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Face Recognition Applications using Active Pixels

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Abstract

In this paper we suggest the Local Active Pixels Pattern, **LAPP[1]**, which in-turn can reduce the computational resources compared to counterpart Local Binary Pattern, LBP. The approach is apt for mobile]based vision applications. The approach has been made use tofusion based face recognition [3,4],3-D feature based face recognition[5]and age classification.

The YALE, 3-D Texas Face Dataset, IRIS visible and infrared data set has been used in the experimentation.

1. Introduction

The accurate and efficient face recognition techniques have recently received utmost attention in the research community due to its widespread applications such as defense, crime prevention, video surveillance, biometric authentication, automatic tagging the images on social networks and so on. At the same time face recognition posed challenges to the research community due to the variabledegree of freedom offered by different face precincts. The problem complexity is further increased due to variable conditions in the capturing environment such as lighting conditions, occlusion and so on. The holistic approaches use all pixels of the image forthe recognition process. These approaches not only consume bulk computational resources but also contain redundant data. The biggest challenge is to decide how many and what features are to be selected for the recognition process. Too many features result in more computational requirements with more redundant information, too few feature results more misclassificationswith reduced accuracy. The PCA, LDA, ICA and so on are proposed to reduce the redundant information. The local recognition approaches proved to be giving better performances due to their powerful discrimination information about the local regions than global approaches. The LBP, local Binary Pattern is one of them. It is originally intended to texture recognition but latter it is extended to even face recognition.

The attention of the researchers is diverted from conventional environmentto the resource constraint environment. The exploration of vision based applications in mobile[2] environment demand alternative approaches as conventional approaches does not givesatisfactory performance.

In this paper we are interested in addressing the issue of limited resources such as memory and processing power by suggesting a new approach, Local Active Pattern (LAPP), that reduces the feature elements without scarifying the recognition accuracy. Paper organization is made so that section 2 deals with LBP while the section 3 concern with Brody Transform. Our proposed approach , its performance evaluation has been discussed in section 4 and section 5 respectively. Subsequent sections deal with experimentation. Conclusions are made in section 7.

2. Local Binary Patterns, LBP

The LBP [,6], is proposed originally for texture recognition, which gradually became most widelyused by researchers and extended it to other pattern recognition disciplines.

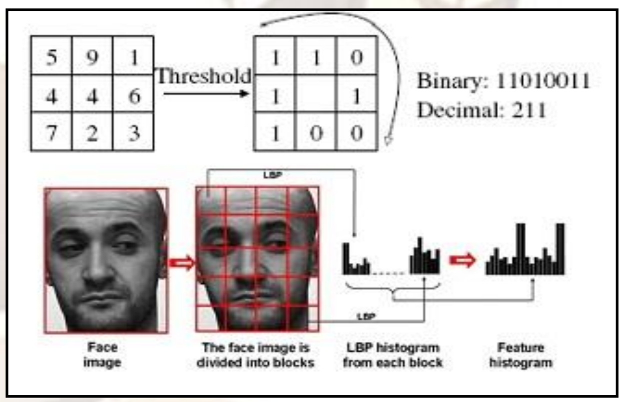


Figure1. LBP Descriptor for 3 x 3 Mask and Histogram Computation

The algorithm is used to construct binary pattern around 8-neighborhood (radius=1), 16-neighborhood (radius=2) of the central pixel. This pattern after conversion into integer forms feature element of that local region.
The local histogram is constructed with these feature elements and concatenated histogram represents the

signature of the image. During the recognition histogram matching is used to know the degree of matching. The researchers used support vector machines, Neural classifiers for matching. LBP descriptor, as shown in figure1, is derived from the input face image before being forwarded to the classifier. The image is divided into blocks and a 3x3 mask is used to construct the binary pattern based on the relationship with the central pixel. The 8-neighbors of the central pixel are assigned withthe binary value '1' if its value is greater than central pixel else it is assigned withzero. The uniform patterns are suggested to reduce the computational complexities. The authors [7] proposed 58 classes that will emerge from the local binary pattern which are latter send to the classifier for the recognition process. Let the $I(x,y)$ be the central pixel of 8-neighborhood then the LBP descriptor of $D_{x,y}$:

$$D_{x,y} \quad = \left(\sum_i u\big(I(x+\delta x, y+\delta y) - I(x,y)\big) * 2^i\right)$$

$$where u(z) = 1\, if z > 0 \;\; else\; 0\,; \quad \delta x, \delta x \epsilon \{-1,0,1\} and (\delta x = \delta y \neq 0)$$

3. Brody Transform

The Brody Transform[8] is one among the several powertransforms proposed to provide shift invariant output from input spectral components. Unlike the others, it uses simple pairof symmetric functions. This Cyclic Shift Invariant Transform is also called R-transform or Rapid Transform, RT, for its faster convergence. The RT results from a simple modification of the Walsh-Hadamard Transform. The signal flow diagram of RT is similar to that of WHT except that the absolute value of the output of the each stage of the iteration is taken before feeding it to the next stage. Figure 2 reveals the translation invariance behavior of Brody transform. Since the Brody Transformation *is not an orthogonal transform, it has no inverse*

1			
1			
1			
1	1	1	

		1	
		1	
		1	
1	1	1	

			1
			1
1	1	1	1

Figure2. Invariance of Brody Transform

The Brody Transform is the same for all the translated versions of the object.

BT {1 0 0 0 1 0 0 0 1 0 0 0 1 1 1 0} = {6 4 4 2 2 0 2 0 2 0 2 0 2 0 2 0}
BT {0 0 0 1 0 0 0 1 1 1 1 1 0 0 0 0} = {6 4 4 2 2 0 2 0 2 0 2 0 2 0 2 0}
BT {0 0 1 0 0 0 1 0 0 0 1 0 1 1 1 0} = {6 4 4 2 2 0 2 0 2 0 2 0 2 0 2 0}

4. Our Approach

The proposed system, as shown in figure 3 , is capable of supporting face recognition in both conventional and resource constraintenvironment.

