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# A SURVEY ON COLOR CHANNEL FUSION OF LOCAL TEXTURE FEATURE FOR FACE IDENTIFICATION

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**Abstract:** Face recognition is most popularly used for identification and image analysis. It is one of the most useful method for biometric and surveillance purpose. Many scientists give its contribution in face recognition technique in recent years. In this paper we discuss various approaches that already implemented in face recognition to use these ideas in new task. This paper is analyzing face recognition system and its various methods of color texture feature extraction and color channel fusion. It presents local pattern and color texture feature technologies and analysis about their results of each method implemented for face recognition.

**Keywords:** Face Recognition, Local Pattern, Color Channel Fusion, Gabor Wavelets

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## INTRODUCTION

Face recognition continuously shown its importance in various sector since last few years. Not only for biometric and pattern recognition but also for e-passport and security, face recognition done vital role in personnel identification. In traditional face recognition, only grayscale images are used for identification and important information extracted from that images. Various effective feature extraction schemes applied one by one on one dimensional and further on two dimension images. Normally in face recognition first normalized the input image in absolute dimension and exploit one of the feature extraction method on that image to reinforce separate ability between pattern classes to maintain and add features and make pattern separable.

It is recognize later that color component in color image spectral may also use for recognition as color provides vital information for indexing and retrieval, segmentation, detection, and recognition. Different characteristics are extracted from different visual task of various types of color spaces like YCbCr, HSV, and RGB. Depend on the required features and variation effect appropriate method of extraction and recognition has been applied on image. Reduction and classification can enhance the recognition rate using color information along with luminance and pose information. Principle component analysis (PCA) is also more useful when these two information used for extraction.

In recent hybrid techniques of face recognition and fusion of extracted features i.e weighted combination of features from different channels according to importance are taken. This paper focus the methods proposed earlier about the color face recognition and local texture feature in II. Proposed scheme of color channel fusion and weighted combination in III. Discuss Analysis of the result of various studied techniques in IV. Going further conclusion and references are in V and VI respectively.

Review on Color Channel Fusion for Face Identification

Approaches and ideas already work out previously to be explained here to find out new ideas and progress our task. It is an overlook on the previous task done by various authors and collection of data from their researches. This session represents a contribution of authors in the area of face recognition.

Color Spaces for Color Texture

G. Paschos has been presents an evaluation study in [1] that represent color texture analysis method and analyze result of various color space on that method. It compare effectiveness among various color spaces, especially two perpetual uniform spaces i.e L*a*b and HSV against generalized RGB color space. A family of Gabor filter uses in the presented methodology as early stage of human visual system to measure specific orientation and size of images. A color texture opposes to grayscale texture where only luminance is considered. The very first step mention in evaluation method is filtering which has been done using Gabor filter by separating positive and negative ones with calculating corresponding individual color points called weighted color difference. The technology applied to extend feature vector from each pixel of image of multidimensional space. Gabor filter with four orientation of 00, 450, 900 and 1350 and three color component are used. Classification is the second step of this evaluation study of effectiveness comparison. Bhattacharyya distance classifier is used here to classify complete set of output resulted by Gabor filters.

| CLASS | 10% | | | 20% | | | 50% | | |
|---|---|---|---|---|---|---|---|---|---|
| | RGB | L*a*b | HSV | RGB | L*a*b | HSV | RGB | L*a*b | HSV |
| 1 | 93.75 | 93.75 | 93.75 | 93.75 | 93.75 | 93.75 | 50.0 | 6.25 | 93.75 |
| 2 | 100.0 | 100.0 | 100.0 | 93.75 | 100.0 | 100.0 | 0.0 | 37.5 | 0.0 |
| 3 | 100.0 | 100.0 | 100.0 | 100.0 | 87.5 | 0.0 | 100.0 | 6.25 | 0.0 |
| 4 | 37.5 | 56.25 | 75.0 | 43.75 | 62.5 | 87.5 | 43.75 | 62.5 | 62.5 |
| 5 | 100.0 | 87.5 | 100.0 | 100.0 | 87.5 | 100.0 | 81.25 | 31.25 | 100.0 |
| 6 | 68.75 | 81.25 | 75.0 | 62.5 | 75.0 | 75.0 | 43.75 | 56.25 | 50.0 |
| 7 | 50.37 | 40.97 | 79.69 | 50.75 | 48.49 | 77.06 | 55.26 | 60.90 | 56.76 |
| 8 | 100.0 | 100.0 | 100.0 | 100.0 | 75.0 | 100.0 | 62.5 | 43.75 | 93.75 |
| 9 | 81.25 | 75.0 | 81.25 | 81.25 | 75.0 | 81.25 | 62.5 | 56.25 | 81.25 |
| 10 | 93.75 | 100.0 | 100.0 | 93.75 | 93.75 | 100.0 | 68.75 | 100.0 | 100.0 |
| AVERAGE | 82.2 | 83.2 | 90.3 | 81.5 | 79.5 | 81.3 | 56.4 | 45.7 | 63.75 |

