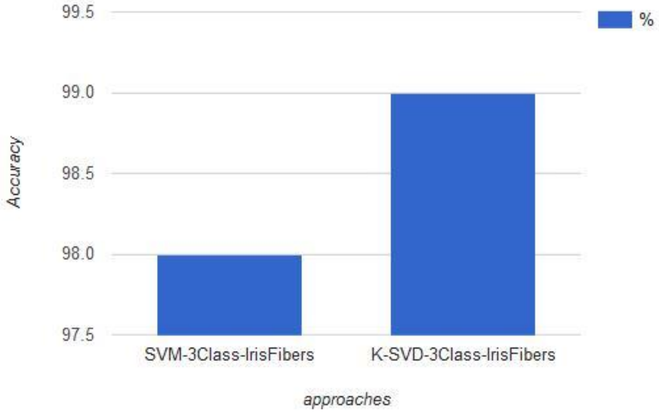


Fig.6: Experimental comparison for SVM-3Class-IrisFibers and K-SVD-3Class-IrisFibers

To evaluate performance of this approach images in dataset is divided to form training set and testing set. For training set 200 images are used where 100 iris images are taken from Stream (Class 1), 50 images are taken from Flower (Class 2) and 50 images are taken from Jewel-Shaker (Class 3). Table 1, gives details of classification with k=50.

Table 1: Classification readings dictionary size K=50

Iris class	Residual parameter		
	0.5	0.005	0.05
Stream	88.5	91.80	95
Jewel-Shaker	100	100	100
Flower	90.1	85.2	92.1

Table 2, gives classification with accuracy considering the testing data set is given with residual error value 0.005 accuracy is 99%.

Table 2: Classification readings on training data set for dictionary sizes K=60, K=90 and K=120

Iris class	Sizes of dictionary		
	60	120	90
Stream	90.1	99	99
Jewel-Shaker	100	99	99
Flower	100	99	99

V. Conclusion

In this paper, we proposed classification of iris is based on K-SVD dictionary learning approach. Depending on the predefined iris fiber structure used for fast classification. We used standard dataset UPOL for calculating our classification accuracy. We assume that K-SVD algorithm is not being used on iris biometric database. Our Future work is link with use of other biometric dataset such as ear, finger prints and hand gesture classification by using K-SVD algorithm. Proposed method will be enhanced with multimodal recognition and classification based on K-SVD algorithm.

REFERENCES

[1] J. G. Daugman, "High confidence visual recognition of persons by a test of statistical independence," in *IEEE Trans. Patt. Anal. Mach. Intel.*, vol. 15, no. 11, pp. 1148-1161, Nov 1993.
[2] J. G. Daugman, "Statistical richness of visual phase information." *Int'l Jour. of Comp. Vision*, 45(1), pp 25-38, 2001.
[3] J. G. Daugman, "Demodulation by complex-valued wavelets for stochastic pattern recognition." *Int'l Jour. of Wavelets, Multi-resol. Inf. Proc.*, 1(1), pp 1-17, 2003.
[4] J. G. Daugman, "How iris recognition works," in *IEEE Trans. Circ. Syst.Video Tech.*, vol. 14, no. 1, pp. 21-30, Jan. 2004.
[5] R. P. Wildes, "Iris recognition: an emerging biometric technology," in *Proceed. IEEE*, vol. 85, no. 9, pp. 1348-1363, Sep 1997.
[6] Z. Sun, H. Zhang, T. Tan and J. Wang, "Iris Image Classification Based on Hierarchical Visual Codebook," in *IEEE Trans. Patt. Anal. Mach. Intel.*, vol. 36, no. 6, pp. 1120-1133, June 2014.
[7] A. Ross and M. S. Sunder, "Block based texture analysis for iris classification and matching," *2010 IEEE Comp. Soci. Conf.Comp. Vision Pattern Recog.*, San Francisco, CA, 2010, pp. 30-37.
[8] H. Zhang, Z. Sun, T. Tan and J. Wang, "Iris image classification based on color information, " *21st Int'l Conf. Patt. Recog.*, Tsukuba, 2012, pp. 3427-3430.
[9] Nalla and Pattabhi Ramaiah, "Iris classification based on sparse representations using on-line dictionary learning for large-scale de-duplication applications, "SpringerPlus,2015:238.
[10] U . Foundation. The rayid model of iris interpretation. http://rayid.com/main/structures.asp, 2009.
[11] Mairal J, Bach F, Ponce J,Sapiro G, "Online dictionary learning for sparse coding In:Machine Learning, "2009 Conf. ACM,pp. 689-696.
[12] K. Engan, S. O. Aase and J. Hakon Husoy, "Method of optimal directions for frame design," *1999 IEEE Inter'l Conf. Acou. Speech, Signal Proc.*, 1999, pp. 2443-2446 vol.5.
[13] I. Ramirez, P. Sprechmann and G. Sapiro, "Classification and clustering via dictionary learning with structured incoherence and shared features," *2010 IEEE Comp. Soci. Conf. Comp. Vision Patt. Recog.*, CA, 2010, pp. 3501-3508.
[14] Huang K, Aviyente S, "Sparse representation for signal classification, NIPS.pp. 609–616 DTIC Document
[15] M. Aharon, M. Elad and A. Bruckstein, " K-SVD: An Algorithm for Designing Overcomplete Dictionaries for Sparse Representation," in *IEEE Trans. Sig. Proc.*, vol. 54, no. 11, pp. 4311-4322, Nov. 2006.
[16] Masek L, "Recognition of human iris patterns for biometric identification, "Master's thesis,University of Western Australia,2003.
[17] I. F. Gorodnitsky and B. D. Rao, "Sparse signal reconstruction from limited data using FOCUSS: a re-weighted minimum norm algorithm," in *IEEE Trans. on Sign. Proc.*, vol. 45, no. 3, pp. 600-616, Mar 1997.
[18] S.Chen,S.A.Billings,and W. Luo, "Orthogonal least squares methodsand their application to non-linear system identification," Int. J. Contr.,vol. 50, no. 5, pp. 1873–96, 1989.
[19] S. Mallat and Z. Zhang, "Matching pursuits with time-frequency dictionaries,"IEEE Trans. Signal Process., vol. 41, no. 12, pp. 3397–3415,1993.
[20] Dobeš M., Machala L.,iris database, http://www.inf.upol.cz/iris/