The **A**ctive **P**ixel [1] is the one which denotes essential information of the image. The first element of Brody Transform is consideredthe cumulative spectral strength of that region. In terms of signals it denotes maximum energyof the region. It can be termed as *CPI*, Cumulative Point Index. The $(n/2+1)^{th}$ element indicates total subtractive spectral strength of the spectral components and termed as *SBI*, *Subtractive Point Index.* These two play decisive rolewhile determining the active pixel. The threshold value is computed as normalized difference of CPI and SBI, $\boldsymbol{T} = \frac{\left(\boldsymbol{BT}(\mathbf{1}) - \boldsymbol{BT}\left(\frac{\boldsymbol{n}}{\mathbf{2}}+\mathbf{1}\right)\right)}{\boldsymbol{n}}$.

A pixel is said be*ACTIVE* if its *n/2* or more neighborhood Brody transform spectral values are greater than the threshold. This conclusion is based on trial and error process. Figure 4 shows the effect of the threshold on computation of active pixel. The image is reconstructed using only active pixels.

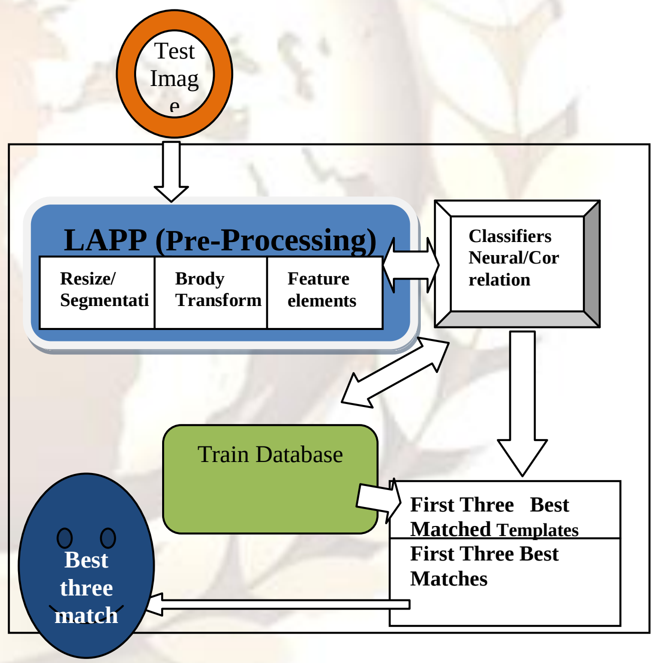


Figure 3. Proposed System

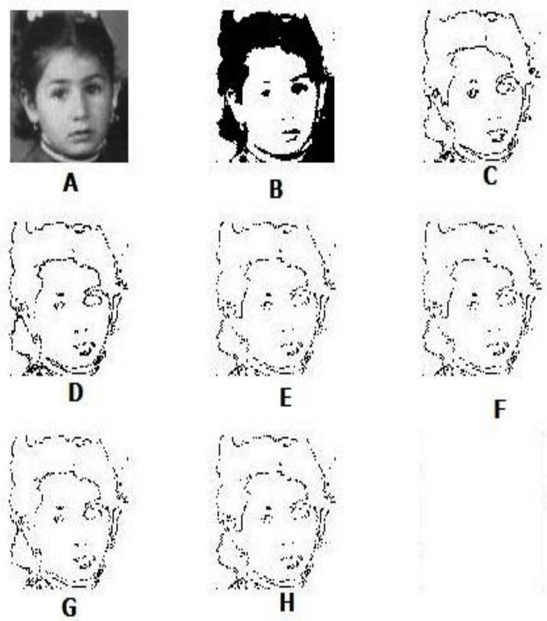


Figure 4. The effect of the threshold, T, on active pixel computation for subject *021A06*, FGAGENET

(A) Original Gray image (B) Black and White (C) BT(1:8) - T ≥ 2 (D) BT(1:8) -T ≥ 3 (E) BT(1:8) -T ≥ 4 (F) BT(1:8) -T ≥ 5 (G) BT(1:8) -T ≥ 6 (H) BT(1:8) -T ≥ 7

The image of FGAGENET[9] face database represents the subject 21 and the photo is taken at 6 years of age. The active pixel count becomes more for (C),(D) which may give a false impression about the background and image.

Procedure for extraction of Active Pixels:

- *Divide the resized image into 8 x 8 blocks.*
- *Use 3 x 3 mask and compute the Brody Transformation for i^{th} pixel gives 8 spectral values.*
- *Compare each spectral value with the threshold,* $T=\frac{\left(BT(1)-BT\left(\frac{n}{2}+1\right)\right)}{n}$
- *Increment Active pixel count if 4 or more spectral values are greater than the threshold.*
- *Move the mask by 3-units and repeat the same until the entire block is covered.*
- *The active pixel count represents feature elementforthis region.*
- *Repeat this for all blocks. The feature vector (combination of each block feature elements) gives the signature of the image.*

A

B

0	0	2	24	25	20	14
0	0	14	22	26	27	25
0	0	19	20	17	11	19
0	0	21	10	10	11	25
0	1	18	24	24	27	25
0	1	10	7	21	11	13
0	0	6	10	32	8	12
0	1	2	14	29	17	14

