the other side. Another drawback of the LGS graph structure is that it contains redundant graph's relationship between neighbours (pixels with value 73 and 75 as in Fig.2).

4. SYMMETRIC LOCAL GRAPH STRUCTURE

SLGS operator has a symmetric graph structure, as in Fig.3, to represent the relationship of pixel's neighbours[10]. The symmetric structure consists of same number of neighbour pixels in both sides, three neighbour pixels on the left and three on the right sides. SLGS graph also does not have any redundant graph's relationship between neighbour pixels. Fig. 3 shows the SLGS operator's operation.

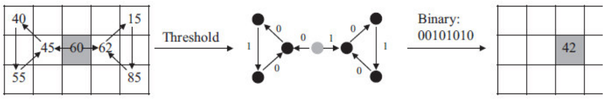

Fig 3. The graph structure of SLGS operator.

The main advantage of this method is the SLGS pixel values represent neighbours with radius of one and two.

5. PROPOSED APPROACH

Proposed approach also is based on graph structure that is symmetric and number of pixel's neighbours are equal and it does n't contain redundant graph's relationship between neighbours. In this approach, pixel's neighbours Somehow are selected that record additional information about the texture of the images. Fig.4 shows the proposed operator's operation.

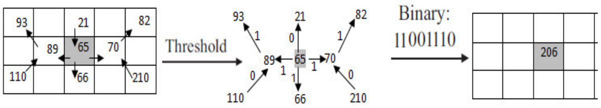

Fig 4. The proposed approach operator.

proposed approach toward other operators also is symmetric from above and below. so that, values of above and below pixels are used for features extraction. In this method also is used neighbours with radius of one and two for each pixels. Thus, Proposed graph structure extracts more spatial information about the texture of the images. In this method, firstly calculated new value for each pixel based on threshold neighbours' pixels. A histogram was generated based on the new calculated values. In training phase, the histograms of all training files will be stored as template for each user. Three distance measures (Euclidean distance, correlation coefficient and chi-square statistics) were used in feature matching step in testing phase. The experiment was repeated for fifteen times with different set of training and testing face images.

6. EXPERIMENTAL DESIGN

A publicly available SenthilKumar Face and Yale face databases were utilised to test the performance of Proposed graph structure. Yale face database contains 165 grayscale face images of 15 individuals. There are 11 images per subject. Each subject has face images with different facial expression and configuration, included centre-light, with glasses, happy, left-light, with no glasses, normal, right-light, sad, sleepy, surprised, and wink. Fig.5 shows some preview images from Yale face database.

Fig 5. Preview images of Yale face database.

SenthilKumar Face database contains 80 grayscale face images of 5 individuals. There are 16 images per subject. The images were taken at different times, lighting, facial expressions (open/ closed eyes, smiling/not smiling) and facial details (glasses/no glasses). All the images were taken against a dark homogeneous background. Fig.6 shows a part of the preview images in SenthilKumar Face database.

Fig 6. Preview images of Senthilkumar face database.

In this experiment, the face images from the databases were divided into two: training set and testing set. Four local feature operators, that are LBP, LGS, SLGS and proposed approach, were used for feature extraction. The operators calculated new value for each pixel based on threshold neighbours' pixels. A histogram was generated based on the new calculated values. In training phase, the histograms of all training files will be stored as template for each user. Three distance measures (Euclidean distance, correlation coefficient and chi-square statistics) were used in feature matching step in testing phase. The experiment was repeated for fifteen times with different set of training and testing face images. The framework used is depicted in Fig.7.

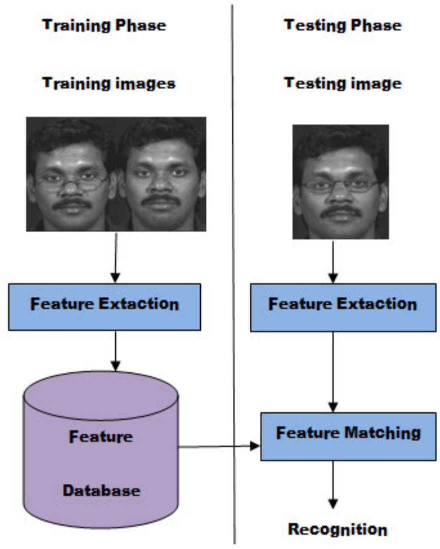

Fig 7. The framework of face recognition system.

