Role of Active Pixels for Efficient Face Recognition on Mobile Environment

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Abstract
With the recent advances in smart phones and their ease of availability to common man, researchers are exploring efficient algorithms for face recognition on mobile devices for entertainment applications. The limited memory and processing power on mobile devices pose significant challenge to the satisfactory of popular face recognition algorithms like LBP, ICA, PCA, Neural Networks etc. In this paper, a novel and efficient algorithm is proposed using Active Pixels which capture the essential local information of the facial image. The brody transform makes the approach more robust to rotational, translational invariance’s. The experiments were conducted on standard face recognition databases like FGNET age dataset and color FERET dataset, Texas 3D Face Recognition Database (Texas 3DFRD). The results demonstrated that our approach reduced memory requirement by 80% and the computational time by 70% in comparison with LBP approach while yielding same or even better recognition accuracy.

Keywords: Active Pixel, Face Recognition, Brody Transform, Eigen Template

1. Introduction
The recent advances in smart phones, World Wide Web and image/ video communications has revolutionized the ways of entertainment for people. Smart phones (i-phones, Android) are becoming increasingly popular among young people as an attractive entertainment device for communication, internet browsing, video downloads and online social networking. Cellular companies such as AT&T have been observing tremendous increase in demands for image and video traffic. These mobile phones are also becoming the hub of entertainment access for new generation, reflected by huge number of customized applications (called as apps) in i- Phone or Android store. Microsoft launched its windows phone 7 last year [1] and recently announced that this cell phone will also serve as its device for mobile gaming. Online Social networking and communications using websites such as Face book, Flicker and YouTube is another increasing trend. The increasing trend toward image and video based entertainment applications has also stimulated interest in image processing community, both in academia and industry. Face Recognition is one of the key image processing techniques for mobile based entertainment systems. For example, Oki Electric's Face Sensing Engine (FSE), enables instant face recognition using the camera on mobile phones to restrict unauthorized access to the information on the mobile phones. Google uses face recognition in Picasa to let users tag some of the people in their photos and then searches through other albums to suggest other pictures in which the same faces appear. Majority of mobile phones are currently equipped with a digital camera. This enables people to easily acquire photos of people they see on the move. Using face recognition techniques on these images makes it possible to perform so called face tagging to tag images with the names of the photographed persons. Also, it can help security personnel on the move to identify a potential suspect by recognizing suspect’s face from the database and accessing his history. Thus, there is great need to
incorporate face recognition technologies onto mobile devices to facilitate such stand-alone mobile applications. However, there are four major problems that need to be solved, namely the limited storage and processing power of the mobile device, connection instability, security and privacy concerns, and limited network bandwidth [2]. Problems of connection instability and limited network bandwidth can be avoided by running the complete algorithm on the mobile device. The system also needs to be trained on a set of images containing faces to become capable of automatically recognizing a person from the training set. However, training a system on thousands or millions of faces on the phone is prohibitively time-consuming on such devices today. Instead, face recognition can be performed on the client using already trained data transferred from a computer (server). This kind of architecture has been conceived for other applications on mobile as well. For example, in [3], the authors present a method for mobile recognition of paper documents and an application to newspapers that lets readers retrieve electronic data linked to articles, photos, and advertisements. To avoid network latency, they keep the database on the phone and the recognition algorithm also executes completely on the phone. The database is periodically updated on the database generator and transferred to the phone. In [4], the author’s uses a DCT-based compression method to store the image database on mobile device and the recognition algorithm runs directly on the compressed database without decompression. This allows on the spot-field usage, reduces the overhead of network transfer, and can address even the security and privacy issues. The solution to other two problems concerning with the limited memory and processing power on mobile devices is also being explored. In a recent master’s thesis [5], some work is done to compare variety of well-known face recognition algorithms on a holistic metric of accuracy, speed, memory usage, and storage size for execution on mobile devices. Based on the results, the author declares LBP as an overall optimal algorithm. However, it was observed by us that the efficiency achieved by even LBP method is not satisfactory enough especially when the size of the database increases. In another work [6][16] also, the author compares many approaches on these metrics for the performance on face book database.