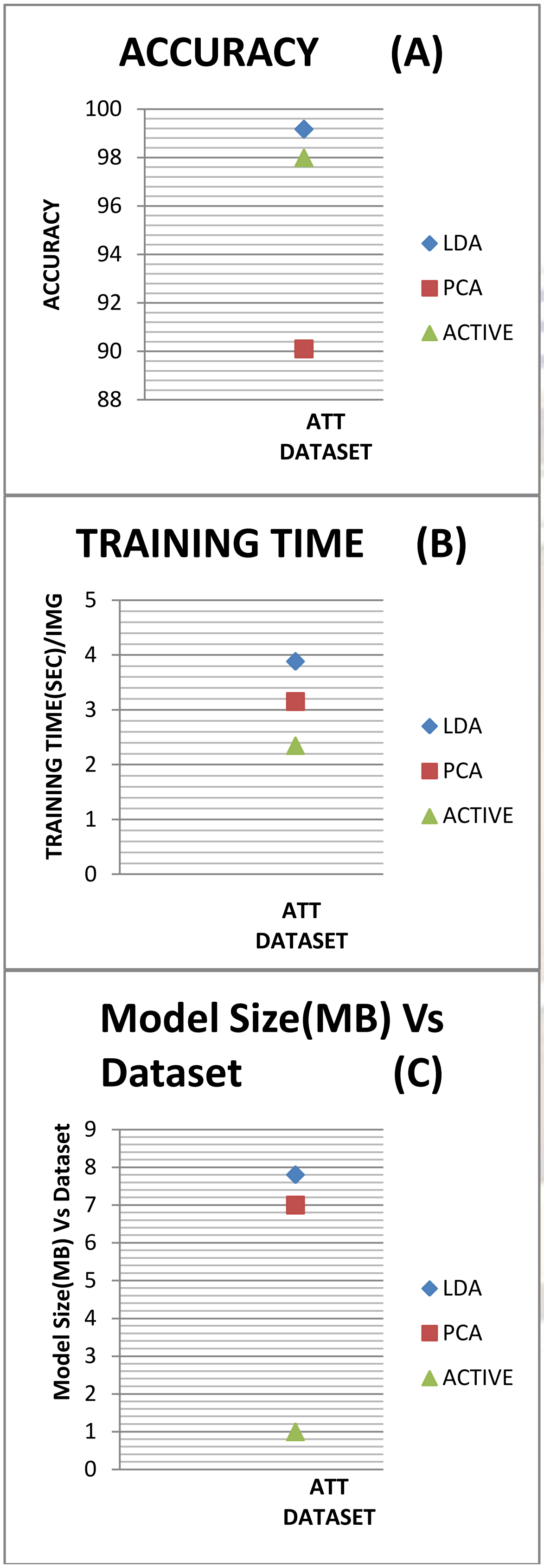
Figure 5. (A) Subject 1, YALEdataset
(B) Active Pixels

Figure 5 denotes the subject 1 of YALE[10] datasetand its corresponding Active pixel strength.The image isresized into 64 x 64 and divided into 8 x 8 blocks. For each block the active pixel count is obtained using the procedure given earlier. The 8 x 8 active pixel count acts as the signature of the images with 64 values. The active pixels retain geometric and local relationships of each block. If the block does not contain any variation the active pixel count in that block is a ZERO. The first two columns of active pixel matrix reveal this. It is apparent that the central blocks covering facial zone contain more active pixel count. The active pixel computation process is performing the function of a high pass filter.

5. Performance Evaluation

The performance of our approach is analyzed using "FACE EVALUATOR 2008" a third party software.The software has a provision for incorporating the new face recognition algorithms and comparing their performance against the standard face recognition approaches. It is used by many researchers as a benchmark while computing the performances.

The ATT (ORL) datasetcontains 40 subjects with 10 images per subject. The face evaluator 2008 is used to compare the proposed method with LDA and PCA. The evaluator performs comparisonamong the algorithms in terms of ACCURACY, TESTING TIME , TRAINING TIME, MEMORY NEEDED FOR TRAINING SET and MODEL SIZE WITH DATASET. The results are indicated by figure6 **A-E.**



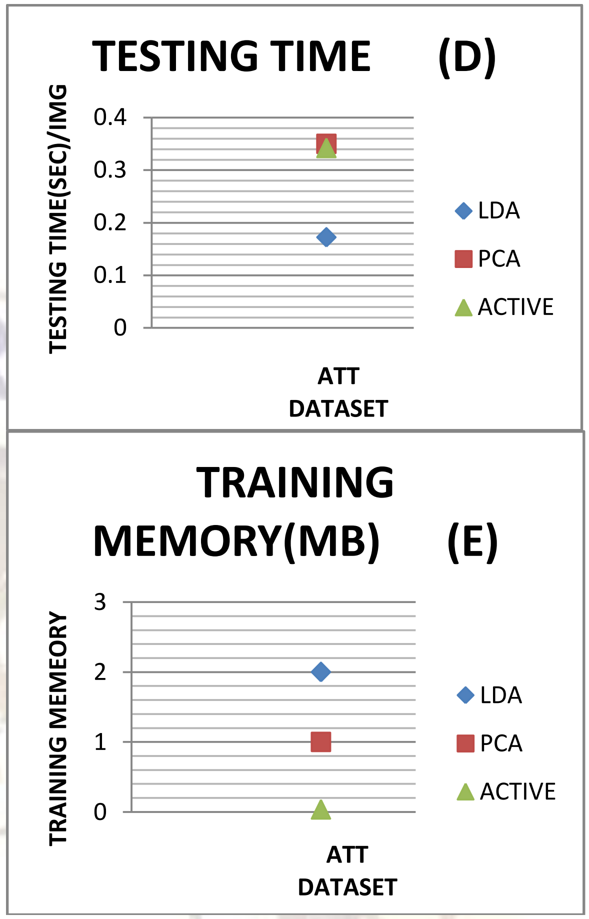


Figure 6. Face Evaluator 2008 Responses (A) Accuracy (B) Training Time (C) Model Size(D) Testing Time (E) Training Memory

Conclusions: The Accuracy of ACTIVE PIXEL approach (98%) is close to LDA (99%). The Training Time, Training Memory and smaller Model Size compared to LDA, PCA approaches.However, due to the two levels testing its testing time is more than LDA and is almost equal to PCA.

