International Journal of Engineering Research-Online
A Peer Reviewed International Journal
Articles available online http://www.ijoer.in; editorijoer@gmail.com

Vol.4., Issue.6., 2016
Nov-Dec.

RESEARCH ARTICLE

ISSN: 2321-7758

HIERARCHICAL SEMANTIC CLASSIFICATION

THIRUMALA LAKSHMI.K[1], USHA KINGSLY DEVI.K[2]

[1]PG Student, Division of Applied Electronics, Department of ECE, Anna University Regional Campus -Tirunelveli, Tamil Nadu, India

[2]Assistant Professor, Division of Applied Electronics, Department of ECE, Anna University Regional Campus - Tirunelveli, Tamil Nadu, India

THIRUMALA LAKSHMI.K

USHA KINGSLY DEVI.K

ABSTRACT

Semantic image classification based on hierarchical Fuzzy Association Rule (FAR) mining is able to classify the semantic concepts effectively in low level with highly specified input data. The fuzzy association rule is a unique and significant combination of image features and a semantic concept, which determines the degree of correlation between features and concepts. The main idea behind this approach is to overcome the semantic gap between low level features and high level semantic concepts using fuzzy association rules. The features extracted for fuzzy association rules are low level features (color and texture) in HSV and L*a*b color space, both in spatial and frequency (Wavelet, Fourier, Cosine and Radon) domains. The fuzzy rules for hierarchical classification are built by selecting the rules with highest weight using three fuzzy factors such as fuzzy support, fuzzy confidence and fuzzy lift. And the fuzzy inference engine is set up for classifying the images hierarchically using fuzzy classifier. Experimental results based on a database of about 10,000 images demonstrate improved performance in fuzzy classifier than Multiclass SVM classifier. To evaluate the performance of the classifier precision, recall and accuracy are calculated.

Keywords— Fuzzy Color Histogram, Spatial Fuzzy Color Histogram, Fuzzy Association Rules, Semantic image classifier, Multiclass SVM.

1. INTRODUCTION

In many application fields, hierarchy is a natural way to organize and classify objects hence it is widely used in semantic classification. Hierarchical Classification means the classification first occurs on a low-level with highly specified input data [15]. The classifications of the individual data are then combined systematically and classified on a higher level iteratively until one output is produced. The final output is the overall classification of the data. Content Based Information Retrieval (CBIR) is one of the major applications in hierarchical semantic classification [7]. The number of web images is increased in rapid rate and searching them semantically has some drawbacks such as semantic evaluation, semantic gap, result formulation etc. The semantic gap between low level features and high level semantics is a well-known challenge in classification and it can get enhanced by using Fuzzy Association Rules [1] which combine both low level and high level features to describe semantic concepts. A Fuzzy Association Rule is a unique and significant combination of image features and a semantic concept which determines the degree of correlation between features and concepts [12].

1.1 Related Work

The growth of world wide web have led to the huge online digital images and videos so there is a strong demand for developing an efficient technique for image classification. In [10], the authors proposed a user driven system to retrieve the image based on semantic concept. It separates the relevant and irrelevant information and feedback into the system by user**.** Then the color, shape and texture features are extracted to classify the image using support vector machine (SVM) classifier. Here the authors used both COREL and CALTECH databases for classification and the main limitation in this paper is no guarantee in retrieval scenario and high complexity. Association classifier is one of the most common data mining techniques that are used to extract semantic concept [9] from large datasets. In [2] the authors proposed an algorithm based on mining association rule. Mining Association Rule map discrete feature intervals into semantic categories by extracting low level features. Then a knowledge-discovery algorithm used this association rules to link low-level image features with high-level visual semantics in an effort to automate the process of retrieving semantically similar images. This method also provides a mathematical model to customize the relevance of feature measurements to semantic assignments. The main limitation is the high semantic gap between low level features and high level Semantic concepts. In [5] the images are classified semantically using Genetic Algorithm. Zernike Moments are calculated by using radial polynomials in both RGB and HSV Color Space. Then to transform the crisp input into degree of match, fuzzification is done. By using the fuzzification value the fuzzy rule base is built with mamdani fuzzy inference system. Genetic Algorithm compares both Fuzzy Inference System and Zernike Moments and obtained an optimum MF for further classification. The authors used COREL dataset to classify the images into five classes with low complexity and overcome the semantic concept gap accurately. Hierarchical classification on different application domains are discussed detailed in [7]. Here, the authors talk about existing hierarchical approaches and based on that approaches a new unifying framework are formed to classify the images hierarchically. In [18] the authors are proved that the association classifier results are better than the other approaches for image classification. The main aim of this paper is to identify the concept of undetermined image feature vector by using set of association rules. The main steps to set up an image classifier based on association rules are 1.extracting the features from the images, 2.association rules are generated by mining the repetitive pair of feature values and concepts, 3.High weightage rules are selected for classification. In order to improve the performance of the classifier, several papers [1,3,13,15] are published based on Fuzzy association rules (FAR). Fuzzy association rules are used to improve the traditional association rules [1], where the fuzzy logic is used in partitioning the domains [15]. In fuzzy association rules three fuzzy factors are calculated such as support, confidence and lift. Based on these three factors fuzzy weight are calculated, and the rules with high weight are selected to build the fuzzy classifier for classifying the images hierarchically. Abolfazl Tazaree *et al* **[1]** proposed a new method to classify the image hierarchically based on fuzzy rule mining. A novel fuzzy association rule is built by extracting fuzzy features. Then by using these rules the images are classified in hierarchical manner. The COREL database is used here to classify the images into 81 concepts such as buildings, waterfall, snow, kitchen etc. with four levels. One of the main limitations in this method is the time to classify the images in dataset. The precision and recall value are 85% and 80% respectively.

