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Efficient Color Image Classification with Varying RTS Using Region Based Intensity Distribution Matrix

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Abstract: The problem of color image classification has been studied in different methods and still the retrieval of similar images from large image data set is a challenging task. The earlier methods use different features of image like color, object and shape and so on, but struggles with the problem of classification accuracy and false ratio. The color image classification adapted with rotation, transpose and scaling is considered here with other features of image. The method uses region based intensity distribution matrix which stores the sectional intensity distribution value of RGB. The method computes the region based similarity according to the intensity distribution, by considering scaling factor, rotational factor and transpose also. The generated feature set is used to compute the region based sectional similarity of intensity distribution values. For scaling, the sectional similarity is computed in all 360 degrees, i.e. the neighbor region features are used, similarly for rotation, the method consider the diagonal neighbor regions and for transpose the method considers the selected neighbor to compute the sectional intensity distribution similarity value. Using computed similarity the method classifies the image in accurate and produce efficient results in color image classification.

Key words: Image Classification · RTS · Intensity Distribution Matrix · Sectional Intensity Distribution Similarity

INTRODUCTION

The image classification is the process of identifying the class of input image and retrieving the related images according to their features. The image classification has great impact in different fields like medical imaging. In medical imaging, the classification is applied to identify the related images for example for a image which is affected by cancer, the method can produce similar disease affected image so that they can easily understand how the skin changes in color or feature. Similarly, for tissue classification, the process of image classification can be used to classify the image as normal, diseased and so on. The application of image classification cannot be restricted to medical domain but also in biometric authentication, where face recognition is applied as a authentication mechanism.

By the development of image processing techniques, the modern research community applies the classification approaches in satellite image classification. They apply the process of image classification in identifying the soil patterns, which helps the user to get soil patterned images from the large set of image data set. Generally there are many features of the image has been applied to perform image classification, like the color the major feature which is applied in various methods and uses the RGB values of the image. Some of the methods have used shape features and some of them have used the object maps and so on. The problem of using color feature is, the same of object present in the input image may appear in different color and the objects may present in different size in case of object based approaches. For example, if you search for a image with particular car in the color of red, the same care may present in different color and different angle and the car may be in different scale. So classifying the image using a single feature of the image is not effective but has to consider many features to improve the classification accuracy.

The intensity distribution matrix is applied to perform classification in this paper, which represents the distribution of red, green, blue values in each region or section of the image and their intensity values.

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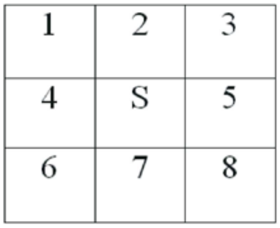


Fig. 1.a Sample region 3×3

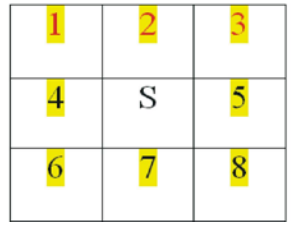


Fig. 1.b Rotation angles

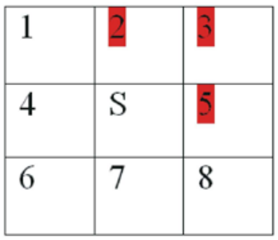


Fig. 1.c Scaling angles

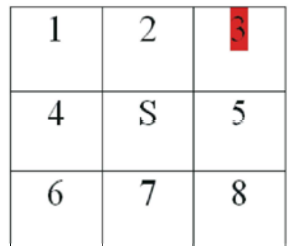


Fig. 1.d Transpose angles

The distribution values are stored in the matrix to compare with the target image features. The generated matrix can be converted into a feature vector and based on that the similarity measures between the source and target class images can be computed.

Sectional Intensity Distribution Similarity measure represents the similarity values of red, green and blue values at each region of source and target image. The similarity measure is computed by including the scaling similarity which represents the similarity of source section's intensity distribution and neighbor sections similarity. Similarly the intensity distribution similarity includes the rotation and transpose factors.

The Figure 1.a shows the sample region considered to compute the sectional similarity with RTS. The Figure 1.b shows the angles included or the neighbor sections included in computing the sectional similarity and the Figure 1.c shows the scaling angles used and the figure 1.d shows the transpose angles used in computing the sectional intensity distribution similarity values.

Related Works: There are number of methods has been discussed for the development of image classification using various features and methods. We discuss few among them in this section to perform comparative study of the approaches.