6. Experimentation

Even though many experiments are conducted for various vision based applications we would like to describe two of them.

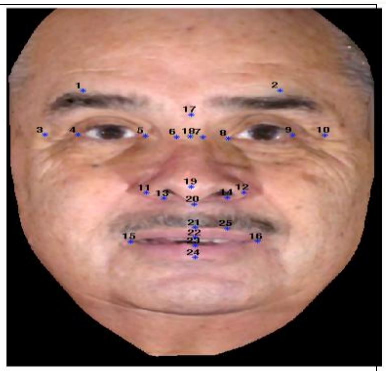
6.1 PersonIdentification using 3-D Feature Set

The complexities associated with expressionand illumination pose in face recognition domainshifted the focus of face detection from 2D domain to 3D domain. The 3-D facial image covers finer details and hence it provides good recognition rate [5]. However the computational complexity is more with 3-D face recognition techniques.

In the experimentation we have used Texas 3D Face Recognition database [11]. In the database for each portrait image 25 anthropometric facial fiducial[1] points are manually located.The database ,as shown table1, contains 1149 range and portrait image pairs of adult human subjects (118) covering gender, age, ethnicity, acquisition camera type, facial expression, and the various data partitions. The contents of the database are as follows:

Table 1. Texas 3D FR database &Fiducial Points

Males	**782**
Females	**367**
age<40	**915**
age>40	**234**
Caucasians	**465**
Africans	**44**
Asians	**381**
East Indians	**253**
Unknown	**6**
Camera Dull	**539**
Camera Bright	**610**
Expression-Neutral	**812**
Expression Non-neutral	**337**



They have provided <x,y> co-ordinates for each fiducial points in a file for each image. The real valued file is then converted into integer values ,as shown in table 2, for each subject. The integers are then processed using Brody Transform and active pixels are computed for each image. The 118 Active Eigen Templates are then computed. The two level correlations are used. The best three matched templates and best three matching within each template is chosen. 100 trails are made to test probe. In each trail 40 randomly chosen images are used in the test probe. Among all the trails 547 (13.675%) images of 4000(100*40) resulted miss classification. On our observation 40% of among miss classifications are with expression non-neutral and camera dull images. The figures 7 reveal this. The table 3 gives the performance comparison of various approaches against LAPP.

Table 2.Fiducial Points & Integer Values

Fiducial Points* (*x co-ordinate, y co-ordinate)		***Integer Equivalents***	
1.4079695e+02	2.0348985e+02	83	72
3.6798477e+02	1.9331726e+02	217	188
7.1284264e+01	2.8232741e+02	42	36
1.0434518e+02	2.8487056e+02	62	53
2.0946193e+02	2.7554569e+02	124	107
2.4421827e+02	2.8232741e+02	144	125
2.6880203e+02	2.8232741e+02	159	137
3.0101523e+02	2.8063198e+02	178	153
3.9256853e+02	2.8063198e+02	232	200
4.3156345e+02	2.8147970e+02	255	220
1.9420305e+02	3.8998731e+02	115	99
3.1203553e+02	3.9253046e+02	184	159
2.0861421e+02	4.0270305e+02	123	106
2.8829949e+02	4.0270305e+02	170	147
1.6707614e+02	4.6882487e+02	99	85
3.2983756e+02	4.6712944e+02	195	168
2.5439086e+02	2.2807360e+02	150	130
2.5523858e+02	2.8147970e+02	151	130
2.5354315e+02	3.8574873e+02	150	129
2.5439086e+02	4.1541878e+02	150	130
2.5100000e+02	4.4254569e+02	148	128
2.5100000e+02	4.6119543e+02	148	128
2.5015228e+02	4.8069289e+02	148	128
2.4930457e+02	5.0019036e+02	147	127
		171	147

Table 3.Recognition Rate

Algorithms	Neutral	Expressive	All
Eigen surfaces	58.1 [54.0 62.7]	52.5 [45.4 60.1]	56.6 [52.9 60.2]
Fisher surfaces	91.7 [89.4 94.0]	95.1 [91.8 97.8]	92.6 [90.6 94.4]
ICP	88.5 [85.6 91.5]	86.3 [80.9 91.0]	87.9 [85.5 90.2]
Anthroface 3D (25 arbitrary)	86.0 [82.9 89.0]	91.3 [87.4 95.1]	87.5 [84.9 89.9]
***LAPP** ***(Random 40*100)**	***89.3*** **[89.5 97.5]**	***86.6*** **[88.6 98]**	***87.95*** **[88 96]**

[1]Shalini Gupta ,**The Texas 3D Face Recognition Database** Laboratory for Image and Video Engineering, The University of Texas at Austin, Austin,

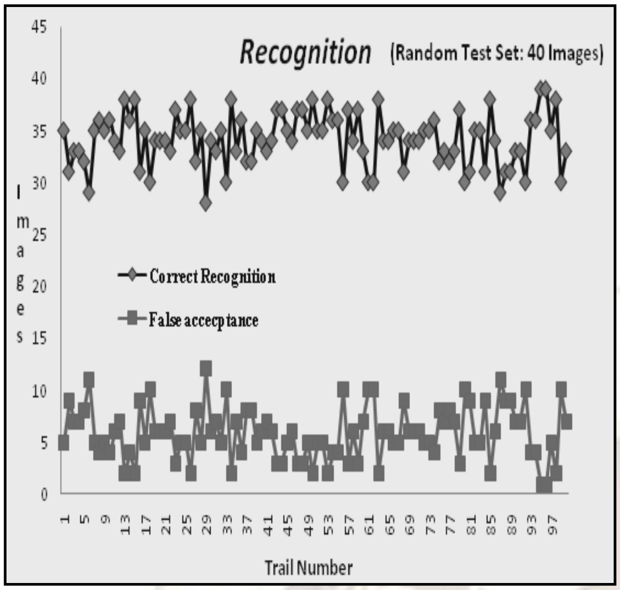
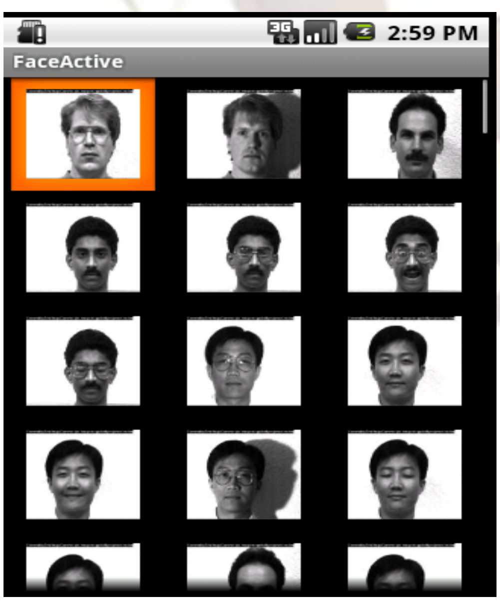