2. The System framework

Fig 1 demonstrates the proposed methodology and the method to classify the images hierarchically includes two phases namely training phase and testing phase. In training phase, first the low level features (Color and Texture) are extracted. Features with strong correlation are selected for fuzzification. Then Fuzzy Association Rule is mined for each concept in all layers and a fuzzy rule base is made up. In testing phase, the hierarchical fuzzy inference engines along with fuzzy rule base determined the concept of test image.

3. Feature Extractions

Feature Extraction is performed in L*a*b and HSV color space [1]. Each feature is extracted from six color matrixes such as H, S, V, L, a and b. Totally, seven types of features are extracted from six color matrixes: three types of color features and four types of texture features. The fuzzy color histogram, Spatial fuzzy linking color histogram and color moments are color features and four types of texture features are contrast, correlation energy and homogeneity.

3.1 Color Descriptor

Color is the first and most straightforward visual feature and it plays an important role in the human visual perception mechanism. Three types of color features extracted here are Fuzzy Color Histogram (FCH), Spatial Fuzzy Linking Color Histogram (SFLCH) and Color Moments (CM). Color moments [11] are used to differentiate images based on their features of color. The color moment is used to measure the color similarity between images. The basis of color moments lays in the assumption that the distribution of color in the image can be interpreted as a probability distribution. If, color in the image follows a certain probability distribution, the moments of that distribution can then be used as features to identify that image based on color. The extracted color moments are moment 1(mean), moment 2(standard deviation), moment 3(skewness) and moment 4(kurtosis). Mean is the average color in the image. The standard deviation is the square root of the variance of the distribution. Skewness can be understood as a measure of the degree of asymmetry in the distribution. Kurtosis is a measure of whether the data are peaked or flat relative to a normal distribution. That is data sets with high kurtosis tend to have a distinct peak near the mean. Data sets with low kurtosis tend to have a flat top near the mean rather than a sharp peak.

