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Conventional entropy quantifier and modified entropy quantifiers for face recognition

Abdullah Gubbi [a,*], Mohammad Fazle Azeem[b], N Z H Nayakwadi[c]

[a]*Dept of Electronics and communication, P.A. College of Engineering, Karnataka 574153, India*
[b]*EE Dept., AMU, Aligarh 202002, India*
[c]*Dept of Computer science, Mazoon College, Muscat 133, Sultanate of Oman*

Abstract

This paper presents theoretically simple, yet computationally efficient approach for face recognition. There are many transforms and entropy measures used in face recognition technology. Recognition rate is poor with binary and edge based recognition techniques. We employ the entropy concept to binary and edge images. We use Conventional Entropy Quantifier (*CEQ*) which counts only the transitions, and Modified Entropy Quantifier (*MEQ*) which considers the positions with transitions for measuring the entropy. The proposed entropy features possess good texture discriminative property. The experiments are conducted on benchmark databases using SVM and K-NN classifiers. Experimental results show the effectiveness of our system.

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Keywords: Binary and edge images; SVM and K-NN classifier;Entropy; Conventional Entropy Quantifier; Modified Entropy Quantifier;k-fold validation;

1. Introduction

Face Recognition (FR) has received considerable interest during the past few decades because of its importance in research areas like computer vision, communication and automatic access control system. FR is one of the biometric methods, the other biometric methods like iris, finger prints etc are much accurate as compared to FR. However

* Corresponding author. Tel.: +91-81473-36952 ; fax: 0-824-228-4705 .
E-mail address: abdullahgubbi@yahoo.com

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human being uses face for recognition but FR is not an easy task for machines, since it has got lot of variations such as (i) pose variation (front, non-front), (ii) occlusion, (iii) image orientation, (iv) illumination condition and (v) facial expression. The challenge for researchers in machine learning is to compute effective and reliable features, which should be computed quickly, and should have less storage space. The features should produce less variance in intra class, and should have large variance in the inter classes.

Recently, many face recognition algorithms have been developed. Zhao *et al.*[1] have carried out a detailed survey on face recognition research.

These algorithms can be broadly divided into three groups,

- Structure-based schemes that make use of shape and other texture of the face along with 3D depth information.
- Appearance-based schemes that uses complete face image to compute holistic features.
- Hybrid scheme: It uses both local features and Appearance-based schemes to recognize a subject. This method could offer potentially better results of the former two schemes.

The Eigen faces[2] (PCA) and Fisher faces[3] (LDA) methods are based on the holistic approach for face recognition. As the face samples involve high dimensional image space, the Eigen-faces approach is likely to find the wrong components on face images, if there is a large variation in illumination. The data points with a maximum variance over all classes are not necessarily useful for classification. On the other hand, the Fisher-faces are computationally expensive. Samad et al[4] presented edge-based feature extraction for recognizing six different facial expressions. Edge detection is performed by using Gabor wavelet and convolution filters. They proposed two convolution kernels that are specific for the edge detection of facial components in two orientations. They have used Principal Component Analysis (PCA) to reduce the feature dimensions. For the classification of expressions Support Vector Machine was used. Phimoltares et al[5] have presented the algorithms for robust (variation of Intensity, pose, structural components and image)face recognition. In their work the faces are detected by using canny edge detection, along with face templates. In the later stage, a neural visual model (NVM) is applied to obtain facial feature positions. Kailash et.al have proposed the Independent Component Analysis of Edge Information for Face recognition[10]. The local features like Local Binary Pattern[6] (LBP) recognition method suffers in the presence of noise and uniform regions, as the noise may change the LBP code. LBP based scheme divides the image to smaller sub blocks typically of size 3x3 and once the LBP image is formed the image is sub divided arbitrarily to compute histogram. This is somewhat arbitrary and it is likely to give rise to both aliasing and loss of spatial resolution[7]. The Local Derivative Pattern (LDP) tends to produce inconsistent patterns in uniform and near-uniform facial regions, and is heavily dependent on the selection of the number of prominent edge responses. The limitation of LDP is it suffers in the presence of uniform regions. Looking at the limitations of Global features like PCA, LDA and local features like LBP and LDP. We propose a simple method which is computationally efficient and requires less storage space.

