ISSN 2229-5518

Weighted Local Active Pixel Pattern (WLAPP) for effective Face Recognition

Mallikarjuna Rao G, Jella Rajesham

Abstract— The complexities associated with Face Recognition continuously attracting the researches to propose new techniques approaches to efficiently address this problem. LBP (Local Binary Patterns) and LAPP (Local Active Pixel Patterns) are some of the local feature extracting approaches for reducing time and space requirements. Authors[6,7] shown that LAPP effectively used Face Recognition on mobile resource constraint environment. In this paper, it is aimed to identify the recognition sensitivity of the local regions through the Weighted Local Active Pixel Pattern(WLAPP) approach. The experimental results using WLAPP on FG-Net Aging Database is confirmed its improved performance compared to the other variants.

Index Terms— Active Pixels, Expression variation, Face Recognition, Illustration conditions, Local Active Pixel Pattern (LAPP), Local Binary Pattern(LBP), Pose variation, Weight, Weighted Boosting Weighted Local Actvie Pixel Pattern (WLAPP).

1 INTRODUCTION

Face Recognition is one of the most relevant applications of image analysis. It is a true challenge to build an automated system which equals human ability to recognize faces. Humans are quite good at identifying known faces, but the skill set is not sufficient while dealing with a large amount of unknown faces. Hence it is warranted to use the machines for dealing these limitations.

However, the strategies[1,2,3,4,5] adopted are not adequate for satisfactory recognition in the environments where varying expression, pose and Illumination conditions are inherent to the environment.

Modern Face Recognition algorithms such as Line Edge Map algorithms[1,2], LBP[3,4,5],LAPP[6,7,8] are proposed to make a grip on lighting factors appeared on the images, edge detection is a good approach to shape the facial features that can be hidden due to unusual lighting conditions.

The paper is organized such that basic techniques LBP, LAPP are discussed in sections 2 and 3. Section 4 is concerned about identifying the weights to the local regions and proposal of new approach WLAPP. Experimental discussion is made in section 5. Conclusions and results are subsequently discussed.

- Mallikarjuna Rao G is currently is presently professor in Dept. of Computer Science, Gokaraju Rangaraju Institute of Engineering &Technology(GRIET), Hyderabad, India. Email: gmr_333@yahoo.com
- Jella Rajesham is currently pursuing Master of Technology in Computer Science &Engineering from Gokaraju Rangaraju Institute of Engineering &Technology, Hyderabad, India, and Pincode: 500090. Email: rajeshamj@gmail.com

2 Local Binary Patterns (LBP)

The LBP gradually became most widely used approach by researchers and extended it to other pattern recognition disciplines, which is proposed originally for texture recognition.

As shown in the above figure1, the LBP of image are constructed as it gives binary patterns as a result. The Authors [6, 7] are clearly explained the procedure how to get local histograms and LBP descriptors.

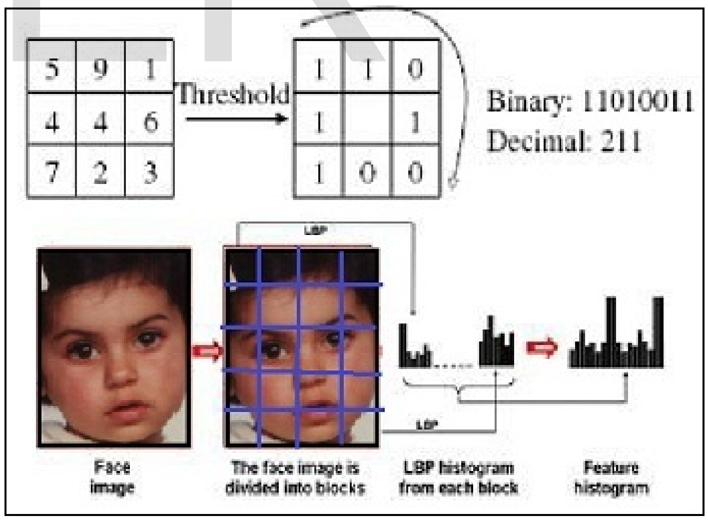

Figure 1: LBP Descriptor for 3x3 Mask and Histogram Computation

Though this approach is the one of the efficient approaches for pattern recognition, the researchers are searching for more efficient pattern recognition approaches/Algorithms. This results a new approach called Local Active Pixel Pattern (LAPP), is discussed in next section.