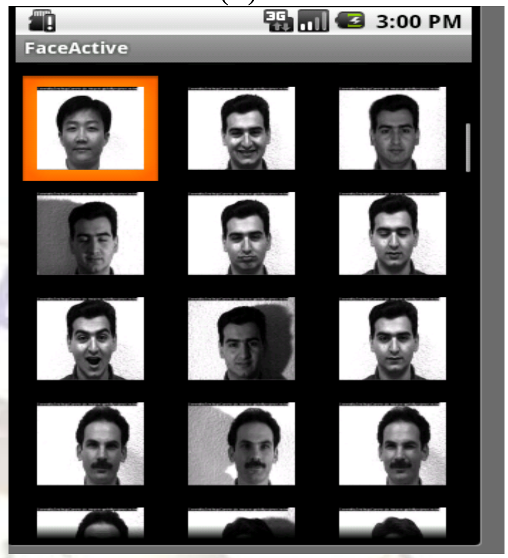
Figure 7. Recognition using LAPP (Random Testing)

6.2 YALE Experimentation on Mobile Device:

When the Application is started the user is given a set of database (**Yale Database**) containing groupof images in a Grid View. The user can select any one image inthat grid view images, as shown in figure 8. The YALE data set is ported on the mobile using android operating system. The Java version of the system is developed and ported on Sony Ericsson with **Android 2.1** Phone memory 128MB MicroSD™ support (up to 16 GB) and Screen 320 x 480 pixels (HVGA) / 16,777,216 color TFT.120 probes are made to android system randomly 117 (97.5%) are recognized correctly in first match.



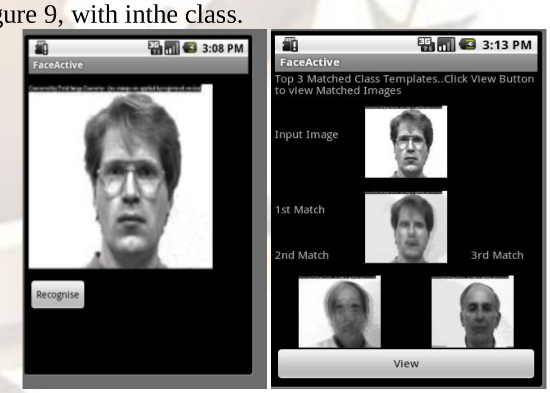
(A)



(B)

Figure 8. Grid A:View ,B: Selection

Now the user haveto select the image by **clicking** on it ,as the image is clicked, the selected image is displayed and it'll show the **RECOGNISE** button to start the recognition process performs first level correlation with active pixel signatureof test imagewith the template. After the first level correlation the system provides best three matched images. The **VIEW** option initiates the second level correlation of the test image active pixel set with inthe best matched class template. The process generates the best three matches, as shown in figure 9, with inthe class.



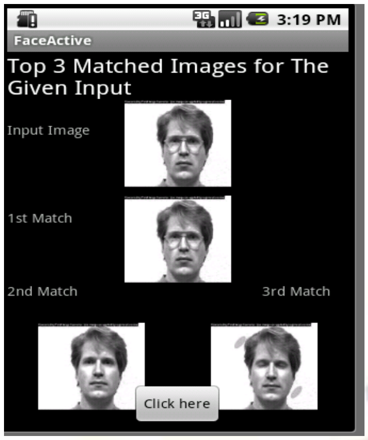


Figure 9. Recognition Process and the Best Three Matched Templates and Image

6.3 Fusion based Face Recognition

Fusion of thermal and visible images has been emerging as one of the promising face recognition approaches as the thermal images (IR) are less sensitive to illumination changes and visible images useful for low resolution imagery. Though the thermal images are more promising in outdoor face detection environmentbut they are sensitive to facial occlusion caused by spectacles. The illumination variations reduce the recognition performance of visible image based approaches. Hence fusion based approaches [3, 4] have been proposed for the face recognition.

6.3.1 Fusion Approaches

The thermal image can at best yield estimate of surface temperature variation that is not specific in the intraclass distinguishing. The visible images are lackthe specificity required for unique identityof the image object. A great effort has been expended on the automated seen analysis using visible imagery and some work has been madein recognizing the objects using thermal imagery. However inconsistency associated with the object recognition using thermal images in outdoor environment reduced the pace of active research in this domain. The same subject may yield different thermal images due to variations in body temperature in response to the outdoor environment. The lighting conditions degrade the performance of the image object recognition using visible image approaches. Thus fusionof visible and thermal images has been[3] proposed to address the difficulties associated with thermal and visible image based approaches.

The fused image is obtained using:

1. Feature level Fusion
2. Decision level Fusion
3. Pixel level Fusion

Feature level fusion requires the computation of all features from multiple sources before fusion. The signal features, in general, belong to time domain, frequency domain and hybrid domain.