In face recognition problem, usually there are large amount of classes and only a few, possibly only one, training sample(s) per class. Thus, nearest-neighbour classifiers with high accuracy are needed. All local features operator, including LBP, LGS, SLGS and proposed approach, will compute a histogram for the values. So, distance measures between histograms are really important component to produce high accuracy recognition. Three distance measures have been used for histograms comparison (X and Y are histograms with i bins):

Euclidean distance (E):

$$E(X, Y) = \sqrt{\sum_i (Xi - Yi)^2} \quad (1)$$

Correlation coefficient (C): (2)

$$C(X, Y) = \frac{\sum_i (Xi - \bar{X})(Yi - \bar{Y})}{\sqrt{([\sum_i (Xi - \bar{X})^2])([\sum_i (Yi - \bar{Y})^2])}}$$

Chi-square statistics (X2):

$$X^2(X,Y) = \sum_i \frac{(Xi-Yi)^2}{Xi+Yi} \quad (3)$$

7. RESULTS

First experiment was conducted to compare the effectiveness of three different distance measures which are Euclidean distance, correlation coefficient and chi-square statistics. The experiment used only the LGS for feature extraction algorithm on the SenthilKumar Face database. Table 1 shows the result of the experiment with different number of training files.

Table 1: The accuracy of LGS using different distance measures with different number of training files.

Training files %	Euclidean distance %	Correlation cofficient %	Chi-square %
10	97.6661	97.6842	97.8633
20	98.2847	98.3128	98.4628
30	98.6139	98.6514	98.7889
40	98.8738	98.9071	99.0508
50	99.0725	99.1125	99.2475
60	99.2113	99.2581	99.3800
70	99.3383	99.3842	99.5008
80	99.4925	99.5238	99.6113
90	99.6925	99.7050	99.7675

Chi-square distance measure gave highest accuracy in all different number of training files. At 20% training files, that is only one training file for each user, chi-square achieved accuracy of 98.46% while Euclidean distance and correlation coefficient only achieved accuracy of 98.28% and 98.31% respectively. Generally, Chi-square show highest performance. The second experiment is to compare the performance of the proposed algorithm, with other well-known algorithms, LBP, LGS and SLGS on SenthilKumar Face and Yale face databases. Measures used to evaluate the performance for all algorithms are Accuracy, False Acceptance Rate (FAR) and False Rejection Rate (FRR).

All of the measures are based on the value of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). TP and TN are conditions where the system correctly identified and correctly rejected the user respectively. The other values, FP and FN, are errors that occur in the system. FP is a condition where the system incorrectly identified illegal users. The last condition, FN is a condition where the system incorrectly rejected genuine users. Accuracy (Formula (4)) is the percentage of a system correctly recognises genuine users and correctly rejects illegal users. The FAR (Formula (5)) is the percentage of illegal or imposter users that are accepted as authentic, genuine users. The last measure, FRR (Formula (6)) is the percentage of genuine users that are rejected as unidentified or unverified by a biometric system. Below are the formulas of all measures based on TP, TN, FP, and FN.

Accuracy:

$$Acc = \frac{\sum_n \frac{(TP+TN)}{(TP+TN+FP+N)}}{n} * 100\% \quad (4)$$

False Acceptance Rate (FAR):

$$FAR = \frac{\sum_n \frac{FP}{(TN+FP)}}{n} * 100\% \quad (5)$$

False Rejection Rate (FRR):

$$FRR = \frac{\sum_n \frac{FN}{(TP+FN)}}{n} * 100\% \quad (6)$$

The performance measures of the proposed algorithm compared with LBP, LGS and SLGS on Senthilkumar and Yale face databases are plotted in Figs. (8-10) and Figs. (11-13), respectively. The graphs show the accuracy, FAR, and FRR of LBP, LGS, SLGS and Proposed approach with different number of training files. Proposed approach obtained the highest accuracy compared with LBP, LGS and SLGS on both databases. The lowest FAR and FRR are produced by Proposed approach.