ISSN 2229-5518

3 Local Active Pixel PATTERN (LAPP)

Authors [6] suggested method for LAPP is capable of supporting face recognition in both conventional and resource constraint environment.

The **A**ctive **P**ixel is the one which denotes essential information of the image and the image can be reconstructed by using only active pixels.

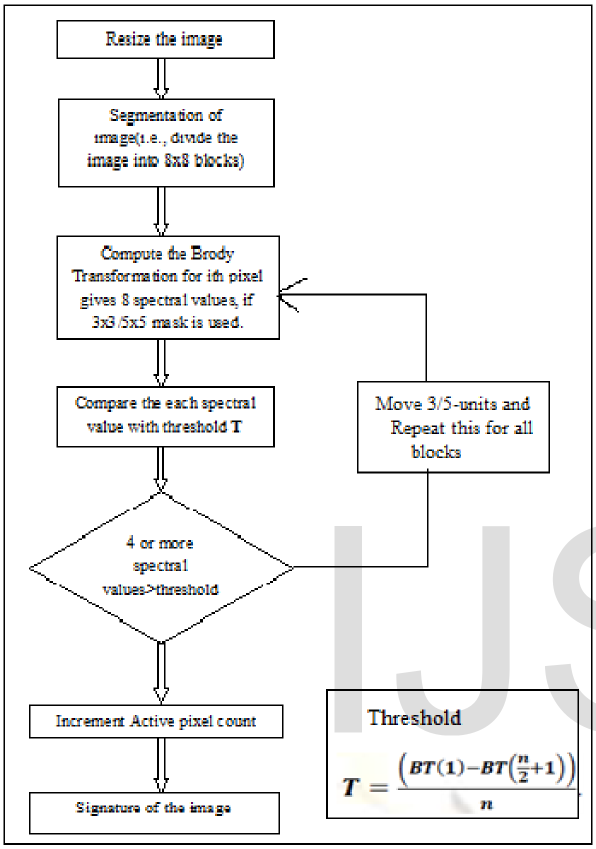

Figure 2: Computation of Active pixels

3.1 Computation of Active pixels:

Computation of Active Pixels uses Brody Transform [6] and extracts the information from images. As a result, an Active pixel matrix is formed. This computation procedure of Active pixels is shown in below Flow chart (figure2).

This process is clearly explained by Authors [6].

3.2 Computation of Active Template:

Active Template is computed from Active pixel matrices of each person images by taking the average of those Active pixels of all images belongs to each person (subject). This can be shown below:

$$\mathbf{ATM = (1/n) \sum APM}$$

Here, ATM-Active Template Matrix
APM-Active Pixel Matrix

3.3 Boosting:

Boosting is performed on Active Pixel Matrices and Active Template by taking the maximum valued element in that matrix and that added to each non-zero element of that matrix. Then correlation is performed among all the images and all templates. The results obtained by this process are used in the efficient Recognition of images; this can be discussed further in results section.

4 Proposed approach WLAPP

The proposed approach, is more efficiently working for taken database, is called **Weighted Local Active Pixel Pattern**, this will discussed in detailed stated with database follows as weight computation process and so on.