The time domain features include waveform characteristics (slopes, zero crossings) and statistics (mean, standard deviation) while frequency domain featurerepresents spectral distribution, periodicity.

The hybrid approaches cover both. The problems associated with feature level fusion are:

- The feature sets of multiple modalities may be incompatible
- The relationship between the feature spaces is unknown
- Concatenating the feature vectors may results very large feature vector which can lead curse of dimensionality problem.

Decision level fusion combines results of multiple algorithms to yield the final fusion. The Bayesian inference, Classical inference and Dempster and Shafer's method are widely used decision level fusion methods.

Pixel level fusion is the combination of raw data from multiple source images into a single image using pixel, feature or decision techniques. The fusion image, Common Operating Relevant Picture (CORP), proposed by Hughes, 2006 contained 70% visible and 30% thermal pixel information.

In our approach we combined the time domain and pixel level fusion. The feature obtained the fusion image:

$$F(X,Y) = (a * V(X,Y) + b * I(X,Y)/(a+b) \text{ -----}\mathbf{1}$$

Where a & b are the weighting factors visible and fusion features, V(X,Y) and I(X,Y) active pixel count of the respective regions of Visual and Infrared images respectively. The figure 10 denote the fusion process with

a=b.

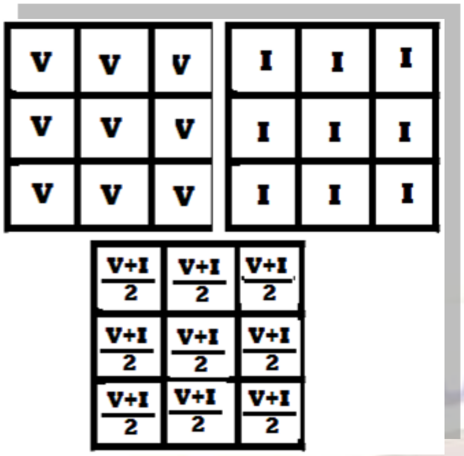


Figure 10. Fusion Process

6.3.2 Experimentation using Fusion of IR & Visible Images

The experimentation is carried on near Infrared & Visible database of Meng. The database[2] contains 3432 images covering 26 subjects with each subject 6 expressions. For each expression it covers 11 visible and 11 thermal images. Five different illumination conditions are used while constructing the database. The figure 11 gives sample Visible and IR database of subject 1 in different lighting conditions.

Figure 11 Visible and IR for subject 1

6.3.3 Experimental Approach

The Active pixels are computed for both IR and Thermal images after resizing to 128 x 128. The class Eigen Active Template is obtained for each subject. Further six Eigen Active Templates are constructed for each expression of each subject. The fusion is performed on the active pixel templates by adding the templates of IR and Visible images. The test probe is correlated with IR, Visible and Fusion templates. The best matched template indicates the subject class. It is then correlated with expression template, as shown in figure 12.

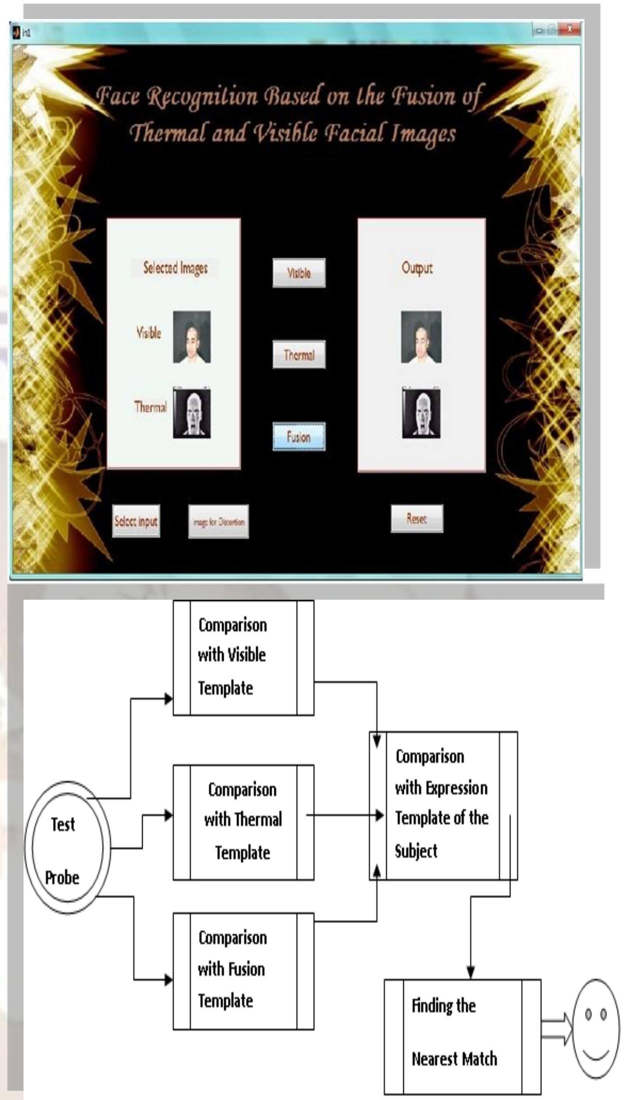


Figure 12 Sample output and Testing Process

6.3.4 Experimental Conclusion

The test probe generates the first matched subject using IR & visible template is shown in figure 12. If the matched subject is not acceptable then fusion response can be used. Thus these approaches are used to supplement and complement each other instead competing. The visible images resulted good accuracy for neutral expressions. The IR images are insensitive to low illumination and shadow presence in captured image. The fusion has given better recognition when portion of image covered by glass opaque.