**Table1: Correct classification rates (%) for the ten-class case where 10%, 20% and 50% noise has been induced in each of the images before classification**

Pixel-wise classification gives low correctness classification rate due to overlaps in the feature space. To improve this result block wise classification is used. In the case of luminance among all three color space HSV achieve highest rate than other two. HSV and L*a*b is superior to RGB by 10% and 3-4% respectively. Test correctness rate for ten class by performing 10%, 20%, and 50% of its pixels classification in the presence of noise.

**Color Segmentation**

O. Ikeda in [2] describe the image detection from the video footage by implementing segmentation method. Also comparison has been done among RGB, HSV And YCbCr colors for convenient color segmentation. Video footage may be illuminated and may other objects similar to background frames included in that video. Video footage frames may vary with respect to color, texture and directions so, single set of segmentation is not sufficient to accurately retrieve image. This paper not only analyzed capability of segmentation but also construct a system for image retrieval. The system first detects scene change and scanning of sampling point at beginning of new scene. If sample point within a color window segmentation done for errors and sets of weight on HSV component. Then segmented image checked for requirements and calculate pattern correlation for the frame. Considered the output with largest correlation and displayed according to correlation values.

Experimentally extract many features using HSV, RGB and YCbCr colors from video footage of 100 frames. This shows that HSV colors extract more features than RGB and YCbCr colors and also most reliably segmented face images. It detect 97 frames out of 100 frames taking single set of weight segmentation. Normally one to eight second require for segmentation depending on number of weights.

Analysis of Color Effect and Face Resolution

In [4] J. Choi et.al, carry out extensive and systematic studies to explore the facial color effect on recognition due to variation in face resolution. This paper demonstrated effect of color on low-resolution faces by comparing color and grayscale features. This paper subjected into two parts- 1) derivation of variation ratio gain (VRG). 2) performance evaluation by extensive and comparative face recognition. The effectiveness of color has been tested successfully on three subspace face resolution methods—principal component analysis, linear discriminate analysis, and Bayesian. To accurately recognize face recognition, effectively use color feature to reduce lower bound. The proposed color face recognition method improves degraded recognition accuracy due to low resolution faces by significant margin compared to intensity-based face resolution.

Variation Ratio

In the recognition performance, intra and extra personal variation parameters of feature subspace are analytical factors are quantitatively represented by the variation ratio. The total variation that resides in the feature subspace is partitioned into intra- and extra personal variations related to IC and EC, respectively. From a classification, the recognition performance enhanced and contains more variation of EC than IC. From this, the ratio of extra- to intra-personal variation is an important parameter that reflects the power of feature space.

Intra- and extra personal Variations in Color FR

Two different intensity components can used to construct the intra- and extra personal variations in a separate manner with luminance. Aside from the independent contribution, since each spectral component of skin color has its own inherent characteristics may differently be changed by practical facial imaging conditions i.e illumination and spatial-resolution variations intra- and extra personal variations in the color-based FR are formed by the composition of variations calculated from each spectral component along with different imaging conditions.

Color Boosting Effect on Variation Ratio Along With Face Resolution

Due to changes in the face resolution identify the color boosting effect on variation ratio. VRG(γ) measures that variation ratio increased by intensity components. Therefore, it reflects the effect of color information with respect to changes in γ. To approve the effectiveness of VRG as a relevant metric for the determination of quantization of the color effect with variations in FR. This is due to luminance contrast sensitivity lowers spatial frequencies faster than chromatic contrast sensitivity. Hence, two intensity components can compensate a decreased extra personal variation made by luminance faces with low resolution. Table 1 Shows FVR comparison.