The organization of the rest of paper is as follows. Section 1.1 discusses the binary, edge images and entropy measure, Section 2 presents proposed method, section 3 presents the experimental results, and Section 4 gives the conclusions of this paper.

1.1.Binary & Edge images

A binary image is an image in which the pixel values will be either zero (black) or one (white). Typically the two colours are used for a binary image are black and white, though any two colours can be used. The colour used for the object(s) in the image is the foreground colour while the rest of the image is the background colour. The binary image in the document scanning industry refers it as *bi-tonal, bi-level* or *two-level* image. The names like black and white (B&W) or *monochrome* or *binary* are often used.

Advantages of using binary images: Smaller memory requirements, Faster execution time, many techniques developed for these systems are also applicable to vision systems which uses grayscale images and computationally less expensive. To obtain binary image the operations like Segmentation and thresholding can be used. The partitioning of an image into object regions is called segmentation and thresholding is a method to convert a grayscale image into a binary image.

Edge detection has received much attention during the past few decades because of its significant importance in many research areas like computer vision, particularly in the areas of feature detection and extraction. Edge detection is a technique of locating abrupt changes in the intensity values. The abrupt changes in pixel intensity values characterize boundaries of objects in an image. Detection of edges for an image may help for image segmentation, data compression, Pattern recognition and image reconstruction. Sakai et al.[8] worked on face detection using edge representation. In their work the objective was to analyze line drawing of the faces, which is done for facial features from the photographs. Curvelets are also used for detection of edges[9]. The edge detection process involves convoluting the image with an operator (2-D filter) mask, which is constructed to be sensitive to large gradients in the image while returning values of zero in uniform regions. Some of the popular edge detection techniques are sobel, canny, prewiit etc.

Sobel Operator: This operator is used for finding edges in an image. It performs a 2 dimensional spatial gradient operation, and therefore highlighting the regions of high spatial frequency which correspond to edges. The operator is a 3×3 convolution kernel with its elements as $\pm 1, \pm 2\ and\ 0$ .The kernels are designed to respond to the edges in horizontal and vertical directions. The two kernels can be applied separately to the input image. The sum within the kernels should be always zero so that the response in the uniform region should be zero.

Canny Edge Detector: This is the most optimal edge detection algorithm. The image boundaries generated by the Canny method are thinner. Canny's ideas and methods can be found in, "A Computational Approach to Edge Detection". Canny followed certain criteria to improve traditional methods of edge detection. The edge detector should have low error rate, i.e. the response to the edges should be high, and the response to the non-edges should be low. The other criterion is the location of edge points should match with the original image edges.

Entropy Measure: In information theory, entropy is a measure of the uncertainty. Entropy can be applied to random variable. Estimating the entropy of finite strings has an application in areas such as event detection, similarity measurement or in the performance assessment of compression algorithms. The Shannon entropy[11] quantifies the expected value of the information contained in a message. Entropy measures the randomness of intensity distribution. Entropy can also be applied to image as we can find randomness in the image. In image processing uncertainty is calculated with the help of entropy. Our work is based on work of EGLIN et al[13] and Sahana D Gowda et al[14]. In EGLIN et al[13] they have used only horizontal direction (rows) for calculation of entropy in a document processing. Sahana D Gowda et al[14].have taken horizontal(row) and vertical direction(column) for calculation of entropy in a document processing, in our proposed method we have extend it to diagonal direction as well, the reason for doing so is increase the discriminative power for the classifier.