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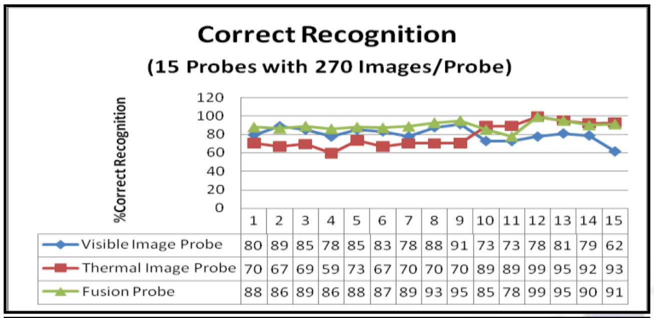
[2]**IRIS Thermal/Visible Face Database**



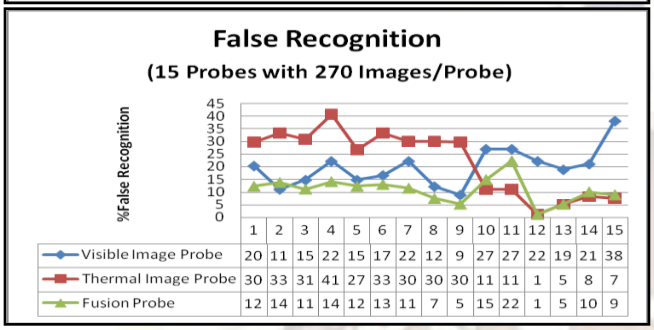


Figure 13 Test Probe with fused images

Table 4. Comparison between Fusion techniques

Image Fusion Technique	Recognition Rate	
Fusion of Wavelet Coefficients (1)Haar (2)Daubechies	87% 91.5%	
Simple Spatial Fusion	91.00%	
Fusion of Thermal and Visual	90.00%	
Absmax selection in DWT	90.31%	
Window based absolute maximum selection	90.31%	
Fusion of Visual and LWIR+PCA	87.87%	
Active Pixel based Fusion (Our approach)	**89.96% using First best match.**	**94.4% using best Three matches.**

6.4 Age classification using Facial features

The recent trends in machine based human facial image processing concerns the topics about predicting feature faces, reconstructing faces from some prescribed features, classifying gender, races, and expressions from facial images, and so on. However, very few studies have been done on age classification.

6.4.1 Present Status of Age classification

Kwon and Lobo first worked on the age classification problem. They referred to craniofacial research, theatrical makeup, plastic surgery, and perception to find out the features that change with age increasing. They classified gray-scale facial images into three age groups: babies, young adults, and senior adults. First, they applied deformable templates and snakes to locate primary features (such as eyes, noses, mouth, etc.) from a facial image, and judged if it is an infant by the ratios of the distances between primary features. Then, they used snakes to locate wrinkles on specific areas of a face to analyze the facial image being young or old. Kwon and Lobo declared that their result was promising. However, their data set includes only 47 images, and the infant identification rate is below 68%. Besides, since the methods they used for location, such as deformable templates and snakes, are computationally expensive, the system might not be suitable for real time processing.

6.4.2 FGNET Aging Database

The FG-NET Aging Database contains face images showing a number of subjects at different ages has been generated as part of the European Union project FG-NET (Face and Gesture Recognition Research Network). The database, summary is given in table 6.4, has been developed in an attempt to assist researchers who investigate the effects of aging on facial appearance.

6.4.3 Our Approach

In this experimentation Boosted active pixel approach has been used person recognition based on age query. The 921 images covering 82 subjects of FGNET Age dataset are used to form 82 Active Eigen templates. The experimentation is done using (i) 128 x 128 resized image (ii) 256 x 256 resized image. The data set cover the images taken at various ages of each subject some of them are grey, some of them are color (RGB) and some of them are black-white with different sizes. Hence in the experimentation is made on the resized grey images.

Procedure:

1) Compute the active pixels for each region of the image.
2) Compute the Class Active Pixel Template for each subject.
3) Boost the active pixel count at each region using global maximum value for each class template.
4) Perform Two-level correlation

Experiment 1: In our experiment all the 921 images have been used as test probe and the first three matched images are extracted from the best matched class template, as shown in figure 14.

Experiment 2: In this experiment we have selected 316 images across the different ages. The selection comprises 65 babies 0-10 years (Female 26, Male 39), 121 young people 11- 30 years (Female 50, Male 71), 68 middle age 31-50 years (Female 43, Male 25) and 66 Old people above 50 years (22 Female, 44 Male). The experimental results are shown in figure 15..

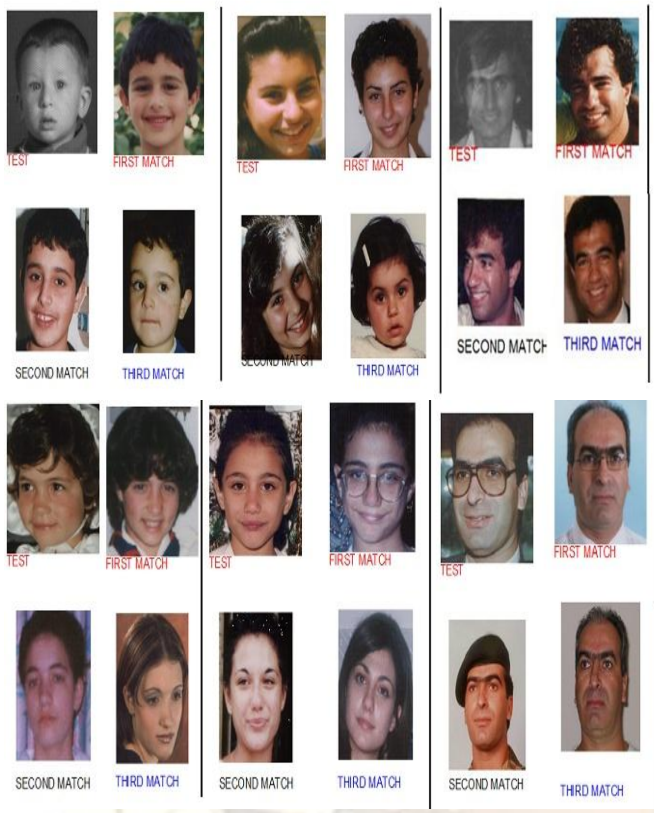


Figure 14 Face Recognition & Retrieval based on Age Probe

6.4.4Experimental conclusion

The experiment one produced 85% correct recognition accuracy with best three matches. The experiment 2 has produced good recognition rate 92% for boys and middle age people 92%. The correct recognition has fallen to 80% to old people. The aging effects are different for different people, hence the recognition rate hasfallen. The recognition accuracy is 78% with best three matches considered with image size 128 x 128 and 85% if the image size is 256 x 256.