Classification of Remote Sensing Image Areas Using Surf Features and Latent Dirichlet Allocation [1], involves two steps, first training the class images and second classifying the testing image which consist of all the classes based on training image. Speed Up Robust Features (SURF) are used to enhance the performance over low level feature like mean and standard deviation. Topic modelling concept is used to obtain Bag of Features (BoF) with Latent Dirichlet Allocation (LDA) algorithm. Threshold value for each class is obtained from BoF and compared with testing image feature values in order to classify it. Experiments are conducted on LANDSAT 7 images obtained from google earth.

Image Classification using Block Truncation Coding with Assorted Color Spaces [2], portrays comprehensive performance comparison of image classification techniques using block truncation coding (BTC) with assorted color spaces. Overall six color spaces have been explored which includes RGB color space for applying BTC to figure out the feature vector in Content Based Image Classification (CBIC) techniques. A generic database with 900 images having 100 images per category spread across 9 different categories have been considered to conduct the experimentation with the proposed Image Classification technique. On the whole nine hundred queries have been fired. The average success rate of class determination for each of the color spaces has been computed and considered for performance analysis. The results explicitly reveal performance improvement (higher average success rate values) with proposed color-BTC methods with luminance chromaticity color spaces compared to RGB color space. Best result is shown by YUV color space based BTC in content based image classification.

Image Classification based on Color and Texture features using FRBFN network with Artificial Bee Colony Optimization Algorithm [3], proposes an image classification system based on combined color and texture features of an image to overcome these problems. This system consists of different stages such as image preprocessing, color and texture features extraction and fuzzy c-means radial basis function neural (FRBFN) network based classification/retrieval with Artificial Bee Colony (ABC) optimization algorithm. In this scheme, the color features are derived using Histogram Equalization method in HSV space and the texture features represented by contrast, energy, entropy, correlation and local stationary over the region in an image derived based on co-occurrence matrix. The proposed neural network based Comprehensive Image Classification (CIC) scheme fuses the low level features of the image such as color and texture to improve the systems classification performance and these features are converted as high level features by Radial Basis Function Neural Network(RBFN) with Fuzzy c-means (FCM) to fix the hidden layer neurons. The weight vectors of the network are reasonably assigned by Artificial Bee Colony (ABC) optimization algorithm.

Efficient HIK SVM Learning for Image Classification [4], present a new svm training method called intersection coordinate descent which is deterministic and faster than general svm solvers. Also the ICD has been extended in order to increase the efficiency of training. The proposed method has been analyzed theoretically.

Improving Color Constancy Using Indoor–Outdoor Image Classification [5], uses variety of strategies and algorithms for classification. It automatically tunes the parameters of algorithms according to the efficiency of image classification. In this method the author considered the problem of uncertainty of indoor and outdoor problems. The proposed approach derived from popular illumination estimation methods of Gevers.

Iris image classification based on color information [6], we propose a novel color feature for iris classification, named as iris color Texton using RGB, HSI and lââ color spaces. Extensive experiments are performed on three databases. The proposed iris color Texton shows advantages in iris image classification based on color information.

Novel color HWML descriptors for scene and object image classification [7], which uses binary patterns to represent the feature descriptors. The feature descriptors are three dimensional one. Another local binary pattern using haar wavelet is used to compute the histogram of orientation features. For the classification, they have used enhanced fisher model which classifies the image according to the rule set provided.

Color Local Texture Features for Color Face Recognition [8], proposed color local texture features are able to exploit the discriminative information derived from spatio chromatic texture patterns of different spectral channels within a certain local face region. Furthermore, in order to maximize a complementary effect taken by using color and texture information, the opponent color texture features that capture the texture patterns of spatial interactions between spectral channels are also incorporated into the generation of CLGW and CLBP. In addition, to perform the final classification, multiple color local texture features (each corresponding to the associated color band) are combined within a feature-level fusion framework [9].

A Rule Based Approach for Classification of Shades of Basic Colors of Fabric Images [9], presents a rule based approach to classify the different shades of basic colors of fabric images. The RGB color features are extracted. The mean and standard deviation of shades of red, green and blue colors are computed. A rule base is designed taking into account, the mean and standard deviation values.