2. Proposed Method

2.1.Conventional Entropy Quantifier (CEQ)

A binary image or edge image consists of 1s and 0s, in order to use these images for face recognition. We compute the features based on transitions from 0-1 and 1-0, and we count the number of transitions from 0-1 and 1-0 in the horizontal (row wise) and vertically (column wise) and also in diagonal direction. The limitation of this method is the position at which these transitions occur are not known. We define entropy of 0-1transition as,

$$H^{+} = p \times log\frac{1}{p} + (1-p) \times log\frac{1}{(1-p)} \tag{1}$$

Similarly we define the entropy of 1-0 transition as,

$$H^{-} = p \times log\frac{1}{p} + (1-p) \times log\frac{1}{(1-p)} \tag{2}$$

Where,

$$p = \frac{Number\ of\ transitions(0-1)\ or\ (1-0)}{Total\ number\ of\ possible\ transitions} \tag{3}$$

The implementation is explained with an example by considering the matrix given below.

$$\begin{bmatrix} 1 & 0 & 0 & 1 & 1 \\ 0 & 1 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 0 & 1 \end{bmatrix}$$

Row 1, 1-0 transitions =1 and 0-1 transitions=1;
Row 2, 1-0 transitions =0 and 0-1 transitions=1;
Row 3, 1-0 transitions =2 and 0-1 transitions=1;
Row 4, 1-0 transitions =1 and 0-1 transitions=2;
Diagonal 1-0 transitions =1 and 0-1 transitions=0;
Column 1, 1-0 transitions =2 and 0-1 transitions=1;
Column 2, 1-0 transitions =1 and 0-1 transitions=2;
Column 3, 1-0 transitions =1 and 0-1 transitions=1;
Column 4, 1-0 transitions =1 and 0-1 transitions=0;
Column 5, 1-0 transitions =1 and 0-1 transitions=1;
Total no of possible transitions in each rows =5-1=4; Total no of possible transitions in each columns =4-1=3;
Total no of possible transitions in diagonal =4-1=3;

For example the entropy 0-1 is denoted by H^+ and for 1st row is, $(\frac{1}{4} log\ 4) + (1 - 1/4) log\ (\frac{1}{(1-1/4)})$

That is, $0.25log(1/0.25) + 0.75log(1/0.75) = 0.5623$

Similarly entropy 1-0 is denoted by H^- computed as =0.5623.
We compute total *Conventional Entropy Quantifier* as,

$$CEQ = H^+ + H^- \tag{4}$$

The above procedure is repeated for column and diagonal elements. Thus CEQ is calculated along the row, column and diagonal direction .In an image each row, column and diagonal elements contributes for a feature vector, for example if an image of size 112X92 gives 112 features from rows, 92 features form columns and 92 features from diagonal elements. The features from rows, columns and diagonal direction are concatenated to yield a total of 296 features, and these features are stored as a vector which will be used either for training or testing.

2.2.Modified Entropy Quantifier (MEQ)

The features are computed on binary or edge images with *MEQ*[14]. The entropy values are computed using equation 5-7. The entropy is calculated based on the location of happening of 1-0 and 0-1 transitions. The *MEQ* is simple to compute, we can replace p in *CEQ* by the location parameter(pos) that compute the relative location of transition across rows, columns and diagonal direction, the height and width of the face image contributes for the area (i.e transition in horizontal and vertical) as indicated in equation 5.

The row Entropy $E(\beta)$ in a row $r\alpha$ is computed between the two columns $c_{\beta 1}$ and $c_{\beta 2}$ if there is an occurrence of transition which is given by:

$$E(\beta) = \left(\frac{r_\alpha}{m}\right)\left(\left(\left(\frac{pos}{n}\right)\log\left(\frac{n}{pos}\right)\right) + \left(\left(m - \left(\frac{pos}{n}\right)\right)\log\left(\frac{m}{m \times n} - pos\right)\right)\right) \tag{5}$$

Where β =1…m.