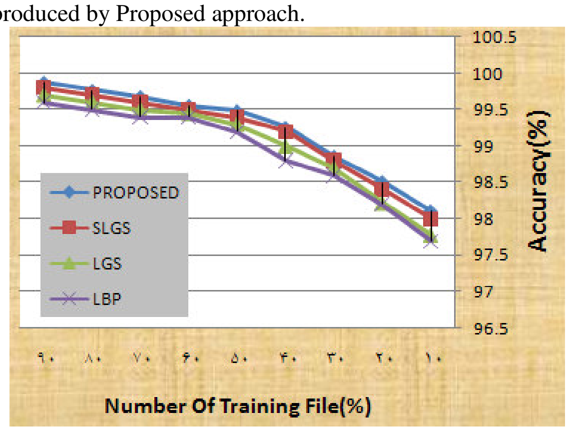

Fig 8. The measures for accuracy of different algorithms with different number of training files on YALE database.

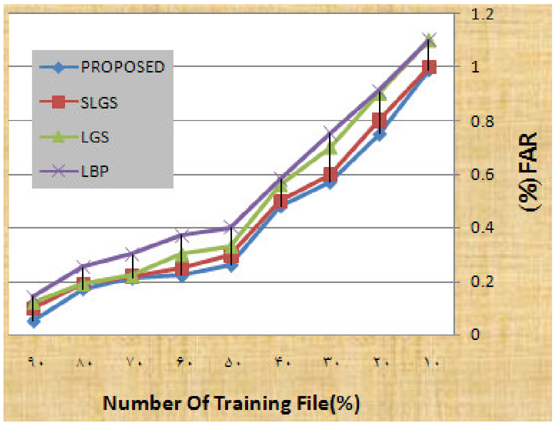

Fig 9. The measures for FAR of different algorithms with different number of training files on YALE database

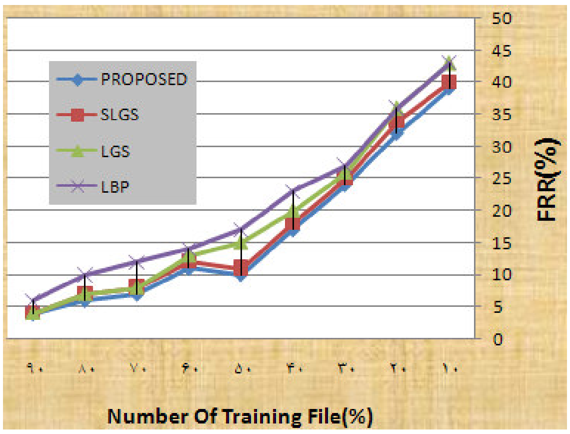

Fig 10. The measures for FRR of different algorithms with different number of training files on YALE database

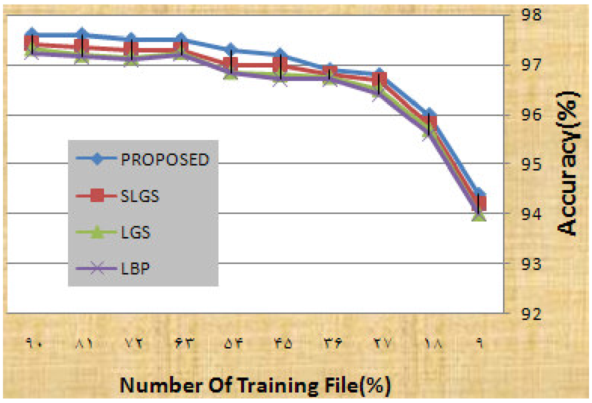

Fig 11. The measures for accuracy of different algorithms with different number of training files on Senthilkumar database

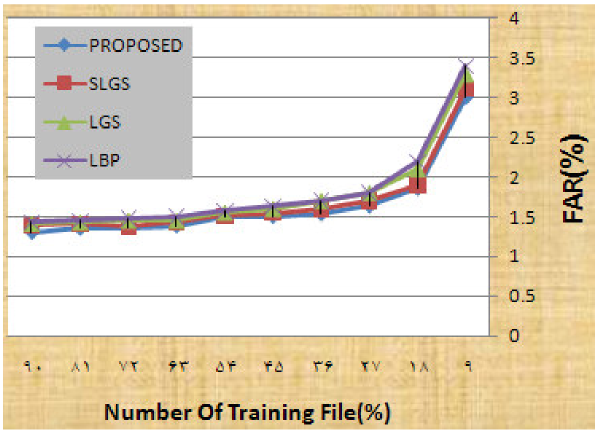

Fig 12. The measures for FAR of different algorithms with different number of training files on Senthilkumar database