Figure 1. 009A01.jpg(courtesy from FGNET ageing dataset)  (A) Original Image (32x32 blocks)  (B) Selected Portion   (C) 8X8 Block of Selected Portion   (D) Active Pixels of selected portion Block  (E) LBP values of the selected portion Block (Non-overlapping)

The Figure 1(A) denote the feature values for active pixel and LBP for a sample portion of size 32 x 32 of a sample image (1280 x 515) from the FGNET aging database. The eye portion, as shown in figure 1(B), of the image is segmented into 16, 8 x 8 blocks, as shown in 1(C), and active pixel count is computed for each block. The first 4 blocks of first row, top row, have low entropy due to most uniform grey intensity variations while the blocks(3,1), (3,4), (4,2) and (4,4) have maximum entropy(local variations). This was reflected by the active pixel count shown in figure 1(D). The same
portion if represented using non-overlapping LBP consume 100 feature elements as shown in figure 1 (E).

In this paper, we have developed a novel and efficient face recognition method using Active Pixels. It is aimed to consume fairly small memory and processing power for performing face recognition task on mobile device. The Brody transform [7] is used for extracting active pixel information of the image. This transform technique is capable of nullifying constant illumination and uniform noise regions. The translation invariance makes the technique more robust to capture object on move. The active pixel information is further processed to obtain Eigen-active pixel template for each category. Correlation is used to measure the matching strength of tested and recognized image rather than histogram based matching approach used in LBP. The LBP is a popular approach for face recognition with local feature while providing the global matching. A typical image of size 128 x 128 generates 1820 feature values using LBP. Further, if overlapping mask is used the feature values increase 5 to 6 times based on the mask size. Whereas, the Active Pixel concept generates 256 feature values for both overlapping and non-overlapping 3 x 3 mask, thus considerably reduction in memory requirement. The figure 1 shows feature values for active pixel and LBP for a sample portion of size 32x32 of a sample image from the FGNET aging database [14].

2. Local Binary Pattern Approach:

The Local Binary Pattern (LBP) was proposed originally for texture recognition [8], which gradually became most widely used by researchers for other domains. Recently it has been applied to face recognition especially to reduce memory and computational requirements. The local features of the image are extracted using LBP operator. The face descriptor is then constructed by these local patterns. Here the image is divided into blocks and a 3x3 mask and is used to construct the binary pattern based on the relationship of neighbors with respect to the central pixel. The 8-neighbors are assigned the binary value ‘1’; if it is greater than central pixel value otherwise it is assigned binary value ‘0’. The weighted sum of these binary bits gives the integer which denotes the local feature. Although LBP is suitable for extracting local features with relatively lower time and space requirements, still it is not optimal for memory and power constrained environments like mobile devices. The 64x64 image (with 3x3 mask) is represented by 4096 values in overlapping mode. The non-overlapping mode requires 448 values. The performance of non-overlapped LBP is always inferior to overlapping mode. Hence researchers proposed variant versions of LBP techniques to address this problem. The authors [9] have explored 58 uniform patterns while computing local invariance.

3 Our Approach

We have proposed active pixels to represent the facial feature and active pixel count is then subsequently used in the recognition process. The sub sections 3.1 and 3.2 concern about the basic aspects of Brody transform and active pixel computation procedure.

