



VISUAL CONCEPT DETECTION IN IMAGES

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ABSTRACT

The traditional method of retrieval of images using text based technique has various limitations, one of which is the huge amount of labor work required to annotate the image manually. The annotation process takes a lot of time. Another limitation is the interpretation of same image by different people differently which may lead to inaccuracy of results. To overcome these limitations we use visual concept detection. This paper proposes an efficient method of concept detection using various features such as color and texture. For extraction of color feature we use color histogram and color auto correlogram. Features related to texture are being extracted using wavelet transform and Gabor wavelet filter. For classification of images, Support vector machine (SVM) is used depending upon their categories and classes. Wang's database is used for implementation. By using precision, recall and accuracy as evaluation parameters the performance of proposed system is evaluated.

Keywords- Visual concept detection, color features, texture features, Auto Correlogram, SVM.

INTRODUCTION

In the recent years, image processing has gained significance importance and we find its applications in various fields of medical and science. One such application is concept detection of images. Visual concept detection aims at detecting the concept of query image from a large and extensive database by extracting various features such as color, texture, edge etc. Text based approach and concept based approach are mostly used in image retrieval. But due to limitations of text based approach i.e. large number of labor work required for manual annotation, concept based approach is preferable. Concept based approach can be used for both image and video detection. Concepts can be generally classified into objects and scenes. To access visual information on concepts such as cars, flowers, beach, house etc, this classification is important. Commonly, systems in image and video retrieval [1, 2] basically use machine learning. These are based on image representations to distinguish between scenes concepts and objects.

Concept detection aims at detecting of images based on detected from the visual content of images. Examples of concepts are scenes ("beach", "school", "office"), actions ("walking," "sleeping") or objects ("books," "bikes"). Use of concept allows textual queries for non-annotated images in databases.

LITERATURE SURVEY

In 2015, Devyani soni [3] proposed a technique for image retrieval dependent on color space. For color it used color histogram and color correlogram technique. For both color spaces RGB and HSV, global color histogram was applied. Also local histogram was applied. For comparing query image with images in database, Euclidean distance was used. Various features like texture and shape were not considered for implementation.

In 2016, Rajkumar jain [4] described a method to integrate Prewitt edge detection for shape feature and HSV color histogram for color feature. Manhattan distance was used for measurement of similarity on the quantized value that were generated for color histogram and edge feature. The proposed system was applied on Wang's database to achieve precision and adaptability. In 2016, KattaSugamya [5] a method was proposed for image retrieval based upon color correlogram, Gabor wavelet and wavelet transformation for extracting features such as color, shape and texture. It uses SVM classifier to obtain image similarity along with different distance metrics. In 2017, Ms. Rinki Nag [6] introduced a system to describe the content of an image based upon visual features such as color and texture. Gabor filter and wavelet moment methods are used for texture feature extraction and color correlogram, HSV Histogram and color moment are used for extraction of color. Also to improve the accuracy of the system this paper includes a color and texture combination. In 2017, Nancy [7] has implemented two various methods of retrieval. Color feature and texture feature are extracted using wavelet moment, color moment and Log- Gabor method. Distance measurements such as Euclidean and chi-square methods are used for retrieval of images. KNN classifier was used for classification of images. Time complexity was reduced also F-measure was obtained. For this spearman's rank correlation function was used.

In 2018, Mohd.Aquib Ansari [8] proposed a two level strategy. First level was to use various feature descriptors in order to extract the pixel level features of an image. For extraction of color and texture features a technique based on color and edge directivity descriptor was used. A 2D-DWT was used for extracting the shape feature of the images. For the second step, SVM classifier was used for classification purposes. For retrieval of all the similar images a similarity measurement is used. This two-step technique was applied on various image databases which provided better output as compared to various other methods.

PROPOSED METHODOLOGY AND MATERIAL

The proposed system is implemented to detect concept of an image using SVM and distance metrics. In the first step various features of images in database are extracted. Feature extraction is used to separate the visual content from the images. It then stores these contents in the form of different feature vectors. The global representation method gives a single vector with values which calculate different features of the images like texture and color. These feature vectors are then used for comparison of query with the database. Feature extraction techniques used for proposed method are as follows:

A. Color feature extraction

It involves extraction of multiple color features like color Auto Correlogram, color moment and HSV histogram.