The column Entropy $E(\alpha)$ in a column $c\beta$ is computed between the two rows rα1 and rα2 if there is an occurrence of transition which is given by:

$$E(\alpha) = \left(\frac{c_\beta}{n}\right)\left(\left(\left(\frac{pos}{m}\right)\log\left(\frac{m}{pos}\right)\right) + \left(\left(n - \left(\frac{pos}{m}\right)\right)\log\left(\frac{n}{m \times n} - pos\right)\right)\right) \tag{6}$$

where α=1…n.

The diagonal Entropy $E(\Upsilon)$ in a diagonal $d\Upsilon$ is computed between the two diagonal $d\gamma 1$ and $d\gamma 2$ if there is an occurrence of transition which is given by:

$$E(\Upsilon) = \left(\frac{d\Upsilon}{M}\right)\left(\left(\left(\frac{pos}{M}\right)\log\left(\frac{M}{pos}\right)\right) + \left(\left(M - \left(\frac{pos}{M}\right)\right)\log\left(\frac{M}{m \times n} - pos\right)\right)\right) \tag{7}$$

where ϒ=1, 2…M where M is the number of diagonal elements of an image matrix.

The total entropy for each row, column or diagonal is the addition of entropy at 0-1 transition (i.e. positive) and 1-0 transition (i.e. negative) indicated as *E (β), E (α)* and *E (ϒ)* respectively. The total horizontal entropy $Eh(\beta)$, vertical entropy $Ev(\alpha)$ and diagonal $Ed(\Upsilon)$ are the addition of $E(\beta)$, $E(\alpha)$ and $E(\Upsilon)$ of all the rows, columns and diagonal of the binary or edge image. Total entropy $E(T)$ is given as,

$$E(T) = Eh(\beta) + Ev(\alpha) + Ed(\Upsilon) \tag{8}$$

In *MEQ,* entropy is calculated at each point of transition in all the rows, columns and diagonal direction of the binary or edge image. All features which are obtained from rows, columns and diagonal are concatenated, and stored as an array for the complete image. The complete database set is divided into train and test set. We have used both k-Nearest Neighbour classifier[15] with cosine distance similarity measure and SVM [16] which is available from PRT tools.

2.3.Databases for Evaluation

Faces94: The faces94 is a face database constructed by Dr Libor Spacek[17]. The faces94 has total of 153 subjects with resolution of 180X 200 pixels. The directories are female 20 subjects, male 113 subjects and male stuff (20) subjects. Each subject is kept in a separate directory. The speech is used to introduce facial expression variation, and there is considerable expression change. The colour images are first converted into grayscale images, and these images are converted into binary or edge images depending upon requirement.

ORL: The experiment is conducted on Olivetti Research Laboratory[18] (ORL) database which has 400 images with 40 different subjects of both male and female, with 10 images per subject of size 112×92. The database is normalized by dividing each pixel with maximum in that image, so as to have values between zero to one.

Senthil: The experiment is also conducted on Senthil kumar[19] face database. This database has 80 face images of 5 subjects.16 images per subject which has large facial expressions, occlusions and brightness conditions. The Facial images are resized to 99X99 to have the 297 features. Fig. 1 and Fig. 2 shows some of the images from Faces94, ORL and Senthil databases.

(a) (b) (c) (d) (e)

Fig. 1. The image (a) Original colour image from FACES94 Database; (b) Grayscale Image; (c) Binary image; (d) Edges from sobel operator; (e) Edges from canny operator.

(a) (b)

Fig. 2. (a) First 4 subjects from ORL Database; (b) some of the images of single subject from Senthil database.

2.4.Classifiers SVM and KNN

We perform the classification using a Support Vector Machine (SVM) to evaluate the features. SVM[16] is a supervised machine learning technique. The SVM classifier with polynomial degree 1 and 2 are used for the evaluation of features. The k-Nearest Neighbour (K-NN) classifier is simple to implement among all machine learning methods. It is a non-parametric method for classifying objects. Meaning one need not worry about underlying structure. Classification is based on how much close is the test pattern to the training examples. An object is assigned to a class based on majority votes of its neighbours. If k = 1, then the object is assigned to the class of its nearest neighbour. The objective is to compare the encoded test vector to the training vectors with the Cos similarity measure.