3.1 Brody Transformation:

The Brody transformation or R-Transform [7], proposed by Reitboeck and Brody is having shift invariant feature and the transformed data are independent of cyclic shifts of the input signal. This works on the similar grounds of FFT which can’t deal with cyclic shift invariance. The Brody transform is effectively used in many pattern recognition problems. This basic R-transform does not provide its own inverse. Many researchers proposed inverse using various symmetric functions so that it contains one to one relation. We have proposed inverse Transform using the elementary operations average sum, absolute difference average. The figure 2 gives the signal flow of Brody Transform and proposed inverse Brody Transformation. The relative magnitudes of the numbers give the clue during the absolute subtraction. If the first number is smaller than second then the $M_{ij}$ bit is set to one. The $M_{ij}$ decide either to perform straight or the cross the connection at the 2-port switch. The butterfly configuration is used for passing the result from first stage to the next stage.
Properties of Brody Transform: The Brody Transform provides cyclic shift invariance, dyadic shift invariance and graphical inverse of the input pattern. The 256 binary combinations generated by 8-bit input pattern yields 36 transformed patterns. The brody transform has a remarkable ability to represent the 58 uniform patterns generated by LBP with only 8 transformed pattern classes as shown in the Table 1.

<table>
<thead>
<tr>
<th>Binary Pattern of 8-neighborhood of 3x3 Mask</th>
<th>Transformed Brody Pattern</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 0 0 0 0 0 0; 0 1 0 0 0 0 0; 0 0 1 0 0 0 0; 0 0 0 1 0 0 0; 0 0 0 0 1 0 0 0; 0 0 0 0 0 1 0 0; 0 0 0 0 0 0 1 0; 0 0 0 0 0 0 0 1</td>
<td>Line end1</td>
</tr>
<tr>
<td>1 1 0 0 0 0 0; 0 1 1 0 0 0 0; 0 0 1 1 0 0 0; 0 0 0 1 1 0 0 0; 0 0 0 0 1 1 0 0; 0 0 0 0 0 1 1 0; 0 0 0 0 0 0 1 1</td>
<td>Corner 1</td>
</tr>
<tr>
<td>1 1 1 0 0 0 0; 0 1 1 0 0 0 0; 0 0 1 1 0 0 0; 0 0 0 1 1 0 0 0; 0 0 0 0 1 1 0 0; 0 0 0 0 0 1 1 0; 0 0 0 0 0 0 1 1</td>
<td>Corner 2</td>
</tr>
<tr>
<td>1 1 1 1 0 0 0; 0 1 1 1 0 0 0; 0 0 1 1 1 0 0; 0 0 0 1 1 1 0 0; 0 0 0 0 1 1 1 0; 1 0 0 0 1 1 1 1</td>
<td>Corner 3</td>
</tr>
<tr>
<td>1 1 1 1 1 0 0; 0 1 1 1 1 0 0; 0 0 1 1 1 1 0; 0 0 0 1 1 1 1 0; 1 0 0 0 1 1 1 1</td>
<td>Edge</td>
</tr>
<tr>
<td>1 1 1 1 1 1 0; 0 1 1 1 1 1 0; 0 0 1 1 1 1 1 0; 0 0 0 1 1 1 1 1 0 0 1 1 1 1</td>
<td>Flat</td>
</tr>
<tr>
<td>1 1 1 1 1 1 0; 1 0 1 1 1 1 1 1</td>
<td>Spot</td>
</tr>
</tbody>
</table>

3.2 Active Pixel:
The active pixel[11] refers to the image portion that contains vital information of local intensity variations. The active pixel count is used to provide the signature of the local region. We call the first element of the spectral distribution of the Brody transformed pattern as the cumulative point index (CPI), which represents the total spectral power of the image portion. The middle element of the Brody...
transform reflects the subtractive point index (SBI) that gives spectral difference of symmetric halves. The difference between CPI and SBI reveals the regional pixel relation. The normalized difference between CPI and SBI is used as threshold which can be used to find the active pixel. The central pixel is said to be active pixel if 4 or more elements of the transformed pattern are greater than the threshold value. The back ground and uniform noise (uniform grey intensities) are successfully eliminated during the course of computation. The active pixel count is then used as a feature element characterizing each block. This forms the basis for our face recognition approach. The feature vector is then constructed for the entire image from these feature elements. The effect of threshold on active pixel computation is shown by figure 4. The image is re-constructed by making the active pixels with grey value 10 and other image pixels with grey value 250. Threshold value plays dominant role in computing active pixels. The ‘T’ denote number of Brody transform pattern elements which are greater normalized difference of CPI and SBI. The smaller the ‘T’ the more the active pixels and consume more resources. We have chosen T as 4 using trial and error approach.