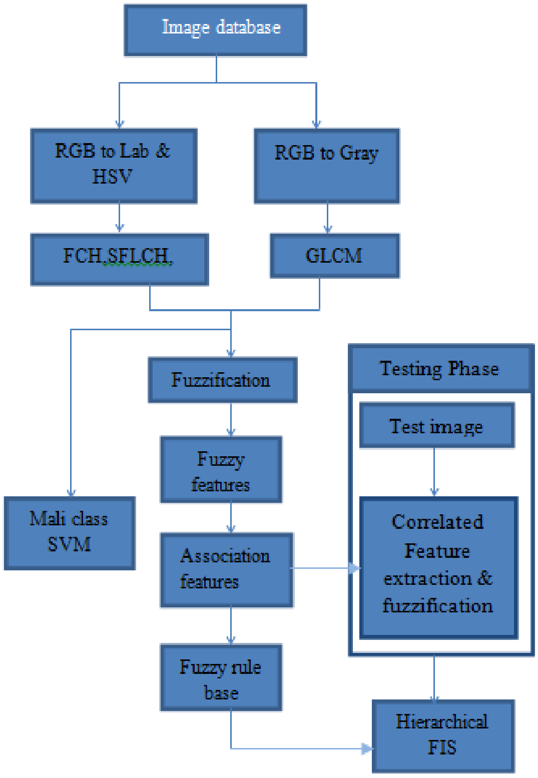

Figure 1: overall process of system framework

3.1.1 Fuzzy Color Histogram

The well-known RGB system represents additive color combinations. Due to high correlation, it is convenient for color image display but not for analysis because if the intensity get changed all R, G and B values also change accordingly. As a result, chromatic information will be lost. Hence the RGB images are converted into two color spaces namely HSV and Lab color spaces. A histogram is created by firstly dividing a color space into a number of bins and then by counting the number of pixels of the image that belongs to each bin. The number of regions that the color space divided is quite large and thus the colors represented by neighboring regions have relatively small differences and produce histograms with dissimilar adjacent bins. In order to present a solution to this problem, this method used a small number of bins produced by linking the triplet from the L*a*b* and HSV color space by means of a fuzzy expert system.

Fuzzy [15] means a form of knowledge representation suitable for notions that cannot be defined precisely, but which depend upon their contexts. Fuzzy logic provides an alternative way for handling of uncertainty. A color histogram based fuzzy model is represented with a set of rules (Mamdani) and some color bins as output. In L*a*b*, L* stands for luminance, a* stands for greenness-redness and b* represents blueness-yellowness. All colors and grey levels can be expressed throughout a combination of these three components. However, L* does not contribute in providing any unique color but for shades of colors white, black and grey. Thus, a* & b* component receives a higher weight with respect to the L component of the triplet. The a* and b* components are partitioned into five regions such as green, greenish, middle, reddish and red for a*, blue, bluish, middle, yellowish and yellow for b*, and L* should be subdivided into three regions: dark, dim and bright areas. The bins of the histograms are: (1) black, (2) dark grey, (3) red, (4) brown, (5) yellow, (6) green, (7) blue, (8) cyan, (9) magenta and (10) white. By using these, 27 fuzzy rules are created to extract fuzzy color histogram in L*a*b color space.

In HSV model, colors are expressed using 3 attributes: hue, saturation (intense vs dull) and value (light vs dark). In HSV the specific color can be recognized regardless of variations in saturation and intensity and hue is invariant to certain types of highlights, shadows and shading. So, it will be much easier to identify the colors that are perceptually close and combine them to form homogeneous regions representing the objects in the image. Hence the image could become more meaningful and easier for analysis. The colors are divided into bins each of which contains 3 fuzzy sets with certain fuzzy values of hue, saturation and value. Hue values are cyclic and vary from 0 to 360. Hue consists of eight fuzzy sets such as Red, Orange, Yellow, Green, Cyan, Blue, Violet and Magenta. The saturation variable are represented by three sets low , medium and high. And the value is subdivided into five regions such as dark, deep, medium, pale and light. By using these three combinations totally 68 rules are created to extract fuzzy color histogram in HSV color space.

The Mamdani type of fuzzy inference is used in which the fuzzy sets from the output MFs of each rule are combined through the aggregation operator which is set to max. The implication factor which determines the process of shaping the fuzzy set in the output MFs based on the results of the input MFs is set to min and the OR and AND operators are set to max and min, respectively. The final fuzzy histogram consists of only 10 bins approximately representing black, dark grey, red, brown, yellow, green, blue, cyan, magenta and white for both HSV and L*a*b color space.

3.1.2 Spatial Fuzzy Linking Color histogram

The fuzzy color histogram [15] defines a both similarity of colors in different bins and dissimilarity of those colors in same bins. It also reduces the complexity of computations by projecting a three dimension histogram into one dimension histogram but shows no information about the location of pixels in the images. Spatial Fuzzy Linking Color [14] histogram combines FCH with spatial information to describe the distribution of color pixels in different regions. Image I is divided into 9 sub-blocks of same size and it is defined as

$$I = \{B_k | B_k \subset I, k = 1,2 \ldots.,9\} \qquad (1)$$

Where, B_k one of sub-blocks in an image I and k is the number of sub-blocks in image I. The fuzzy color histogram is applied to each block B_k in an image I to extract the color features, hence each block contains 10 number of histogram bins. In other words, totally $9 \times 10(90)$ bins are extracted from each image in the dataset. The Fuzzy histogram only provides a coarse distribution of color in the images and it discard all the spatial information. Unlike FCH, SFLCH can easily notice the dominant color in each of the images with spatial knowledge.