4.1 Weight Computation Process:

Sensitivity of the region on recognition each region is matched (correlated) with associated region and the relationship among weight, sensitivity and Active pixels is shown below:

$$\boldsymbol{weight \propto sensitivity \propto Active\ pixels}$$

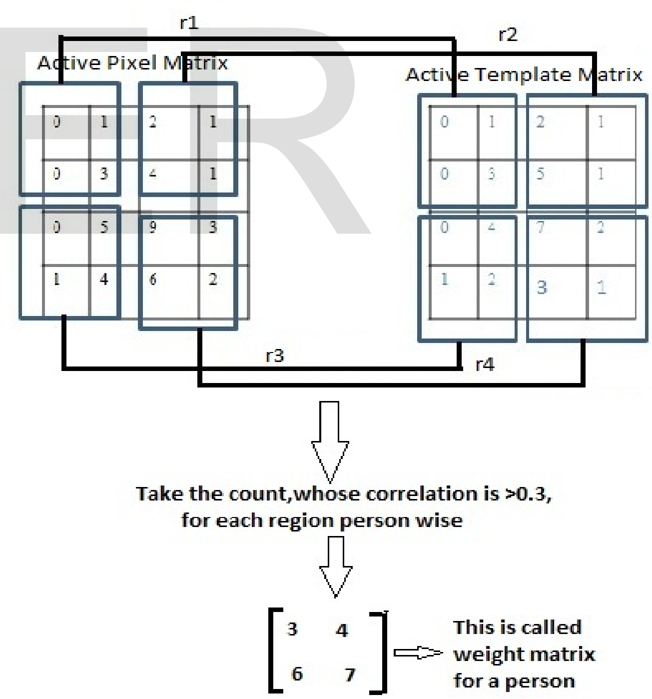

Figure 3: Weight computing process

The weights of individuals are computed by matching their active pixels with associated template. This process is as follows:

- First Active pixel matrices and their template are divided into 2x2 matrices.
- Then this Active pixel 2x2 matrices are correlated with corresponding template 2x2 matrices.

- The correlation values can be obtained by predefined MATLAB function **r=corr2(A,B),** where r is a scalar value**.**

  r=corr2(Activepixels,template)
- These correlation values which are **>0.3** is considered and a count is taken for each person individually so that individual count for each region is obtained. This is said to be sensitivity of that region.
- Combination of these values for each person is represented by a matrix called **weight** of the individual person.

This process can be shown in figure3.

4.2 Algorithm:

A new algorithm called WLAPP is shows the computation of Weighted Active pixels and Weighted Templates as follows:

- First Weight is computed for individuals as explained in the above section 4.1.
- After obtaining weight for each person, Active pixel matrices elements are multiplied by those weights of region as each region contains separate weight.
- Here Weighted Active Pixel matrices and Weighted Template matrices are computed by using Product Block approach, which means element by element multiplication is performed for matrices instead of matrix multiplication.
- This can be called Element-wise multiplication in MATLAB and represented in MATLAB notation as follows:

$$WAPM = Weight.*APM$$
$$WATM = Weight.*ATM$$

  Here, WAPM-Weighted Active Pixel Matrix
  APM-Active Pixel Matrix
  WATM-Weighted Active Template Matrix
  ATM-Active Template Matrix

- Now correlation is performed among Weighted Active Pixel Matrices and Weighted Active Template matrices.

$$r = corr2(WAPM, WATM)$$

- This process is called **Weighted Boosting.**

After that Recognition of images is performed, is discussed in next section.

5 Experimentation

In traditional approaches, images are to be compressed before the processing to reduce the space requirement. However the compression process results in information loss and influenced the recognition accuracy.

In this experimentation to retain the final details of images, enhanced images of size 256x256 are used here so the space requirements are reduced at the same time it gives effective feature set. The local relations are explored using 8 neighbourhoods on segmented local blocks whose size is varied. The effect on block size is on recognition accuracy is also investigated.

5.1 Dataset (FG-Net Aging Database):

The FG-NET Aging Database contains face images showing a number of subjects at different ages have been generated as part of the European Union project FG-NET (Face and Gesture Recognition Research Network). The database has been developed in an attempt to assist researchers who investigate the effects of aging on facial appearance.

Images of a person with different ages, poses and illumination conditions of FG-Net Aging Database

Figure 4: A person images of FG-Net Aging Database

Face Recognition on FG-Net aging Database is turned into challenging problem as the dataset contains Facial images of the same person taken at different ages (0-65years) with different backgrounds and with different illumination conditions of pose variation and varying facial expressions, contains totally 921 images of females and males of different age groups, is shown in below Table1.