![Figure 3](image)

**Figure 3:** Threshold effect (T) on active pixel computation

A: Grey Image  B: Binary Image  C: T > 2  D: T > 3  E: T > 4  F: T > 5  G: T > 6  H: T >= 7

### 3.3 Memory requirements for LBP and active pixel based approaches

The feature vector of the image in active pixel approach contains less feature elements than LBP approach. The following Table 2 gives memory requirements of LBP, Active-Pixel based approach.

<table>
<thead>
<tr>
<th>Image Size</th>
<th>Nature of method (using 3x3 mask)</th>
<th>Number of Feature elements</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>LBP</td>
</tr>
<tr>
<td>32 x 32</td>
<td>Non-overlapping</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>Overlapping</td>
<td>1024</td>
</tr>
<tr>
<td>64 x 64</td>
<td>Non-overlapping</td>
<td>448</td>
</tr>
<tr>
<td></td>
<td>Overlapping</td>
<td>4096</td>
</tr>
<tr>
<td>128 x 128</td>
<td>Non-overlapping</td>
<td>1820</td>
</tr>
<tr>
<td></td>
<td>Overlapping</td>
<td>16384</td>
</tr>
<tr>
<td>256 x 256</td>
<td>Non-overlapping</td>
<td>7280</td>
</tr>
<tr>
<td></td>
<td>Overlapping</td>
<td>65536</td>
</tr>
</tbody>
</table>

### 3.4 Similarity Computation

The similarities between two objects can be found using various distance measurements like Minkowski distance, Euclidean distance and correlation. In our approach we have used correlation as a similarity measure. The two highly correlated images are also said to be closely matching.
3.4.1 Correlation

Spearman Rank Correlation measures the correlation between two sequences of values. The two sequences are ranked separately and the differences in rank are calculated at each \( i \)th position. The distance between sequences \( X = (X_1, X_2, \text{etc.}) \) and \( Y = (Y_1, Y_2, \text{etc.}) \) is computed using the following formula:

\[
\frac{6 \sum_{i=1}^{n} (\text{rank}(X_i) - \text{rank}(Y_i))^2}{n(n^2 - 1)}
\]

where \( X_i \) and \( Y_i \) are the \( i \)th values of sequences \( X \) and \( Y \) respectively. The range of Spearman Correlation is from -1 to 1. Spearman Correlation can detect certain linear and non-linear correlations.

The Correlation block computes the cross-correlation of the first dimension of a sample-based N-D input array \( u \), and the first dimension of a sample-based N-D input array \( v \). The blocks can also independently cross-correlate a sample-based vector with the first-dimension of an N-D input array. For frame-based inputs, the Correlation block computes the cross-correlation of analogous columns of an \( M_{UXN} \) input matrix \( u \) and an \( M_{VXN} \) input matrix \( v \). The Correlation blocks can also independently cross-correlate a single-channel frame-based column vector with each column of a multiple-channel frame-based matrix. When the inputs to the Correlation block are an \( M_u \)-by-\( N \) frame-based input matrix \( u \) and an \( M_v \)-by-\( N \) frame-based input matrix \( v \), the output, \( y \), is a sample-based \((M_u+M_v-1)\)-by-\( N \) matrix whose \( j \)th column has elements

\[
y_{uw}(i,j) = \sum_{k=0}^{\text{max}(M_u,M_v)-1} u_{h,k} v_{i-k,j}^* \\
y_{uw}(i,j) = y_{ew}^{*}(-i,j) \\
- M_v \leq i < 0
\]

Where * denotes the complex conjugate. Inputs \( u \) and \( v \) are zero when indexed outside of their valid ranges. The correlation coefficient gives the degree of similarity. The higher the value of the correlation coefficient the better the similarity with test probes.