3.1.3 Texture Descriptor

Texture gives [6] us information about structural arrangement of surfaces and objects in the image. It depends on the distribution of intensity over the image, not defined for a separate pixel. Grey level co-occurrence matrix (GLCM) is one of the methods for representing texture features of images. Four features are extracted in texture such as contrast, correlation, energy and homogeneity. Co-occurrence matrix, which is necessary for computing texture descriptors, are extracted in four directions of 0, 45, 90 and 135 degrees by two distances of 5 and 10 pixels thereby eight co-occurrence matrixes are obtained from each color matrix. In this way, 32 texture descriptors are extracted from each color matrix because four texture descriptors are extracted from each co-occurrence matrix. Co-occurrence matrix (P) is based on second order statistics [11] that is the spatial relationships of pair of grey value of pixels in digital texture images. It counts how often pair of grey level of pixels separated by a certain distance and lie along a certain direction. The grey-level co-occurrence matrix (p) is obtained by normalizing the co-occurrence matrix (P).

Energy is a texture measure of grey-scale image represents homogeneity changing, reflecting the distribution of image grey-scale uniformity of weight and texture.

$$Energy = \sum_x \sum_y p(x,y)^2 \quad (2)$$

Contrast is the main diagonal near the moment of inertia; it reflects the image clarity and depth of the texture. If the contrast is large, then the texture is deeper. It returns a measure of the intensity contrast between a pixel and its neighbor over the whole image. Contrast is 0 for a constant image and its range is [0 (size (GLCM, 1) - 1) ^2].

$$Contrast = \sum_{x,y} |x-y|^2 \,(p(x,y)) \quad (3)$$

Correlation measures image texture randomness, when the space co-occurrence matrix for all values is equal, it achieved the minimum value .On the other hand, if the value of co-occurrence matrix is very uneven, its value is greater. Therefore, the maximum entropy implied by the image grey distribution is random. It returns a measure of how correlated a pixel is to its neighbour over the whole image. Correlation is 1 or -1 for a perfectly positively or negatively correlated image. Correlation is 0 for a constant image and its range is [-1 1].

$$Correlation = \sum_{x,y} \frac{(x-\mu_x)(y-\mu_y)p(x,y)}{\sigma_x \sigma_y} \quad (4)$$

Homogeneity measures the number of local changes in image texture. It returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. Homogeneity is 1 for a diagonal GLCM and its range is [0 1].

$$Homogenity = \sum_{x,y} \frac{\boldsymbol{p(x,y)}}{\boldsymbol{1+|x-y|}} \quad (5)$$

Where *x* is the pixel value in row, *y* is the pixel value of column, *p*(*x*, *y*) is the grey-level value at the coordinate (*x*, *y*), μ_x and μ_y are the mean value of row and column in the grey-level co-occurrence matrix *p*, σ_x *and* σ_y are the standard deviation value of row and column in the grey-level co-occurrence matrix *p.* After performing feature extraction in the spatial domain, the six color matrices H, S, V, L, a, b are be transformed into four frequency domains such as wavelet transform, Fourier transform, Radon transform and Cos transform. Then the color and texture features are extracted again.

3.4 Frequency Domains

3.4.1 Fourier Transform

Fourier Transform decomposes an image into its sine and cosine components. In the Fourier domain, each point represents a particular frequency contained in the spatial domain. The spatial domain is the normal image space, in which a change in position in I directly projects to a change in position in S and the frequency domain is a space in which each image value at image position F represents the amount that the intensity values in image I vary over a specific distance related to F. The DFT is the sampled Fourier Transform and therefore does not contain all frequencies forming an image, but only a set of samples which is large enough to fully describe the spatial domain image. The number of frequencies corresponds to the number of pixels in the spatial domain image, *i.e.* the image in the spatial and Fourier domain is of the same size.

The two-dimensional DFT is given by:

$$f(k,l) = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} f(i,j) e^{-i2\pi(\frac{ki}{N}+\frac{lj}{N})} \quad (6)$$

Where $f(i,j)$ is the image in the spatial domain and the exponential term is the basis function corresponding to each point *f (k ,l)* in the Fourier space. The equation can be interpreted as: the value of each point *f (k, l)* is obtained by multiplying the spatial image with the corresponding base function and summing the result. The basic functions are sine and cosine waves with increasing frequencies. That is, *f(0,0)* represents the DC-component of the image which corresponds to the average brightness and *f(N-1,N-1)* represents the highest frequency.