3. Results and Discussions

In our proposed method the features are computed on binary, Canny and Sobel edge images with *CEQ* and *MEQ*. The Matlab tool is used for computation of features and for classification. All the images in the database are normalized to have the values between 0 to1. Further the grayscale images are converted to binary or edge images.

Results with faces94 on *CEQ*: The *CEQ* is calculated along the rows, columns and in the diagonal direction. We store the computed features as a single vector for a complete binary or edge image. The binary images has given a recognition rate of 98.82% with SVM POLY1,for the same train and test ratio with canny edges have given a recognition rate of 99.69% with SVM POLY1. The K-NN has given 97.25% on binary images, for the same train and test ratio K-NN has given a 100% recognition rate with canny edges.

Results with ORL and Senthil on *CEQ*: For ORL database we got 86.66% as recognition rate with 7 training and 3 testing feature vectors with SVM POLY1 on binary images. Better results are obtained with Senthil database having different facial expressions, occlusions and brightness conditions. Binary images and canny edges have achieved 90% results on Senthil database as shown in Table 1. Numbers written as (15:5) specifies, 15 images are used for training and 5 images for testing.

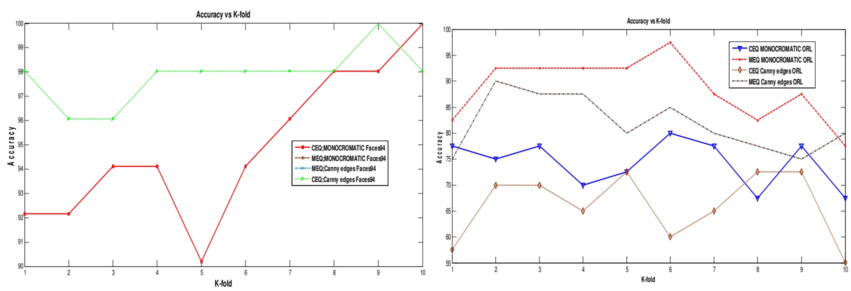
Table 1. Recognition rates with *CEQ* for 75% training and 25% testing.

	Binary images			Canny edges			
Databases	SVM POLY1	SVM POLY 2	K-NN	SVM POLY1	SVM POLY 2	K-NN	# Features Per image
Faces94(15:5)	98.82	97.64	97.25	99.69	99.60	100	560
ORL(7:3)	86.66	85.33	85	79.16	79.16	70	296
Senthil(12:4)	85	90	89	85	90	90	297

Results with *MEQ*: The results for the normalized images for Faces94, ORL and Senthil databases are given in Table 2. The *MEQ* is computed using equations 5-8.The important feature of *MEQ* is that the exact position at which the transitions occurs are taken into account for computation of facial features. Better results of 99.60% is reported with both SVM POLY1 and SVM POLY2 with canny edges on Faces94.The better results of 90% are reported with SVM POLY1 with binary images on senthil database as indicated in Table 2.

Table 2. Recognition rates with *MEQ* for 75% training and 25%testing.

	Binary images			Canny edges			
Databases	SVM POLY1	SVM POLY 2	K-NN	SVM POLY1	SVM POLY 2	K-NN	# Features Per image
Faces94(15:5)	96.47	95.29	96.47	99.60	99.60	98.43	560
ORL(7:3)	81.66	78.33	79.16	76.66	75	75.83	296
Senthil(12:4)	90	85	85	85	85	85	297