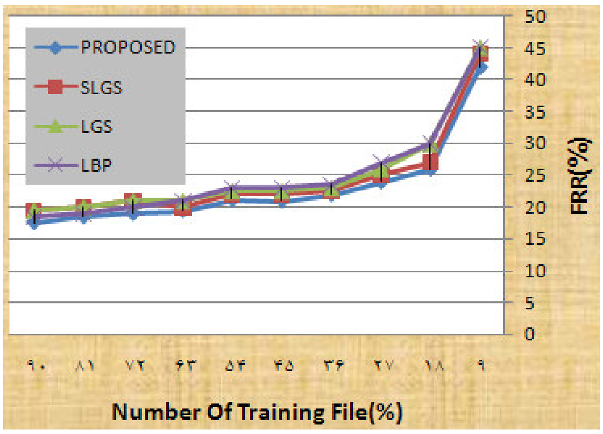

Fig 13. The measures for FRR of different algorithms with different number of training files on Senthilkumar database

8. DISCUSSION AND CONCLUSION

We extended the idea of the graph representation and proposed a symmetric graph structure. In this approach, the graph structure of a pixel in an image has better representation with its neighbours' pixel. Face recognition is performed using a nearest neighbour classifier in the computed feature space with Euclidean distance, correlation coefficient and chi-square as distance measures. From the experiment, chi-square produces highest accuracy among others. The proposed algorithm and other control algorithms were implemented and compared based on Senthilkumar and Yale face databases. The databases are very suitable to compare face recognition algorithms. The experimental results clearly show that the proposed method outperforms LBP, LGS and SLGS on Senthilkumar and Yale face databases. proposed approach achieved the highest accuracy and the lowest FAR and FRR. proposed technique brings an innovative and improved way of texture-based image recognition. It is very easy to be implemented and yet produce very outstanding results. It can be applied to many other area of image processing.

REFERENCES

[1] Zhao, W. Chellappa, R. Phillips & Rosenfeld. A. (2003). Face recognition : A literature survey. ACM Computing Surveys, 35(4), 399–458.

[2] Turk, M. A. & Pentland.A. P. (1991). Face recognition using eigenfaces. In Computer vision and pattern recognition (pp. 586–591).

[3] Etemad. K & Chellappa. R. (1997). Discriminant analysis for recognition of human face images. Journal of the Optical Society of America, 14(8), 1724–1733.

[4] Bartlett. M. S , Movellan. J. R , & Sejnowski. T. J. (2002). Face recognition by independent component analysis. In IEEE transactions on neural networks (13,pp. 1450–1464).

[5] Ojala.T, Pietikainen.M & Harwood.D. (1996). A comparative study of texture measures with classification based on feature distributions. Pattern Recognition,29(1)51–59.

[6] Sayeed. S, Yusof. I, Bashier. H. K & Hossen. J. (2013). Plant identification based on leaf shape and texture pattern using local graph structure (LGS). Australian Journal of Basic and Applied Sciences, 7(11), 29–35.

[7] Liu.Y.H & Chen.Y.T. (2007). Face recognition using total margin-based adaptive fuzzy support vector machines. IEEE Transactions on Neural Networks, 18(1), 178–192. Retrieved from <http://www.ncbi.nlm.nih.gov/pubmed/17278471>.

[8] Abusham. E. E. A, & Bashir. H. K. (2011). Face recognition using local graph structure (LGS). Lecture Notes in Computer Science, 6762, 169–175.

[9] Ojala. T, Pietikainen. M, & Harwood. D. (1994). Performance evaluation of texture measures with classification based on kullback discrimination of distributions. 12th IAPR international conference on pattern recognition – Conference A: Computer vision & image processing (Vol. 1, pp. 582–585).

[10] Mohd Fikri Azli Abdullah, Md Shohel Sayeed, Kalaiarasi Sonai Muthu, Housam Khalifa Bashier, Afizan Azman, Siti Zainab Ibrahim(2014). Face recognition with Symmetric Local Graph Structure (SLGS), Expert Systems with Applications 41 (2014) 6131–6137