Table1: Dataset details

	Female	Male	Total
Babies (0-10years)	26	39	65
Young People (11-30years)	50	71	121
Middle age (31-49years)	43	25	68
Old People (Above50years)	22	44	66

In this experimentation, all 921 images are considered either for Training or for Testing without any pre-processing and pruning.

The experimentation on different segmentations and different masks of 256x256 resized images is performed. Those are:

1. 4x4 segmentation and 3x3 mask
2. 8x8 segmentation and 3x3 mask
3. 8x8 segmentation and 5x5 mask
4. 16x16 segmentation and 3x3 mask
5. 16x16 segmentation and 5x5 mask

The results of the above different types are shown in figure 11. Among them, it is found that 8x8 segmentation with 5x5 mask as provided 95.98% accuracy. The following table2 reveals it. (Note that mask is taken as per the Brody transform [6, 7, and 8]).

Table 2: Recognition Accuracy

Methods-->	Without Boosting	Boosting	**Weighted Boosting**
Trained images	921	921	**921**
Tested images	921	921	**921**
Correctly Recognized images	746	696	**884**
False Recognized Images	175	225	**37**

The accuracy is calculated as correct rate which is obtained from the ratio, number of correctly recognized images to total number of images, is multiplied by 100.

Figure 5: Example Trained, Tested and Recognized images

The figure 5 shows the sample images of 2 sets which are used for recognition and testing. Then recognized images are also shown.

6 SCALABLE WLAPP

In this paper we are also proposing parallel, scalable model [9] for LAPP. Since the traditional way of programmability and serial execution has reached its limit, the current trend is not only the programmability but also parallelism to meet the growing demands of high performance computing. The presences of multicores in the state of art computing machines enrich their computational power. However, problem solutions have to be reorganized to tap the computational power of these machines. As the Visual applications need enormous computational recourses, the research community focuses more on this area and responding with new approaches/techniques which paralyze traditionally serial methods. Face Recognition is one of them with inherent complexities associated with traditional methods such as PCA, ICA etc., for extracting scalability and parallization. MPI, OMP open source resources support the paralysation of the software. In this regard we attempted scalability of LAPP. Three main methods used are:

1. Broadcasting the pixel values among the parallel workers (cores/threads).
2. Performing the pre-processing for LAPP parallel by all these workers
3. Gathering the computed values to form the feature vector.

6.1 Parallel Software: Open Source

OpenMP is easier to program and debug than MPI, directives can be added incrementally (called gradual parallelization). It can still run the program as a serial code and serial code statements usually don't need modification. In this code is easier to understand and may be more easily maintained.

OpenMP can only be run in shared memory computers, requires a compiler that supports OpenMP and is mostly used for loop parallelization.

Message Passing Interface (MPI) passes messages to send/receive data between processes, and it is outgrowth of PVM software. MPI runs on either shared or distributed memory architectures that can be used on a wider range of problems than OpenMP. In this each process has its own local variables and distributed memory computers are less expensive than large shared memory computers. On the other hand MPI requires more programming changes to go from serial to parallel version, can be harder to debug and performance is limited by the communication network between the nodes.

The figure 6 shows the work among the worker in MPI environment.