3.4.2 Wavelet Transform

Wavelet transform is an excellent alternative to Fourier transforms in many situations. Fourier analysis is decomposed into periodic components but wavelet analysis is decomposed into components localized in both time and frequency domains. The basic idea behind wavelet transform is to analyze different frequencies at different scales. High frequencies are analyzed using low scales and low frequencies are analyzed by high scales. To be more specific, in wavelet transform, all of the basic functions, which are called wavelets, are derived from scaling and translation of a single function, called mother wavelet. The wavelet transform computation of a two-dimensional image is also a multi-resolution approach, which applies recursive filtering and sub-sampling. At each level (scale), the image is decomposed into four frequency sub-bands, LL, LH, HL, and HH where L denotes low frequency and H denotes high frequency. Daubechies wavelet with single level transform is used here to extract both color and texture features in frequency domain.

3.4.3 Radon Transform

The Radon transform (RT) of an image represented by the function *f (x,y)* can be defined as a series of line integrals through *f (x,y)* at different offsets from the origin. The RT can be obtained by applying the 1-D inverse Fourier transform to the 2-D Fourier transform restricted to radial lines going through the origin. The Radon transform of an image function *f* (*x*, *y*) is defined by

$$A(t,\theta) = R(t,\theta)\{f(x,y)\} \tag{7}$$

$$A(t,\theta) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x,y)\delta(t - x\cos\theta - y\sin\theta)dxdy$$

where *t* is the upright distance of a line from the origin, θ is the angle vector formed by the distance vector, and δ (•) is the Diract delta-function.

3.4.4 Cosine Transform

The discrete cosine transform (DCT) separates the image into parts with respect to the image visual quality. The DCT is similar to the discrete Fourier transform but it can approximate the lines well with fewer coefficients

The general equation for a 2D DCT is defined by the following equation:

$$f(u,\ v) = \frac{2^{\frac{1}{2}}}{N}\frac{2^{\frac{1}{2}}}{M}\sum_{0}^{N-1}\sum_{0}^{M-1} A(i).A(j).\cos[\frac{\pi.u}{2.N}(2i+1)] \cos[\frac{\pi.v}{2.M}(2i+1)].f(i,j) \tag{8}$$

Where $f(i,j)$ is the intensity of the pixel in row *i* and column *j*, $f(u,\ v)$ is the DCT coefficient in row and column of the DCT matrix**.** After extracting the features from four frequency domain and spatial domain, the most correlated features are selected. The features with strong correlation with concepts are selected to build the fuzzy rule base. Normalization and fuzzification of feature vectors are done after selecting the most correlated features. Triangular membership function is used for fuzzification. In fuzzification the original feature values are replaced with the relative degree of feature in all membership functions such as Low, Middle and High.

3.5 FUZZY RULE BASE

Association rules [1] address the value of correlation between feature and concept. Fuzzy association rule is more predictive than non-fuzzy association rule. FAR depends upon the fuzzy factors such as fuzzy support, fuzzy confidence and fuzzy lift. These three fuzzy factors are measured form the three values in the fuzzy feature vector. Consider the sample set S and concept C, for each concept c belongs to C the image set can be split into positive samples s_c^+ and negative sampless_c^-. The basic Fuzzy Association Rules are shown as

$$f\ is\ MF_i^l\ \rightarrow concept\ is\ C_k^l\ with\ W_j\ confidence$$

Fuzzy count of a rule in the image set D means the total degree of membership of the feature to MF_i^l in images containing the concept. *Fuzzy support* of a rule in the image set D indicates fuzzy percentage of images including both the feature and concept. For example fuzzy support of a rule $f\ is\ MF\ \rightarrow C_k^l$ is equal to 0.5 means, that 50 % of images had both the feature and conceptC_k^l. *Fuzzy confidence* of rule addressed the percentage of image containing both the feature and concept C_k^l toward the total image containing the feature f.

Fuzzy confidence presented the implication of a rule and addresses the accuracy of its prediction. *Fuzzy lift* calculates the prediction power of a rule. It is the ratio of fuzzy confidence to expected confidence which is equal to the distribution of concept c in image set. *Growth Rate* is the ratio of positive to negative sample of a rule which evaluates the separating power s_c^+ from s_c^-. Hence to separate the negative samples from positive samples. Then finally *Rule Weight* is calculated to find the overall quality of the rule. Rule Weight is measured by combining the Fuzzy confidence, Growth Rate and Fuzzy lift. The weight of the rule specifies the effectiveness of the rule in classification. Since the rule base composed the most effective rules, the rules with highest weight are inserted to the rule base.