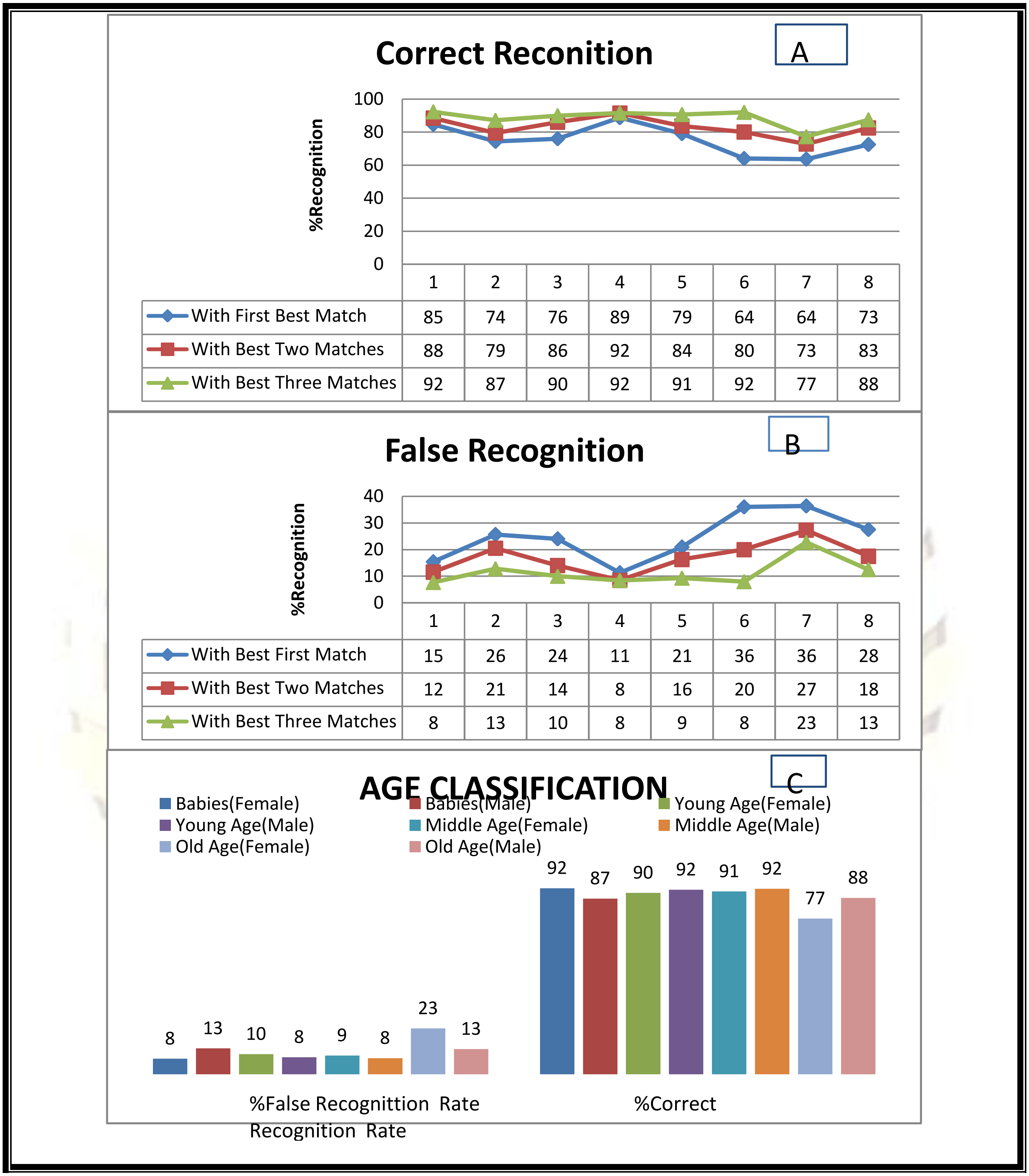


Figure 15. Age Classification (A),(B) Recognition with 3-Ranks(C) Test Probes across various ages

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8. Conclusions

In the YALE experimentation 120 probes are made to android system randomly 117 (97.5%) are recognized correctly in first match. Among the other three one was recognized in second match. The 2-probes have given false recognition (1.6%). The first two best matches together results 98.33% s correct recognition.

From the experiments it is concluded that the performance of LAPP is almost on par with Anthroface 3D algorithm and is better than Eigen surfaces. The performance of Active Pixel approach is compared against the claimed performance of various algorithms. The best performance,
,as shown in table 3, given by Iterative Closest Point (ICP) algorithm (Besl and McKay 1992). However the computational complexities are fairly high for both Anthroface 3D and ICP. The Antrhoface 3D require genetic algorithm to perform ranking and ICP require LDA and PCA for feature processing. Hence it is concluded that Active Pixel approach take lesscomputational resources and maintain almost same success.

Fusion of visible and thermal images,the experimentation has given overall visible image recognition rate 72% (2471 images) and thermal image recognition rate is 55.6% (1909 images) and with fusion the recognition reached to 83% (2849 images).

The LAPP reduces the feature elements compared to LBP and also it reduces the computational time [1]. Hence, the face recognition approach based on LAPP is quite suitable for both conventional and resource constrained environment.

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