4. Face Recognition Procedure:

The face recognition was implemented using Two-Level matching approach of active pixels is adapted. In the Training stage Eigen templates are computed for each class. The normalized active pixels of the class forms Eigen-template. Later in the testing phase the first level matching is done by correlating the active pixels feature set of test image with each Eigen template. The best rank class in then further correlated with each image in that class. The top two ranked images form the matched set. The Texas 3D Face Recognition (Texas 3DFR) database is a collection of 1149 pairs of facial color and range images of 105 adult human subjects[12]. The experiments using active pixels have given 87% correct recognition rate. We have applied 25 test trails and each trail 40 images are chosen from data base. The average correct recognition rate with best three matches is found as 92%. Figure 4 gives sample test result.
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Figure 4. Recognition using active pixel on 3-D Facial data(Texas dataset)

Pseudo code:  Face Recognition System

Function Eigen_Template(Train_image Set)
Input : Training Image Database for N classes
Output: E_template
Procedure
// For each class C_p, C_j Є C_{L,L=1,N} Eigen_temp
For j=1,N
//For each image I_i of class C_L, I_i Є C_{Li,i=1,M}
compute active_pixel feature set
For i=1:M
Y_{i(16x16)}=Active_pixel(i)
End;
Eigen_temp_j= 1/M ( Σ Y_k )
End;
E_template()= Eigen_temp_j
End;
Return E_template
End

Function Active_pixel(i)
// Input image i
Output A_pixel(16x16) //Active pixel matrix
Procedure
//Resize the image into 128 x128
// Divide into 8 x 8 blocks
[ 128 128 ] = Imresize(i)
// for each image block IB_{k,m}=1,16, m=1,16
compute active pixel count
For k=1:16
For m=1:16
active=mal5(i(k:k+8, l:l+8));
// for each 3x3 neighborhood obtain Brody
// Transform using mal5 function, let the
// threshold=4. // Update active count if feature
// value is greater than threshold
A_pixel(k,m)=active
End;
End;
Return A_pixel
End

Function Test_image(i)
Input Test_image i
Output matched_set // best 2 matched images
Procedure
// compute the correlation between test image active pixel feature set and Eigen_template of each class
[r1 r2...rk]= correlation(Test_image(A_pixel), E_template)
//Best match is given by largest correlated class, Rank1=r1
// correlate the test image j,j=1,m with each image of class r1
[m1 m2....mk]=correlation(Test_image(A_pixel), r1 (A_pixel))
Matched_set = [m1 m2]
Return Matched_set
End
5. Experimentation:

The exhaustive experiments are performed on FG NET age database, FERET color data set, Yale data set using Brody Transform and active pixels. The dataset FG age NET contains 921 images of 82 subjects, FERET Data set contains 7703 images of 1194 subjects and Yale Data Set contains 120 images covering 15 subjects.

5.1 FGNET age dataset

In our experimentation we used, FGNET aging database Part A [14] that covers 82 subjects. The images were taken at different age of each subject. All together 921 images are used. The wide variations in the pixel patterns of the images poses challenge while recognizing the subject.

Figure 5. Test images: 004A31.jpg (taken at 31 year), 078a03.jpg (taken at 3 year) and associated best two matches

![Subject 078a and its images taken at different ages](image)

The two best matches, as shown in figure 5, are computed from the train dataset that closely resembles in the age with respect to the tested one. All the 921 images are randomly tested against each active pixel Eigen template. The Brody active pixel approach has given 78% recognition accuracy while LBP approach has given 57%.