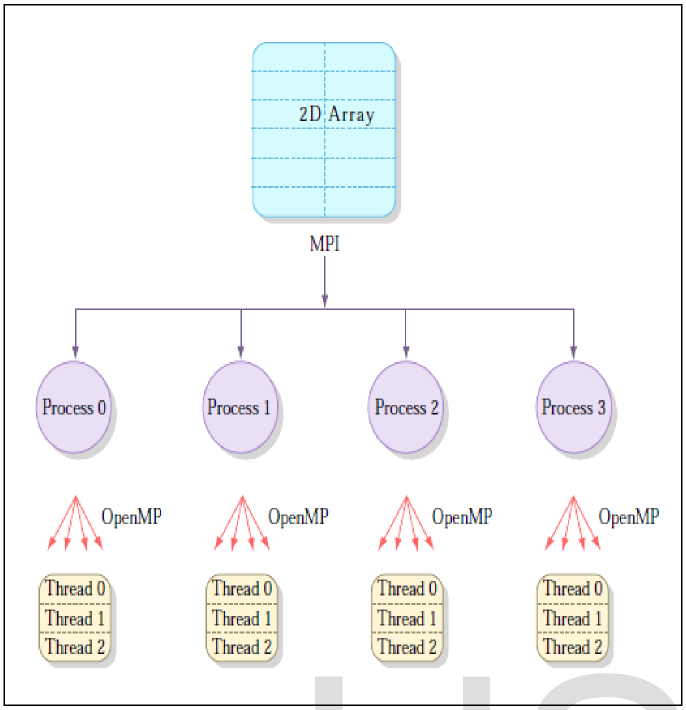

Figure 6: OpenMP and Message Passing Interface (MPI)

6.2 LAPP: Parallel Approach

The parallel approach for LAPP is based upon its scalability. The image division, neighbourhood extraction and computation are performed in parallel. For an image of size 256x256 is divided into 8x8 sub-regions using 1024 parallel workers. Each sub-region is then processed to compute active pixels using overlapping 3x3 neighbourhood. The parallel approach required 49 workers for each subject. The following figure 7 gives the implementation aspects.

6.3 Parallel Approach for Weight Computation

The recognition sensitivity of each sub-region is used while computing weight for the feature value. The weight computation process is illustrated in the section. In this section it is proposed to compute the weight parallel using 128 workers for each subject. Each image contains 16, 8x8 regions and 8 images are considered for each subject. Thus 128 parallel workers (16x8) are used for this computation, while generating the weights of the features. Weighted features for all 82 subjects are obtained similarly. The figure 8 illustrates parallel model for weight computation of a subject.