4. Hierarchical Fuzzy Classification

Class hierarchies [7] are a common way for reducing the complexity of the classification problem, especially when dealing with a large number of classes because some classes are more closely related than others. While flat classification techniques might reach the minimum performance in dealing with a large number of classes, the hierarchical classification techniques are able to overcome the problem by training in a hierarchical structure in a stepwise manner. Thus Hierarchical classification has more advantages than flat classification such as using posterior probability of each concept, exploiting association between concepts, capability of performing parallel classification and improving the accuracy of classification. It would be beneficial to apply a recursive top-down approach to hierarchical classification: first, to discriminate the subsets of classes at the top level of the hierarchy and then to recursively separate the classes (or sets of classes) in those subsets. Here the image databases are split up manually into four layers as a hierarchical structure. A number of Mamdani fuzzy inference engines are exploited to perform the classification. Defuzzification is performed using the central average method, which has three advantages of simplicity, understandably and continuously. The method to classify the images hierarchically includes training phase and testing phase. In training phase the fuzzy rule base are built by selecting the rule with the highest weight. In testing phase the first step is adaptive feature extraction and fuzzification of test image. It means that for the given test image, the feature vector that are used to build the rule base are extracted again. Then finally the hierarchical fuzzy inference engines along with the fuzzy rule base determined the concept of test image.

4.1 Multi class SVM classifier

Support Vector Machines are inherently two class classifier that is the class labels can only take two values ± 1 whereas Multiclass SVM classifier are one versus all classifier. Many real world problems have more than two classes. To get M-class classifier a set of binary classifier $f^1, f^2, f^3, \dots\dots\dots.., f^m$ are constructed, each trained to separate one class from rest.

5. Experimental Results

The database contained 2400 general purpose images including 8 semantic concepts from COREL database, such as Lab, Buildings, Vehicle, Non-Bird, Bird, Kitchen, waterfall and snow. Each class contained about 150 images. For classification the database are divided manually in hierarchical manner with four levels. In level 1 the whole dataset are divided into Artificial and Natural Images. In level 2 the Artificial images are split up into Indoor and Outdoor images and Natural images are split up into Animals and plants, then again at level 3 Outdoor images are split up into Vehicle, Buildings etc. and Animals are split up into Bird and Non bird. In final level the non-bird is divided into three sub classes such as elephant, horse, dinosaurs and so on.

First the RGB image are converted into two color spaces because both HSV and L*a*b color spaces are very close to human visual perception and from these color spaces the features are extracted. Then the above mentioned seven features are extracted from two color spaces. For L*a*b color space the input image is divided into three channels (L*, a*, b*). L consist of 3 fuzzy sets, a* and b* consist of 5 fuzzy sets. For HSV color space H consist of 8 fuzzy sets, S and V consist of 3 and 5 fuzzy set respectively. The output fuzzy color histogram for both color space consist of 10 color bins. The fuzzification of the input is accomplished by using triangle membership function then by using this, totally 68 rules are created for HSV color space and 27 rules are created for L*a*b color space. The bins of the histogram are (1) black, (2) dark grey, (3) red, (4) brown, (5) yellow, (6) green, (7) blue, (8) cyan, (9) magenta, (10) white. The dominant colors in the image can noticed easily. For example figure 2 shows the concept of vehicle (bus), the bins 1, 2, 3 and 7 are mostly activated because of the black shadows, cyan because of the cyan color in bus and red because of the red color words in the bus. In the concept of bird (butterfly) the bins 6, 7, 8 and 9 are mostly activated because of the blue color butterfly, cyan because of the cyan color lightness and green because of the green color leaf in the scene.

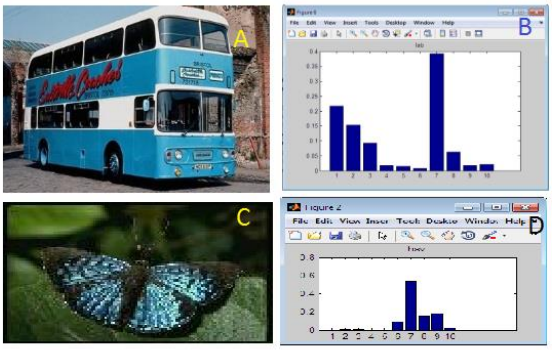

Figure 2. (a) , (c) input image, (b) , (d) fch

On comparing the results of two color spaces in fuzzy color histogram, the L*a*b color space shows the best result than HSV. Hence only L*a*b color space conversion have been done for spatial fuzzy linking color histogram. The following figure shows the result of spatial fuzzy linking color histogram.