5.2 FERET color Data Set:

In our experimentation we have considered 1194 subjects with total 7703 images from standard color FERET Data set[13]. The images are chosen such that they cover diversified expressions, poses and illumination conditions for each subject. The Eigen Templates are formed for each subject TWO level recognition process is adopted. The correlation is used as similarity measure between TEST probe and Train probes. All 7703 images are randomly tested with all Eigen templates .The experimentation is done with images of size 64 x 64(non-overlapping and overlapping) 128 x 128(overlapping &non overlapping). The experimental results are shown in the Table 3.
Table 3. Performance of active pixel approaches on color FERET database

<table>
<thead>
<tr>
<th>Method</th>
<th>fb</th>
<th>fc</th>
<th>dup I</th>
<th>dup II</th>
</tr>
</thead>
<tbody>
<tr>
<td>Difference histogram</td>
<td>0.87</td>
<td>0.12</td>
<td>0.39</td>
<td>0.25</td>
</tr>
<tr>
<td>Homogeneous texture</td>
<td>0.86</td>
<td>0.04</td>
<td>0.37</td>
<td>0.21</td>
</tr>
<tr>
<td>Texture Histogram</td>
<td>0.97</td>
<td>0.28</td>
<td>0.59</td>
<td>0.42</td>
</tr>
<tr>
<td>LBP (non-weighted)</td>
<td>0.93</td>
<td>0.51</td>
<td>0.61</td>
<td>0.50</td>
</tr>
<tr>
<td>LBP, weighted</td>
<td>0.97</td>
<td>0.79</td>
<td>0.66</td>
<td>0.64</td>
</tr>
<tr>
<td>LBP PCA, MahCosine</td>
<td>.85</td>
<td>.65</td>
<td>.44</td>
<td>.22</td>
</tr>
<tr>
<td>LBP Bayesian, MAP</td>
<td>.82</td>
<td>.37</td>
<td>.52</td>
<td>.32</td>
</tr>
<tr>
<td>LBP EBGM optimal</td>
<td>.90</td>
<td>.42</td>
<td>.46</td>
<td>.24</td>
</tr>
<tr>
<td>Active Pixels with correlation Overlapping (128 x 128)</td>
<td>.93</td>
<td>0.78</td>
<td>0.73</td>
<td>.70</td>
</tr>
</tbody>
</table>

The non-overlapping approach covers lesser information of the image due to weak neighborhood and hence it is having less recognition rate than overlapping approach. More features of the image are captured if there exists more local regions, thus the more the resized image the better the accuracy. The 64x64 image has less recognition rate (58.8%) when compared to 128x128 images (74.33%). The correlation strength for 56.18% is more than 80% while the correlation strength is greater than 60% for other 18.17%. All 7703 images were made random tested with the associated Eigen- template (class representation). The images in Eigen template cover fa set, contains frontal images, fb set, the subjects were asked for an alternative facial expression than fa, fc set the photos were taken under different lighting conditions dup1 (hr1) the photos taken at latter in the time and dup(hr) the photos taken at least one year before In test probe we have chosen images from fb, fc, dup1 and dupII. The fa of Eigen-template is then used as matched one. The results are compared with the LBP approach [9]. The Table 4 gives the recognition accuracy comparison of active pixels with LBP.

Table 4. Recognition rate of LBP variants and Active Pixel approach

<table>
<thead>
<tr>
<th>Image Size</th>
<th>Acceptance Ratio</th>
<th>Rejection Ratio</th>
<th>Acceptance with Correlation &gt;80%</th>
<th>&gt;60%</th>
</tr>
</thead>
<tbody>
<tr>
<td>64x64 Non-Overlapping</td>
<td>3760 48.88%</td>
<td>3943 51.18%</td>
<td>2370 30.76%</td>
<td>1390 18.04%</td>
</tr>
<tr>
<td>64x64 Overlapping</td>
<td>4520 58.67%</td>
<td>3183 41.3%</td>
<td>2856 37.07%</td>
<td>1664 21.60%</td>
</tr>
<tr>
<td>128x128 Non-Overlapping</td>
<td>4810 54.26%</td>
<td>3740 48.55%</td>
<td>3740 48.55%</td>
<td>1030 13.37%</td>
</tr>
<tr>
<td>128x128 Overlapping</td>
<td>5726 74.33%</td>
<td>4326 56.16%</td>
<td>4326 56.16%</td>
<td>1400 18.17%</td>
</tr>
</tbody>
</table>