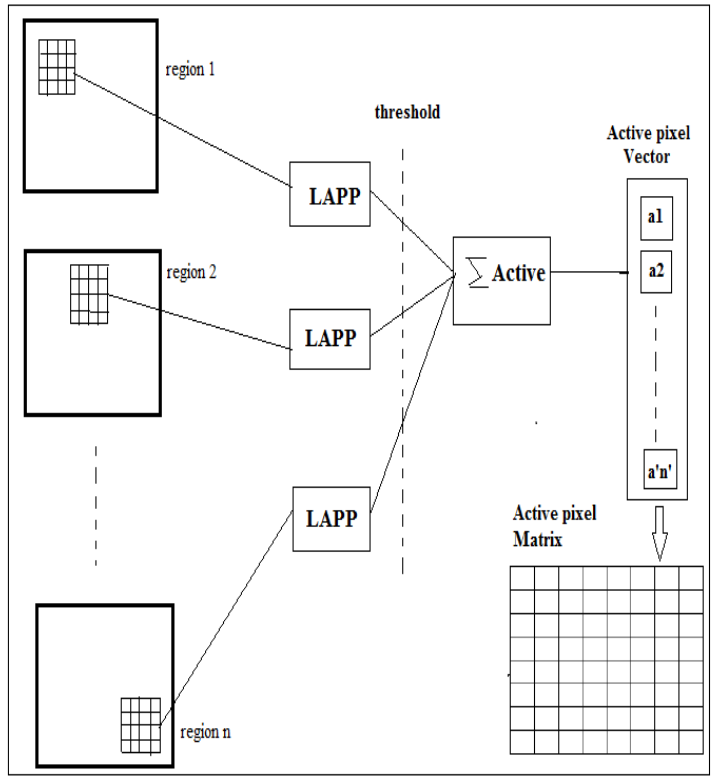

Figure 7: Local Active Pixel Pattern (LAPP) Feature Extraction

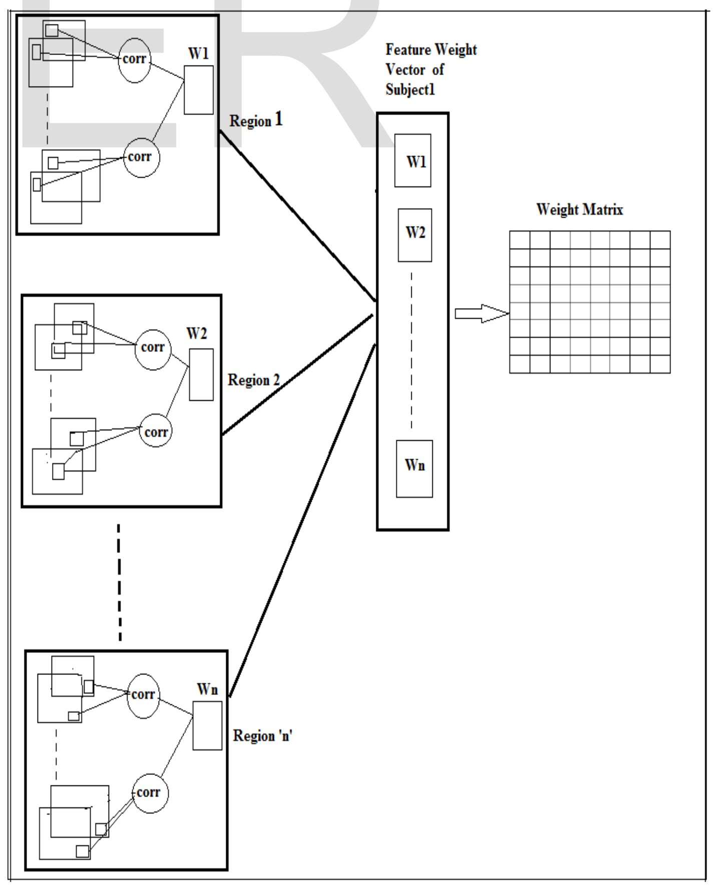

Figure 8: Feature Weight Vector for a subjects

6.4 Parallel Model for Weighted Active Pixels Matrix Computation

Weighted Active Pixel Matrix is computed, as discussed in section 3 using 921 parallel workers. Each worker will take 16 feature elements and 16 weights corresponding to subject covering 16 sub-regions. The dot product is computed to form a 4x4 weighted active pixel feature matrix. All 921 images of the database are used while computing the respective feature matrix. Figure 9 is showing the process.

The Weighted feature template for each subject is then computed using average weighted features of all images of the concerned subject. In this database 8 images are considered for Weighted feature template construction. 656 parallel workers are used for this purpose (82x8).

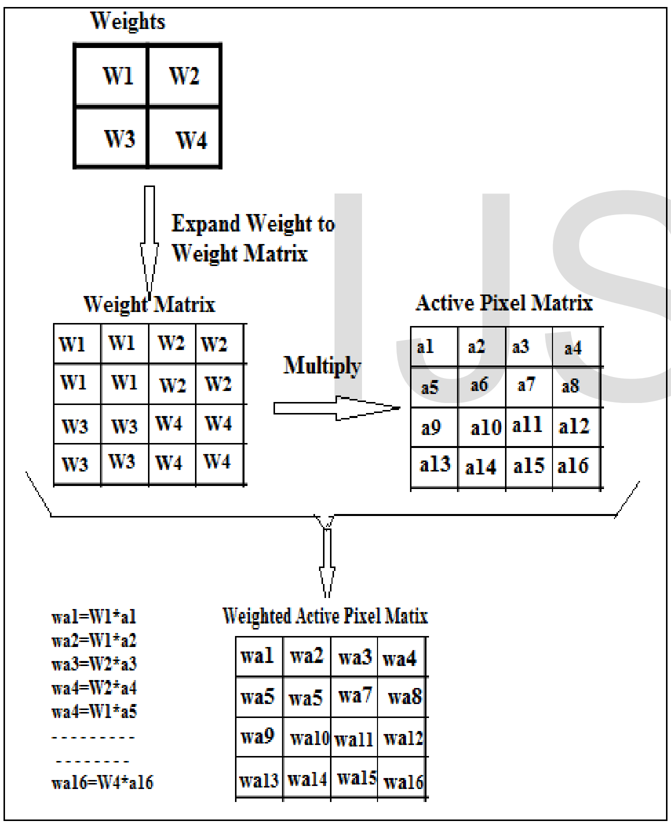

Figure 9: Weighted Active Pixel Matrix Extraction (WLAPP)

6.5 Parallel Matching for Test Probe

Figure 10 illustrate testing process of the selected image. The Weighted Active Pixel Feature set of the test probe is matched (correlated) in parallel with each of the 82 Weighted Template feature Matrices. The best match is found by selecting highest correlated Weighted Template which in term provides the class to which test probe belongs. The results confirmed its serial approach by drastically reducing the computational time, shown in Table 3.