Figure 3 [a] Input image,[b] L*a*b* color space,[c] The input image is split up into 9 sub-blocks,Fig [d] : Fuzzy Color Histogram (FCH) is applied to each block,Fig [e]: result of SFLCH. InB_3, bin 6 is highly activated because of green leaves in this block. Due to white shade of flower bin 10 is most activated in all blocks. B_5, cover the center block of the image and hence bin 2 is highly activated because there are almost gray color in that block. From the above example it is cleared that the SFLCH reflects color distribuion from top to bottom and left to right in the given input image. on compare with FCH, SFLCH contains the color distribution as well as spatial information. To built the Fuzzy rule base, Fuzzy association rules are mined for each concept in all layers by using three factors such as Fuzzy support, Fuzzy confidence and Fuzzy lift.

5.1 Performance measure

The basic measures to evaluate the system for classification are accuracy,Precision ,Recall and F-Measure. Before enter into the performance evaluation some basic concepts are discussed here,True Positive(TP): Number of images from dataset, that are correctly assigned to class i, True Negative(TN): Number of images did not assign to class i and actually did not belongs to that, False Positive (FP): Number of images incorrectly assigned to class i but actually did not belong to that, False Negative (FN) : Number of images did not assign to class i but actually belongs to that.Precision is defined as the total number of images correctly classified among all the images assigned to class i. Recall defined as percentage of correctly images among all the images, which must be assigned to class i [1]. To evaluate the performance of classifier the results are compared with Multi class SVM classifier. Multiclass SVM classifies the images by using same features which are used for fuzzy classifier. The table [1] shows the results of classifier performance and also the features performance in the classifier. From the Table 1 it is cleared that for both Multiclass SVM and Fuzzy classifier the accuracy are high in SFLCH features than FCH. Hence for image classification Fuzzy classifier proved to be a highly accurate classifier when compared to Multiclass SVM classifier.

6. Conclusion

Hierarchical Semantic Classification is able to classify the semantic concept efficiently in low level with highly specified input data. And the semantic gap between the low level features and high level semantic concepts are combined by using FAR. A Fuzzy Association Rule is used to improve the traditional Association Rule. The low level features such as color and texture are extracted in both spatial and frequency domains, then the normalization and fuzzification is done for the features which are strong correlation with concept. Finally, the Fuzzy Association Rule base is constructed by using three fuzzy factors such as fuzzy support, fuzzy confidence and fuzzy lift to build Hierarchical Semantic Classifier. In training phase the most correlated features which are used to build FAR are extracted again. To evaluate the performance of the classifier, precision, recall and accuracy is calculated for each concept and also for both Fuzzy and Multiclass SVM classifiers. Among these two classifiers the experimental result demonstrates that the Fuzzy classifier with SFLCH features had the factors of best classifier than other classifier. Classifying the image hierarchically using fuzzy association rules is time consuming because the fuzzy inference engines have to process a more number of rules in each layer. So further this method will be modified to reduce the number of rules as well as the time to classify the image hierarchically.

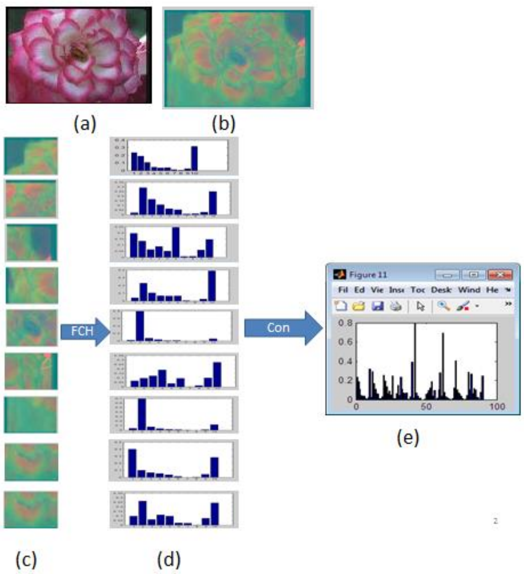

Figure 3. Result of SFLCH

Table 1 Classifier results

Classifier	Features	Precision	Recall	Accuracy
Multiclass SVM	FCH,CM,GLCM	79	69	73
Multiclass SVM	SFLCH,CM,GLCM	77	75	78
Fuzzy Classifier	FCH,CM,GLCM	83	85	84
Fuzzy Classifier	SFLCH,GLCM	89	96	91

References

[1] Abolfazl Tazaree & Amir-Masud Eftekhari-Moghadam.," *A semantic image classifier based on hierarchical fuzzy association rule mining*" Springer , Verlang London Dec 2014.