Vector-valued images such as RGB color images [10], propose a new notion of treating vector-valued images which is based on the angle between the spatial gradients of their channels. Through minimizing a cost functional that penalizes large angles, images with parallel level sets can be obtained. After formally introducing this idea and the corresponding cost functionals, we discuss their Ga^teaux derivatives that lead to a diffusion-like gradient descent scheme. We illustrate the properties of this cost functional by several examples in denoising and demosaicking of RGB color images. They show that parallel level sets are a suitable concept for color image enhancement. Demosaicking with parallel level sets gives visually perfect results for low noise levels. Furthermore, the proposed functional yields sharper images than the other approaches in comparison.

Image Quality Assessment for Fake Biometric Detection [11], present a novel software-based fake detection method that can be used in multiple biometric systems to detect different types of fraudulent access attempts. The objective of the proposed system is to enhance the security of biometric recognition frameworks, by adding liveness assessment in a fast, user-friendly and non-intrusive manner, through the use of image quality assessment. The proposed approach presents a very low degree of complexity, which makes it suitable for real-time applications, using 25 general image quality features extracted from one image (i.e., the same acquired for authentication purposes) to distinguish between legitimate and impostor samples.

Coding Visual Features Extracted From Video Sequences [12], propose, for the first time, a coding architecture designed for local features (e.g., SIFT, SURF) extracted from video sequences. To achieve high coding efficiency, we exploit both spatial and temporal redundancy by means of intra frame and inter frame coding modes. In addition, we propose a coding mode decision based on rate-distortion optimization. The proposed coding scheme can be conveniently adopted to implement the analyze-then-compress (ATC) paradigm in the context of visual sensor networks. That is, sets of visual features are extracted from video frames, encoded at remote nodes and finally transmitted to a central controller that performs visual analysis. This is in contrast to the traditional compress-then-analyze (CTA) paradigm, in which video sequences acquired at a node are compressed and then sent to a central unit for further processing. In this paper, we compare these coding paradigms using metrics that are routinely adopted to evaluate the suitability of visual features in the context of content-based retrieval, object recognition and tracking.

The above discussed approach suffers with the problem of classification accuracy and produces irrelevant results, which motivates to design novel Image classification methods.

Color Image Classification with Varying Rts Using Region Based Intensity Distribution Matrix: The proposed image classification approach has various stages namely, preprocessing, Region based IDM Generation, Image Classification. We discuss each of the stage in detail in this section.

Preprocessing: The preprocessing stage, performs scaling of image to the fixed size. The scaled image is applied with histogram equalization technique, to enhance the quality of the image. The method identifies the all unique intensity values present in the image and for each unique intensity value computes the probability of distribution. According to the distribution probability computed the pixel value will be replaced and the image quality is improved. The quality improved image is split into number of small sized images according to the size of box used.

Procedure:
Input: Image img
Output: Preprocessed image Integral image IImg
Start
Perform rescaling of image Rimg = rescale(Rimg).
Initialize Box Size into X.
Identify unique intensity values present in the image Iv.
Iv = $\int_{i=1}^{size(Rimg)} \sum(Pi.intensity \in RImg) Iv$
for each intensity value Iv_i from Iv
Compute possible intensities pn.
Pn = $\int_{i=0}^{size(iv)} \frac{Number\ of\ pixels\ with\ intensity\ Iv(i)}{total\ number\ of\ pixels}$ (2)
End.
for each intensity Iv_i from Iv
Compute histogram of pixels with Iv_i as Hg. Hg= Floor(L-1) $\sum_{n=0}^{I(i,j)} pn$ -
For each pixel Pi with intensity Iv_i
Replace the pixel Rimg(j,k) = Hg.
End.
End.
Generate Integral image Set IImg =ΣCrop($\frac{size(Rimg) \times size(Rimg)}{X}$)
Stop.

Regional Intensity Distribution Matrix: The regional distribution matrix is generated from the integral image set provided. For each integral image generated, the method computes the intensity distribution matrix. The method identifies the sum of all pixel values of red, green and blue. For each layer the method computes the sum of all values at each layer and computes the distributional factor. Similarly the method computes the distributional value for each layer and generates three values and stores in the feature vector.

Procedure:
Input: Integral Image Set IImg
Output: Feature Vector Fv.
Start
For each integral image I_i from IImg
Red Layer Rl = RedLayer(I_i).
Compute red value distribution factor rdf = $\frac{\sum values(Rl)}{X \times X}$
Extract Green Layer Gl = GreenLayer(I_i)
Compute green value distribution factor gdf = $\frac{\sum values(Gl)}{X \times X}$
Extract Blue Layer Bl = Blue Layer(I_i)
Compute blue value distribution factor bdf = $\frac{\sum values(Bl)}{X \times X}$
Generate Feature vector Fv_i = {rdf,gdf,bdf}.
End
Stop.