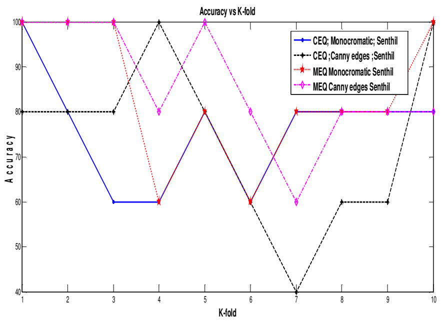


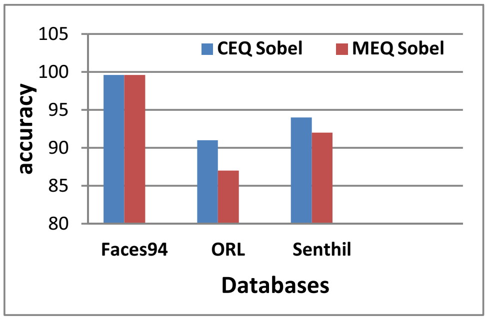
(a) (b)

Fig. 3. (a) Accuracy vs. k-fold on Faces94 database; (b) Accuracy vs. k-fold on ORL database.

The k-fold test is conducted with SVM polynomial degree1 on Faces94.The accuracy of recognition with *CEQ* on binary images varies from 90.19% to 100%, and an average recognition rate of 94.90% is achieved. The k-fold accuracy on *MEQ* with binary and canny edges has given 100% for all the ten folds.

The *CEQ* on canny edges varies from 96.16% to 100% with average recognition rate of 97.84%, as shown in Fig. 3(a). The Fig. 3(b) shows the Accuracy vs. k-fold for ORL database, we have observed a lot of variation in results. The range of accuracy we got for this method is varies from 55% to 72.5% with the average of 66%.The best performance is given by *MEQ* on binary images. The result obtained varies from 77.5% to 97.5% with the average recognition rate of 88.5%. The image enhancement techniques can be applied to improve the recognition results. The Senthil database is having only 5 classes. The better results are obtained from *MEQ* with canny edge detector. The accuracy of recognition with *CEQ* on binary images varies from 60% to 100%, and with an average recognition rate of 76%. The *CEQ* on canny varies from 40% to 100% with average of 74%, as shown in Fig. 4(a). The *MEQ* on binary images varies from 60% to 100% with an average of 84%. The *MEQ* on canny varies from 60% to 100% with average of 86%. The Fig. 4 (b) shows the recognition rates with Sobel edge detector, the best performance is given by both *CEQ* and *MEQ* on Faces94 database.





(a) (b)

Fig. 4. Accuracy vs. k-fold on Senthil database; (b) Recognition rates with Sobel edge detector on Faces94, ORL and Senthil databases.

3.1. Comparison of Results

Muhammad Akmal Khan et al[20] carried out experiments with ORL face database. They have tried to improve face recognition rate with the help of Sub Holistic (SH-PCA) method.SH-PCA has showed an improvement of recognition rate for complete ORL database. For 40 classes the results obtained are 82% with PCA and 87% with SH-PCA.

Table 3. Recognition Rates on various implementation[21]

Recognition rate	PCA	LDA	KPCA	FA
ORL Database (with noise)	66.07%	86.07%	49.29%	85.70%
Proposed database (without noise)	66.43%	89.29%	51.07%	86.07%

where, PCA- Principle component analysis, LDA- Linear Discriminant Analysis, KPCA- Kernel Principle component analysis and FA- Fisher Analysis. Abdul-Ameer[21] the authors have conducted the experiment using Haar 10 wavelet de-noising on different face recognition method (PCA, LDA, KPCA, FA) to compare the recognition rate on ORL database. The results of PCA, LDA, KPCA and FA are given in Table 3.