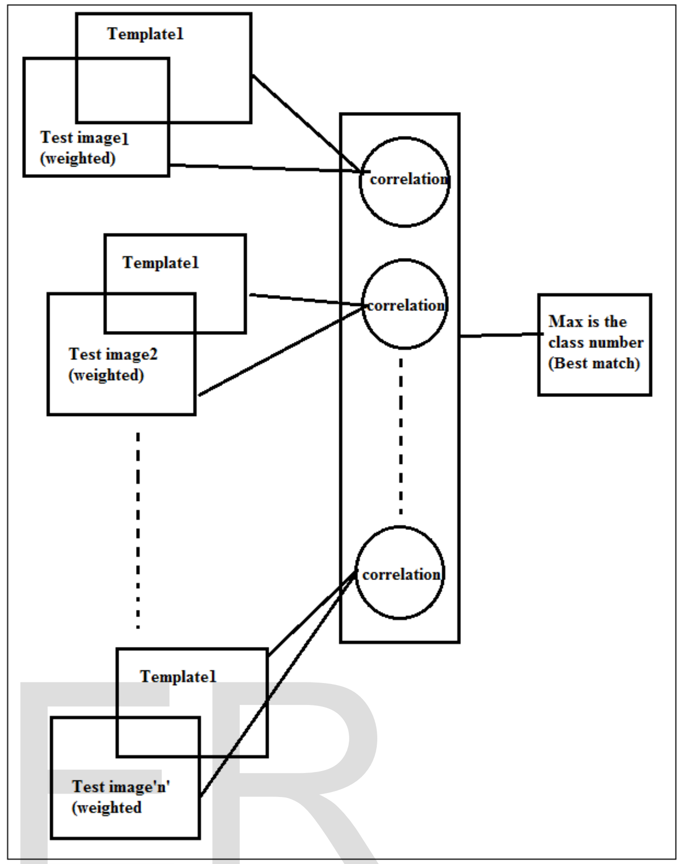

Figure10: Test of Images (finding Best match)

7 CONCLUSION

The images of each person are correlated with all the persons images in the Dataset are tested in 3 ways including this WLAPP as follows:

- The Active pixels of images are taken without any Pre-processing and correlate with all the images.
- Boosting is performed on the Active Pixels and Templates, and then correlation is performed with all the images.
- Weighted Boosting is performed on the Active Pixels and Templates, and then correlation is performed with all images.

The Results of above 3 cases are shown in below figure 11.

These results are obtained by 3 different cases are comparatively in increasing order shows the effectiveness of the methods. When comparing the results are obtained by without pre-processing of the images with Boosting are comparatively good(except some cases) and Weighted Boosting posses quite good results and dominated both the cases discussed before.