Image Classification: The classification process is performed based on the measures computed using the feature vector generated in the previous stage. With the feature vector of source image, the feature set of trained set FvT is retrieved. The input feature vector which has collection of distribution factors and with the input feature vector, the method computes the sectional similarity measure in three four way, namely corresponding, scaling, rotation and transpose. Finally based on all the four similarity measure, a cumulative intensity distribution similarity value is computed. If the cumulative similarity measure falls within the threshold then the image is classified as the class being considered or in case of retrieval, the class with most similarity value is concluded as required image class and the images from the class is retrieved and ranked according to the similarity measure.

Procedure:
Input: Feature Vector Fv, Training Set FvT.
Output: Class label Cl.
Read training set FvT.
for each Feature vector FV_i for Fvt
For each distribution factor DF_i
Compute distance in red distribution Rdf = Euclidean(DF_i.rdf-Fv.rdf).
Compute similarity in green distribution Gdf = Euclidean(DF_i.gdf-Fv.gdf).
Compute similarity in blue distribution Bdf = Euclidean(DF_i.bdf, Fv.bdf).
Compute Sectional Similarity measure SSM = $\frac{Rdf+Gdf+Bdf}{3}$
Identify neighbor sections feature instances NFv.
NFV = ΣFv(FvT)©DFi
Compute rotational sectional similarity RSS.
Rss = $\int_{k=1}^{size(NFv)} \sum \frac{Rdf(NFv(k))+Gdf(NFv(k))+Bdf(NFv(k))}{Size(NFV)\times 3}$
Compute Scaling Sectional Similarity SSS.
SSS = $\int_{k=1}^{3} \sum \frac{Rdf(NFv(k))+Gdf(NFv(k))+Bdf(NFv(k))}{3}$
Compute Transpose sectional similarity Tss.

$$Tss = \int_{k=1}^{3} \sum \frac{Rdf(NFv(k))+Gdf(NFv(k))+Bdf(NFv(k))}{3}$$

Compute Cumulative sectional similarity measure CSSM.

$$CSSM = SSS+ \frac{RSS+SSS+Tss}{3}$$

End

End

Choose the class with maximum similarity measure.

Class = Max(CSSM).

Stop.

RESULTS AND DISCUSSION

The proposed regional distribution matrix based color image classification has been implemented in matlab and the approach has been evaluated for its efficiency in classification with different data sets. The performance of the proposed approach also compared with other methods.

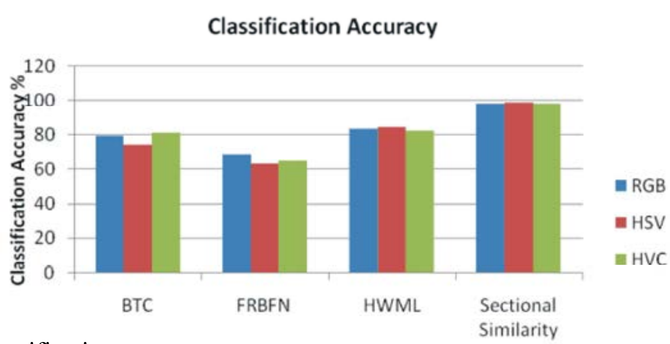
The Graph 1, shows the classification accuracy achieved by different methods. It shows that the proposed region based intensity distribution matrix approach has produced efficient classification compared to other methods. Also it produced less false positive results.

Table 1: Shows the accuracy of classification with different algorithms

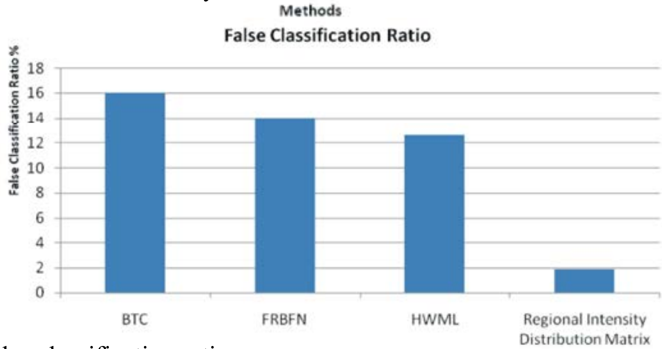
Color Space	BTC	FRBFN	HWML	Regional Feature Distribution Matrix
RGB	83	85	87	98
HSV	81	83	86	98.6
HVC	83	82	85	97.9

The Graph 2 shows the comparison of false classification ratio produced by different methods. It shows clearly that the intensity graph based approach has produced less false rate than other methods.