4. Conclusion

A new approach for face recognition using binary and edge images is established, which is easy to compute and occupies less memory space has been proposed in this paper.The *CEQ* and *MEQ* are used for extraction of features, and has given good recognition rate on Faces94 and Senthil databases. *CEQ* considers only the count of transitions from 0-1 and 1-0 to calculate the entropy, and *MEQ* considers the location of occurrence of transitions from 0-1 and 1-0 for the calculation of entropy. The *MEQ* and *CEQ* worked well with small database like Senthil database having different facial expressions, occlusions and brightness conditions. A comparison of performance of the proposed approach is made with PCA and other holistic approches using k-nearest neighbour and SVM classifiers. Better results are reported with both SVM and K-NN. A human face is a dynamic object with smooth texture within a limited area. It is an not easy task to detect dynamic objects and texture features for machines. The development of a robust face recognition algorithm is still a challenging problem in computer vision. Further work can be done to design a new classifier and new edge detection techniques that can be developed to improve the recognition rate.

References

1. Zhao, Wenyi, Rama Chellappa, Jonathon Phillips P and Azriel Rosenfeld. Face recognition: A literature survey. *Acm Computing Surveys*; 2003. p. 399-458.
2. Jolliffe, Ian. Principal component analysis. *John Wiley & Sons*, Ltd; 2005.
3. Scholkopft, Bernhard and Klaus-Robert Mullert. Fisher discriminant analysis with kernels. *Neural networks for signal processing;* 1999.
4. Samad, Rosdiyana and Hideyuki Sawada. Edge-based Facial Feature Extraction Using Gabor Wavelet and Convolution Filters; 2011.
5. Phimoltares, Suphakant, Chidchanok Lursinsap and Kosin Chamnongthai. Face detection and facial feature localization without considering the appearance of image context. *Image and Vision Computing* ; 2007. p. 741-753.
6. Xiaoyang Tan and Bill Triggs Enhanced Local Texture Feature Sets for Face Recognition Under Difficult Lighting Conditions *IEEE Transactions On Image Processing*; 2010.
7. Ahmed F and Kabir MH, Directional ternary pattern DTP for facial expression recognition, *Proceedings of the IEEE international Conference on Consumer Electronics*, Las Vegas, USA; 2012.
8. Sakai T, Nagao M and Kanade T, Computer analysis and classification of photographs of human faces in *Proc. First USA—Japan Computer Conference;* 1972. p. 2-7.
9. Starck JL, Murtagh F, Candes EJ and Donoho DL. Gray and color image contrast enhancement by the curvelet transform. *IEEE Transactions on Image Processing;* 2003. p. 706–717.
10. Kailash J.Karande & Sanjay N Talbar Independent Component Analysis of Edge Information for Face recognition *International Journal of Image Processing*; 2012.
11. Shannon CE, A mathematical theory of communication. *Int. J. Bell. Syst. Technical*; 1948. p. 379-423.
12. Mohinnuddin, KM, Lossless binary image compression based on pattern matching, Proc. *International Conference on Computers, system and signal processing*; 1984. p. 447-451.
13. Veronique EGLIN, Stephane BRES, LIRIS-RFV and INSA de Lyon, Document image similarity based on layout visual saliency: Application to query by example and documents classification, *IEEE Computer society. ICDAR* 2003,
14. Sahana D.Gowda, P.Nagabhushan Entropy Quantifiers useful for Establishing Equivalence between Text Document Images *International Conference on Computational Intelligence and Multimedia Applications;* 2007.
15. J. G. Skellam, Studies in statistical ecology. I. *Spatial pattern, Biometrica,* 1952. p. 346-362.
16. http://www.csie.ntu.edu.tw/~cjlin/libsvm/
17. http://cswww.essex.ac.uk/mv/allfaces/faces94.html
18. http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html
19. http://www.geocities.ws/senthilirtt/Senthil%20Face%20Database%20Version1
20. Muhammad Akmal Khan, Dr Javed and Muhammad Anjum Akbarl., Face Recognition using Sub – Holistic PCA, *British Journal of Science,* 2011. p. 111-120.
21. Isra'a Abdul-Ameer Abdul-Jabbar, Jieqing Tan , Zhengfeng Hou Wavelet Based Image De-noising to Enhance the Face Recognition Rate IJCSI *International Journal of Computer Science*; 2013.