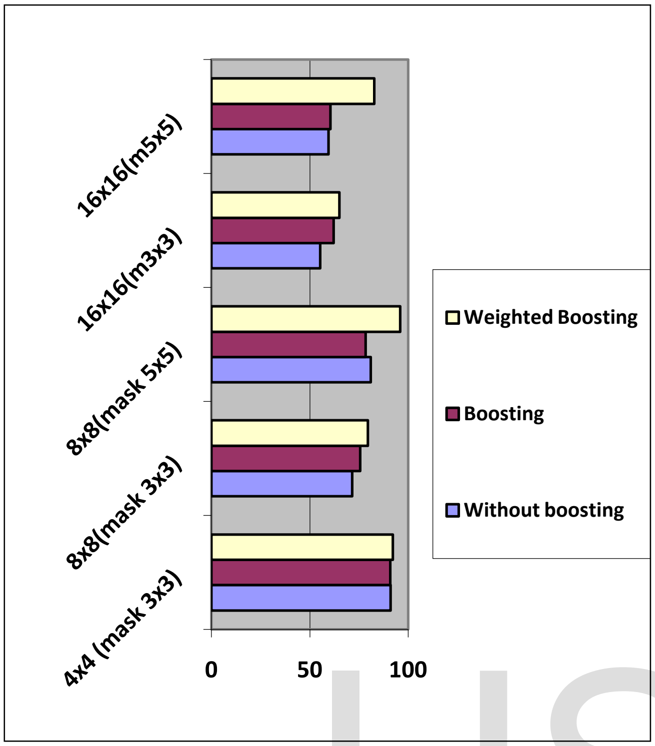

Figure 11: Results comparison

Table 3: Comparison between Serial and Parallel approach

Serial approach			Parallel approach		
Tested images	Recognition Accuracy	Convergence time	Tested images	Recognition Accuracy	Convergence time
921	95.98	180 min	921	96.20	32 min

Finally the serial and parallel approaches are compared in the table 3. From this table 3 we can conclude that time is saved as parallel processing is performed and little better recognition rate is found.

ACKNOWLEDGMENT

We would like to thank management of GRIET for the support extended and director Shri P.S.Raju for constant motivation.

REFERENCES

[1] Takács, 1998. Comparing face images using the modified hausdorff distance. Pattern Recogn., 31: 1873-1881

[2] Antitza. D. and J.L. Dugelay, 2011. Frontal-to-side face re-identification based on hair, skin and clothes patches. IEEE International Conference on Advanced Video and Signal-Based Surveillance, pp: 309-313

[3] Muhammad, S., M. Sajjad, Y.J. Muhammad and A.A.Muhammad, 2012. Single Image Face Recognition Using Laplacian of Gaussian and Discrete Cosine Transforms. IAJIT

[4] Ran, H., Z. Wei-Shi and H. Bao-Gang, 2011, Maximum correntropy criterion for robust face recognition. IEEE T. Pattern Anal., 33(8): 1561-1575

[5] Joe, Y., W. De Neve, K.N. Plataniotis and Y.M. Ro, 2011. Collaborative face recognition for improved face annotation in personal photo collections shared on online social networks. IEEE T. Multi., 13(1)

[6] Mallikarjuna Rao G, VijayaKumari G, Babu G.R, Face Recognition Applications using Active Pixels, International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622 www.ijera.com Vol. 2, Issue 4, July-August 2012, pp.466-477

[7] Mallikarjuna Rao G, Vijaya Kumari G, Babu G R, Rajesh V, 5023Fast Local Binary Patterns for Efficient Face Recognition/ J. of Sci. and Eng. Vol. 2(2):22-26, Dec. 2011, Mallikarjuna Rao G. et al. ISSN: 2086

[8] G. Mallikarjuna Rao, Praveen Kumar, G. Vijaya Kumari, Amit Pande, G. R. Babu: An Investigation into the Use of Partial Face in the Mobile Environment. ISVC (2) 2011: 526-535

[9] J. Cho, B. Benson, S. Mirzaei, R. Kastner, "Parallelized Architecture of Multiple Classifiers for Face Detection", Proc. IEEE International Conference on Application-specific Systems, Architectures, and Processors, 2009, pp. 75-82.

Authors:

1. Mallikarjuna Rao G, is presently professor in Dept. of Computer Science, GRIET, Hyderabad. He completed first Masters Degree in Digital Systems from Osmania University in the year 1993 and second masters degree in CSE from JNTU Hyderabad in the year 2002. He is currently pursuing the PhD in Image Processing area from JNTUH. In his credit there are 1 journal publication and, 6 international conference publications. He won the best Teacher award in 2005 at GNITS. His research interests are Neural Networks, Pattern Recognition.

2. Jella Rajesham, is pursuing Master of Technology in computer Science from GRIET, Hyderabad.