| FR features | Face Resolution | | | | | |
|---|---|---|---|---|---|---|
| | 112 X112 | 86 X 86 | 44 X 44 | 25 X 25 | 20 X 20 | 15 X 15 |
| PCA (R) | 68.65 % | 65.65% | 64.01% | 41.89% | 44.86% | 40.01% |
| PCA ($RQC_r$) | 72.23% | 75.13% | 68.37% | 62.16% | 62.43% | 55.69% |
| FLDA(R) | 78.64% | 76.75% | 75.94% | 32.70% | 28.91% | 10.81% |

| | | | | | | |
|---|---|---|---|---|---|---|
| **FLDA(RQC$_r$)** | 83.51% | 80.00% | 77.57% | 69.45% | 69.72% | 64.86% |
| **Bayesian(R)** | 79.16% | 75.19% | 76.33% | 65.72% | 62.72% | 52.70% |
| **Baysian(RQC$_r$)** | 82.06% | 78.32% | 77.18% | 76.56% | 74.10% | 68.32% |

**Table 1: FVR comparisons at a far of 0.1% between grayscale and color features with respect to six different face resolutions**

- R from the RGB color space was used as a grayscale feature,
- RQCr configuration was employed as a color feature.

Two sets of experiments have been done to demonstrate the color effect on low-resolution faces. The first is to assess the impact of color on recognition performance with changing face resolutions of given multi resolution feature subspaces. While, the second experiment is to conduct the same when a single-resolution feature subspace with high-resolution facial images is available to the actual testing operation. According to that, there was a commonly hard drop-off of identification and VER rates generated by a low-resolution grayscale image in PCA, FLDA, and Bayesian methods. The performance sensitivity depending on variations in face resolution, it is found that FLDA is the weakest to low-resolution grayscale faces of all three methods. On the contrary, color's boosting peculiar of the extra personal variation, color features in FLDA outperformed by 24.86% and 50.81% margins in case of 15 × 15 pixels, compared to corresponding grayscale images. Bayesian is more robust to face resolution variations than PCA and FLDA. The variation in performance between 112 × 112 and 25 × 25 pixels was not higher than 8.54% compared to 15.40% and 25.66% from PCA and FLDA, respectively.

Extraction of Color Local Texture Features

J. Choi et.al, in [6], represents two types of color features extraction from individual color channel of multi spectral colors. The color information which are tried to extract is extended form of the grayscale features. These two commonly used techniques are Gabor feature and Binary Pattern which is nothing but Color Local Gabor Wavelets and color local binary pattern as they uses color information.

Extraction of CLGW

Due to robustness against illumination variation Gabor wavelets widely used in face recognition. Gabor wavelets retrieve with the help of Gabor filters by detecting gray values of the pixel. Three local images with the same facial component represent different Gabor pattern. To reserve locality and encircle color texture feature of image, equivalent information used here. At the end, fusion of all Gabor wavelet representations and normalization of vector feature takes place called CLGW feature.

Extraction of Color LBP

Color component and channel-wise LBP feature computed by uniform LBP operator with small number of LBP values. To obtain LBP features, centre pixel values of face image compared with all neighboring pixel values forming a binary pattern Calculate binary pattern for each pixel of the face image and retrieve more important information from image according to these patterns.

Combining Color Local Texture Features For FR

Techniques for fusing multiple evidences subjected to classes one is feature level fusion and other is decision level fusion. Author proposed a method where feature-level fusion used as it gives better classification result and better FR performance compared to another one. They implement a global feature vector technique by concatenating feature-level information fusion and color local texture features technique. Further applying most suited globalized methods that normally used for face recognition. This technique overcomes limitations of aforementioned and low-dimensionality.

Analysis given in Table 2.

| **Method** | | **Low-dimensional feature extraction technique** | | | |
|---|---|---|---|---|---|
| | | **Illumination Variation** | | **Pose Change** | |
| | | **CLBP** | **CLGW** | **CLBP** | **CLGW** |
| **PCA** | **ZRG+FL** | 79.27±1.01 | 81.89±1.18 | 67.10±1.42 | 59.20±1.01 |
| | **RQC$_r$ +FL** | 78.90±1.65 | 83.01±1.86 | 65.81±1.79 | 58.08±1.37 |
| **FLDA** | **ZRG+FL** | 88.05±0.12 | 87.34±2.67 | 80.59±0.53 | 75.00±1.23 |
| | **RQC$_r$ +FL** | 87.57±0.82 | 86.23±1.77 | 79.10±0.19 | 74.99±0.82 |
| **KDDA** | **ZRG+FL** | 91.09±1.37 | 90.31±0.11 | 85.45±1.74 | 80.21±1.50 |

| | | | | | |
|---|---|---|---|---|---|
| | **$RQC_r$ +FL** | 92.86±1.87 | 91.31±1.77 | 83.50±1.46 | 78.12±1.62 |
| **ERE** | **ZRG+FL** | 96.30±1.54 | 93.27±1.51 | 88.87±0.85 | 83.28±0.65 |
| | **$RQC_r$ +FL** | 94.43±0.54 | 94.46±1.68 | 86.92±1.43 | 82.09±0.54 |