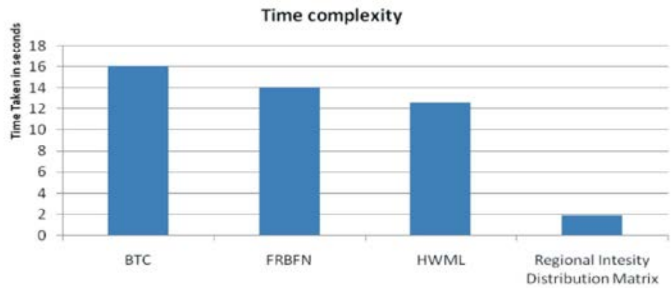
The graph3 shows the comparison of classification time taken by different methods. It shows clearly that the proposed method has produced less time complexity than the other approaches. The time complexity produced by



Graph 1: Comparison of classification accuracy.



Graph 2: Comparison of false classification ratio



Graph 3: Comparison of time complexity in classification.

the proposed method is less and it varies with the number of samples being used in each class of images. In all the size of image samples the method has produced less time complexity than other methods.

CONCLUSION

We proposed region based sectional intensity distribution matrix approach for the classification of color images. The approach rescales the images in to same size at the preprocessing stage and then the image is enhanced for its quality by performing histogram equalization technique. The enhanced image is split into number of small scale images by integral image generation and for each integral image, the method splits the layers in to three and computes the red intensity distribution factor, green intensity distribution factor and blue intensity distribution factor. Similarly with the target feature vector the method computes the same and computes the rotational similarity, scaling similarity and transpose similarity values. Using all these measures, for a target image , the method computes the cumulative sectional intensity distribution similarity measure and based on that a single class is identified as the target class. The proposed method increases the performance of image classification by producing more accuracy in classification with less time complexity and false ratio.

REFERENCES

1. Chandraleka, M., 2013. Classification of Remote Sensing Image Areas Using Surf Features and Latent Dirichlet Allocation, International Journal of Advanced Research in Computer Science and Software Engineering, 3(9).
2. Kekre, H.B., Sudeep Thepade, Rik Kamal Kumar Das and Saurav Ghosh, 2012. Article: Image Classification using Block Truncation Coding with Assorted Color Spaces¸ International Journal of Computer Applications, 44(6): 9-14.
3. Chandrakala, D. and S. Sumathi, 2014. Article: Image Classification based on Color and Texture features using FRBFN network with Artificial Bee Colony Optimization Algorithm. International Journal of Computer Applications, 98(14): 19-29.
4. Wu Jianxin, 2012. Efficient HIK SVM Learning for Image Classification, IEEE Transaction on Image Processing, 21(10): 4442-4453.
5. Biancos, 2008. Improving Color Constancy Using Indoor–Outdoor Image Classification, IEEE Transactions on Image Processing, 17(12): 2381-2392.
6. Hui Zang, 2012. Iris image classification based on color information, Pattern Recognition ICPR, pp: 3427-3430.
7. Banerji, S., 2012. Novel color HWML descriptors for scene and object image classification, Image Processing Theory Tools and Applications, pp: 330-335.
8. Jae Young Choi, 2012. Color Local Texture Features for Color Face Recognition , Ieee Transaction on Image Processing, 21(2): 1366-1380.
9. Basavaraj, S., 2015. A Rule Based Approach for Classification of Shades of Basic Colors of Fabric Images, International Journal of Signal Processing, Image Processing and Pattern Recognition, 8(2): 389-400.
10. Ehrhardt, M.J., 2014. Vector-Valued Image Processing by Parallel Level Sets, IEEe Transaction on Image Processing, 23(1): 9-18.
11. Galbally, 2014. Image Quality Assessment for Fake Biometric Detection: Application to Iris, Fingerprint and Face Recognition, IEEE Transaction on Image Processing, 23(2): 710-724.
12. Baroffio, 2014. Coding Visual Features Extracted from Video Sequences, IEEE Transaction on Image Processing, 23(5): 2262-2276.