5.3 Yale Dataset

The exhaustive experiments are performed on YALE [15] data set using Brody Transform and active pixels. The YALE database contains 165 images of 15 subjects covering different facial expressions. There are 11 faces for each subject of size 243 x 320. In our experimentation partial faces are selected using dynamic cropping. Figure 6 reveals the partial matching. The partial matching reduces the computational resources. The sensitivity of recognition is tested against different sizes of cropping.
Table 5. Recognition within Rank 3

<table>
<thead>
<tr>
<th>Dynamic Cropped Size (% of Full image)</th>
<th>Within Rank 3(120 samples) Recognition</th>
<th>%Recognition</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Correct</td>
<td>False</td>
</tr>
<tr>
<td>35x79 (3%)</td>
<td>78</td>
<td>42</td>
</tr>
<tr>
<td>33x104 (4%)</td>
<td>89</td>
<td>31</td>
</tr>
<tr>
<td>100x42 (5%)</td>
<td>102</td>
<td>08</td>
</tr>
<tr>
<td>56x145 (10%)</td>
<td>115</td>
<td>05</td>
</tr>
<tr>
<td>81x186 (19%)</td>
<td>116</td>
<td>04</td>
</tr>
<tr>
<td>212x91 (25%)</td>
<td>119</td>
<td>01</td>
</tr>
<tr>
<td>121x219 (34%)</td>
<td>120</td>
<td>00</td>
</tr>
<tr>
<td>239x318 (98%)</td>
<td>120</td>
<td>00</td>
</tr>
</tbody>
</table>

Total 120 images are selected randomly in the testing process. The Table 5 gives the correct recognition, false recognition rates with first best match (Rank 1) and within best 3 matches (Rank 2). The recognition process contains Two-levels. In the first level the partial portion is tested against the 15 Eigen active pixel templates. The matched template gives the subject class and secondary matching is made to get the best two similar images.

6. Conclusions

The active pixel approach has given better recognition for FGNET age database compared to LBP. The approach is capable of recognizing the person in spite of the natural changes on facial information of a person due to the age and time. The experimental results of color FERET dataset, as in shown in Figure 7, reflects almost all approaches have given good recognition with fb (Max 93% and min 82%) but not able to perform well under different illumination conditions (Fc), face angles (dup1) and backgrounds (dup2).

YALE data set shows that even a portion of the image is sufficient for recognition process. The correct recognition rate increases with the size of cropped region. It was noticed that even 10% of the image provides correct recognition rate above 95%. This is primarily help the mobile devices while saving the computational resources and extending the volumes entertain applications to the users. Most of the LBP approaches use computationally expensive detectors in the recognition process. The LBP features with other detectors such as PCA, LDA and correlation are tested during our experimentation. We also did the timing analysis of the above techniques along with active pixel for comparing execution time. The programs were executed using MATLAB 7 on Dual core 1.88 GHZ processor with 2GB RAM. The results on FERET database of 7703 images are summarized in Table 6. This clearly demonstrates that the computational requirement for active pixel based approach is fairly smaller in comparison to
LBP based approaches. Hence active pixel approach is better suited for efficient execution on mobile devices by consuming less memory and computational resources. This is primarily help the mobile devices while saving the computational resources and extending the volumes entertain applications to the users.

Table 6. Computational Time for LBP variants and Active Pixel

<table>
<thead>
<tr>
<th>Approaches</th>
<th>LBP with PCA</th>
<th>LBP with LDA</th>
<th>LBP with correlation</th>
<th>Active Pixel with correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>10 hrs</td>
<td>12 hrs</td>
<td>8 hrs</td>
<td>1 hr and 45 min</td>
</tr>
</tbody>
</table>


7. Acknowledgments

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8. References


YALE Face Data base, http:// www.vision.ucsd.edu


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