**Table 2: Average rank-1 identification rates (in percent) and corresponding standard deviations for evaluating the effectiveness of color local texture features on Illumination Variation and Pose Change**

Color Channel Fusion

In [9], Ze Lu et.al, a color channel fusion method is proposed to make use of reliability and importance of features in different color channels. The fusion of color channel is an important step in proposed color face recognition (FR) systems. Existing methods identifying the importance of features however it concentrate on channel wise feature extraction rather than identifying reliability of features on separate color channels. This paper simply a color channel fusion (CCF) approach along with dimension reduction to select more vital features from discriminative channels. By integrating the dimension reduction rule of a single color channel across all three color channels, a more effective channel fusion method is achieved. The effectiveness of proposed color channel fusion approach is validated by applying it to two quite different dimensionality reduction methods (PCA and ERE) using two different types of features i.e image-pixel values and color local Gabor Wavelets. Experiments using two different dimension reduction approaches, two different types of features on three image datasets to validate the effectiveness and robustness of the proposed CCF method. Show that CCF achieves consistently better performance than color channel concatenation (CCC) method which deals with different color channels equally. It outperforms CCC method and WDF method in the field of dimension reduction, types of features and image variations.

Proposed Scheme

In our proposed method HSV color channel fusion has been perform and color local texture features retrieve from each local region of that channel. CMU PIE, or FERET datasets are used for experiment of face detection. Two types of color features i.e color local binary pattern and color Gabor texture wavelet are extracted from color spectral. PCA is most commonly used technique for reduction which is used here to get more accurate features from face images. Proposed face recognition scheme divided in five major steps:

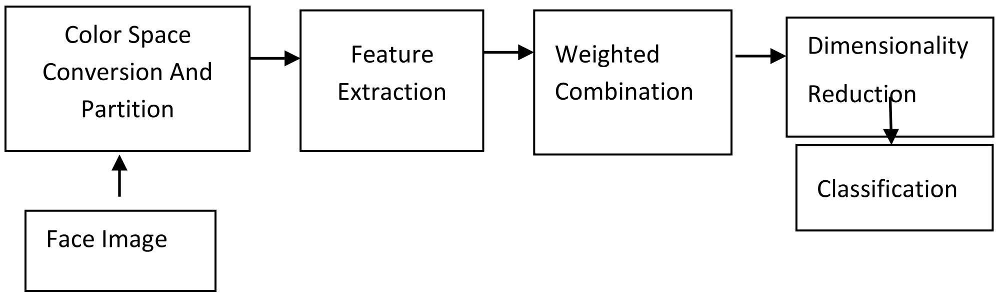


**Fig 1: Color Face Recognition System**

Color space conversion and partitioning:

By resembling and translating align color face images in RGB to a fixed template in first step. Subsequently performed a color space conversion to convert an RGB image into in a new color space image on each spectral are partitioned into a standard local regions.

Color feature extraction

Texture feature of local binary pattern and Gabor wavelet texture features are computed separately for each region. CLBP and CGTW extracted independently from these regions and that feature called local texture feature.

Weighted Combination

Local texture features from each spectral images combines in order to form a unique features representing color face image with the help of weightage given to each features.

Dimensionality Reduction

To reduce the complexity of the featured image either one or two dimensionality reduction method like PCA, EPR are used to select most important information from it.

Classification

It is the last step to recognize actual face image using nearest distance technique.

## CONCLUSION

In this paper we discussed different approaches for detecting the face image, extraction of required features and recognition of face. Face Recognition under the different lighting conditions and poses are the major challenges. Different face recognition techniques has been discussed here to fix the illumination and pose variation problem, and also about the accuracy of the recognition rate used for the different face recognition approaches. Face recognition has become one of the important application in the recent years as it will allow the unique identification of the human face without machine contact and it also provides more recognition accuracy than other methods like palm print, finger print etc. For interpretation of face recognition results does not need any technical expert and the face recognition software works under existing configurations. Face recognition can be practiced either on the video or the still images. More efficient techniques can be developed to enhance the results.

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