1) Color AutoCorrelogram

Color Auto correlogram captures only the spatial relation between similar colors. It shows how with distance, the spatial relation of pairs of colors varies. The difference in correlogram and auto correlogram is that correlogram can be stored as a table. The table includes the pairs of colors i, j where d^{th} entry depicts the probability of finding a pixel j from pixel i at distance d . It can be saved as a table that shows color i where d^{th} entry depicts the probability of finding a pixel i from the same pixel at distance d . A feature vector of 1×64 is generated by quantizing the image in RGB space. The autocorrelogram (I) of the image I , defined for color c_i for distance d by,

$$\alpha_{c_i}^d(I) = \gamma_{c_i}^d \cdot c_i(I) \quad (1)$$

2) HSV Histogram

Histogram is a method of representing the color contents of an image. An HSV color histogram can be obtained by using the same approach which is being used for RGB color space. There are many color models for representing the images such as RGB, HSV and CMY etc but HSV model is actually apt for human visual perception. For detecting the color feature the image is converted from RGB (Red Green Blue) space to HSV (Hue Saturation Value) space. For extracting the color feature, the first point is to convert the image from RGB plane to HSV plane. Once the conversion is done, the next step is to quantize the image. The hue scale is split up into eight different groups whereas the saturation scale is split into two different groups. The intensity scale is split up into two different groups. Quantization is the procedure of reducing the number of color space by putting the similar color in same bin. Due to this quantization, computation and comparison time is reduced. By combining each of these groups, a feature vector of 1x32 is generated. For the combined HSV values, the respective histogram component can be determined. After this the particular histogram component is incremented by one for each pixel.

3) Color Moment

Color moments provide measurement of color resemblance between the images. They are scaling invariant and rotation invariant. In order to find and retrieve a similar image one image is compared with a database of images. A similarity score is obtained after each comparison between images. Lower score means the two images are more similar to each other. A feature vector of 1x6 is constructed, containing the first color moment mean and the second color moment standard deviation from each RGB.

Mean: The first color moment is mean. It gives the average of colors in the images. It is defined by the following equation:

$$E_i = \sum_{j=1}^N \frac{1}{N} p_{ij} \quad (2)$$

Where,

N - No. of pixels in an image and

p_{ij} - value of the j th pixel of the image at the i^{th} color channel.

Standard Deviation: It is the second color moment. It is computed by taking the square root of the variance of the color distribution and it can be calculated as:

$$\sigma_i = \sqrt{\left(\frac{1}{N} \sum_{j=1}^N (p_{ij} - E_i)^2\right)} \quad (3)$$

Where, E_i - mean value for the i^{th} color channel of the image.

B. Texture feature extraction

For the examination of images, texture is the foremost characteristic. Along with high frequencies in the image range, textures are distinguished by dissimilarity in brightness. The potential to match on similarity of texture can be helpful in finding out areas of images having same colors. It is difficult to define a texture. It doesn't take place over a point, but instead it takes place over entire region. It can be examined by computable and subjective study. It involves extraction of different texture features such as Gabor wavelet and Wavelet transform.

1) Gabor Wavelet

Gabor wavelet is a function for calculating Gabor features of a gray scale image. It is used to extract texture feature for retrieval of images. Gabor function evaluates Gabor features like mean amplitude and mean squared energy for each scale. For computing the mean square energy and mean amplitude we create Gabor filters. Gabor filters are a group of wavelets that capture energy at a particular direction and at a particular frequency. Designing of these filters is done as follows: For a given image I with size $M \times N$, its Gabor wavelet transform is provided by a convolution and the convolutions are done via the FFT. Filters are constructed with respect to two components. One is the radial element which controls the frequency band to which the filter replies to. Second element is the angular element which controls the direction that the filter replies to. Both these elements are then multiplied in order to form the total filter. A feature vector consisting of value of mean amplitude and mean energy each having size of 1×24 is generated.

2) Wavelet Transform

Details from the signal at various scales are extracted by wavelet transform by sending the signal through high pass filters and low pass filters. Wavelet provides multi resolution proficiency along with high quality energy. Wavelet transform are calculated linearly with time which aids for faster algorithm. Single level discrete 2D wavelet transform command `dwt2` is been used. A single level two dimensional wavelet decomposition is performed by the `dwt2`. A 1×20 feature vector comprising of the first two moments of wavelet coefficients is generated. The wavelet coefficients are mean and standard deviation.

For detection of concept in images two different techniques are implemented, Support vector machine and distance metrics as discussed below.

Support Vector Machine (SVM): SVM is one of the strongest tools for binary classification. It is capable of developing faster classifier functions provided a proper training mechanism.

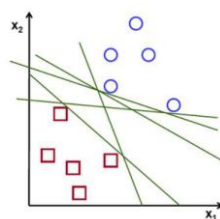


Fig.1 Possible hyperplanes

The data shown in Fig.1 are of two types which are circle and square. These data can be separated linearly by drawing a straight line which passes through these two data. SVM finds a straight line with largest minimum distance to the training samples. This straight line separating the data into different parts is known as hyperplane or decision boundary as shown in Fig. 2.