[2] Adrian S.Barb Member,Chi-Ren-Shyu .," *Visual semantic modeling in content based geospatial information retrieval using associative mining technique*", IEEE Transaction on geoscience and remote sensing VOL.7,NO.1 Jan 2010.

[3] Alcal J. and Alcal A.,"*A fuzzy association rule based classification model for high dimensional problems with genetic rule selection and lateral tuning*", IEEE Trans Fuzzy Syst.

[4] Alphonsa Thomas and Sreekumar K.,"*A Survey on Image Feature Descriptors-Color, Shape and Texture*", International Journal of Computer Science and Information Technologies, Vol. 5 (6) , 2014, 7847-7850.

[5] B.Someyh Mousavi,Fazlollah Soleymani , Navid Razmjooy.," *Semantic image classification by Genetic Algorithm using optimized fuzzy system based on Zernike moments*", Verlang – London , April 2012.

[6] Calvin C.,Gotlieb and Herbert E.Kreyszig,"*Texture descriptor based on co-occurrence matrices*",Computer vision graphics and image processing 51,70-80(1990).

[7] Carlos N. Silla Jr. Alex A. Freitas.," *A Survey of Hierarchical Classification Across Different Application Domains*",Thesis.

[8] Chamorro J. and Sanchez D., "*Histograms on linguistic color variables based on fuzzy naturals*",Comp science and Artificial Int.

[9] Chen Z. and Chen G.,"*Building an associative classifier based on fuzzy association rules*",Int J comput Intell Syst 1:262-273.

[10] D.Djordjevic , E.Isquierdo,"*An object and user driven system for semantic based image annotation and classification",* IEEE Transactions on circuits and systems for video technology , VOL 17,NO 3,March 2007"

[11] Gaurav Mandloi., "*A Survey on Feature Extraction Techniques for Color Images*", International Journal of Computer Science and Information Technologies, Vol. 5 (3) , 2014, 4615-4620.

[12] Han J. and Kai-Kaung., "*Fuzzy color histogram and its use in image retrieval*", IEEE Transactions on image processing, 11(8):944-952.

[13] Hua Y. and Chena S., "*Mining fuzzy association rules for classification problems*", Comput Ind Eng 43:735-750.

[14] Jie Zhao.Gang Xie,"*A modified fuzzy color histogram using visual perception variation of pixels at different locations*",Springer Multimed Tools Appl 2014.

[15] Konstantinidis K. and Gasteratos A., "*Image retrieval based on fuzzy color histogram processing*", Opt Commun 248:375–386.

[16] Kuok C, and Wong M., "*Mining fuzzy association rules in databases*", ACM SIGMOID 27:159-168.

[17] Lu D. and Weng Q. , "*A survey of image classification methods and techniques for improving classification performance*", Rem Sen 28:823–870.

[18] Pakizar S. and Atsushi I., "*Fuzzy color space for apparel coordination*", Inf Sys, Vol.1,Issue 2.

[19] Xiaoyun C,Wei C .,"*Text categorization based on classification rules tree by frequent patterns*", Softw17:1017–1025-2006.

[20] Yi-Chung Hu, Ruey-Shun Chen, Gwo-Hshiung Tzeng," *Mining fuzzy association rules for classification problems*", Elsevier Science ,Computers & Industrial Engineering 43 (2002) 735–750.

[21] Zuolinga chen,Guoqing chen.,"*Building an associative classifier Based on Fuzzy Association Rules*", International Journal of Computational Intelligence Systems, Vol.1, No. 3 (August, 2008), 262 – 273.

Biography Corresponding Author

K.Thirumala Lakshmi was born in INDIA in 1993. She entered Anna university Tuticorin campus as an undergraduate student in 2010, received the B.E degree - ECE in 2014. She received the M.E in 2016 in Applied Electronics from the Anna University Regional Campus-Tirunelveli. She interested in image processing.