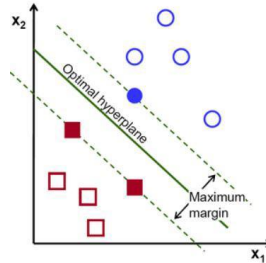


Fig.2 Hyperplane in SVM

There are various ways for SVM classification difficulty with multiple classes:

- One against all classification is the one where only one binary Support Vector Machine for each class is used to split up the data of the class from data of the remaining classes.
- One SVM decision function tries to classify all the classes in a Multiclass Support Vector Machine.
- In Pairwise classification, one binary SVM for each pair of classes is assigned. These pair of classes tries to differentiate data of one class from data of the other classes.

In multiclass SVM labels are given to the occasions, here the tags are taken from a limited set of various components. For overcoming this problem we need to convert it into multiple binary classifications. Different techniques for such type of reduction involve designing of binary classifiers that will differentiate between one of the tags with the remaining also known as one versus all or between every pair of classes known as one versus one. The new instances classification for the first technique is done by a winner takes all strategy. In this the classifier having the highest output function will assign the class. For the second technique the classification is done by a max wins voting strategy. In this, out of the two classes, each classifier allots the point to one class. After which the vote for the allotted class is incremented by one. In the end the class which has the majority votes decides the class out of the two.

Distance Measurements

Various distance metric techniques can be used for implementation of concept detection. Distance metrics such as Manhattan, Euclidean, Cosine, Chebyshev, Spearman, Cityblock, Mahalanobis, Minkowski, Relative deviation are been used. A few distances are discussed below.

A. Manhattan Distance

It is the distance defined as the distance between two different points measured along the right angles. The name Manhattan is given because it is the distance a car will drive in a city for example Manhattan.

If point P1 is at (x) and point P2 is at (y) then distance is calculated as:

$$d_{max}(x, y) = |x_1 - x_2| + |y_1 - y_2| \quad (4)$$

B. Euclidean Distance

A straight line between two points or distance between two points which measures the length of a segment connecting the two points is known as Euclidean distance or L2 distance.

If the points (x_1, y_1) and (x_2, y_2) are in two dimensional space, then the L2 distance between them is

$$EU = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \quad (5)$$

IMPLEMENTATION OF METHOD

Fig. 3 depicts the proposed methodology block diagram using SVM technique. Various features of all the images from the database as discussed in section II are extracted and their feature vectors are generated and stored. For concept detection of a query image its features are first extracted and its feature vector is generated. This feature vector and feature vectors of images from the database are applied to SVM classifier. The performance of concept detection is evaluated using precision, recall and accuracy.

Similarly concept detection using proposed distance metric technique is implemented. Fig. 4 shows the block diagram for proposed methodology using distance metrics technique.

PERFORMANCE ANALYSIS

The proposed system is demonstrated using Wang's database which consists of 10 various classes each class having 100 images, i.e total of 1000 images. Fig.5 shows a sample of images of each class. Visual concept detection is implemented using SVM and distance metrics.

For evaluation of the system we use precision, recall and accuracy.

A) Precision

Precision is the ratio of number of relevant images to the total retrieved number of images and is defined as follows:

$$\text{Precision} = \frac{\text{number of relevant image retrieved}}{\text{total number of images retrieved}} \quad (6)$$

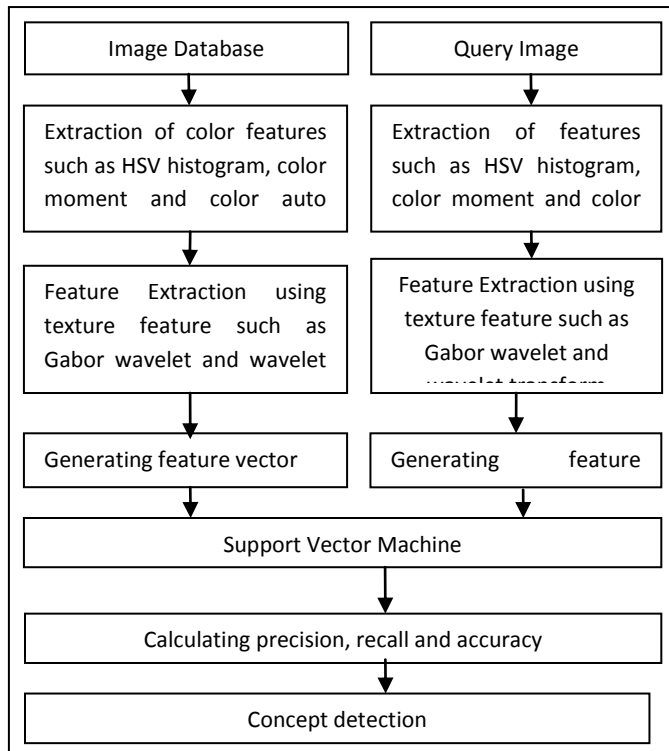


Fig.3 Block diagram of visual concept detection using SVM.

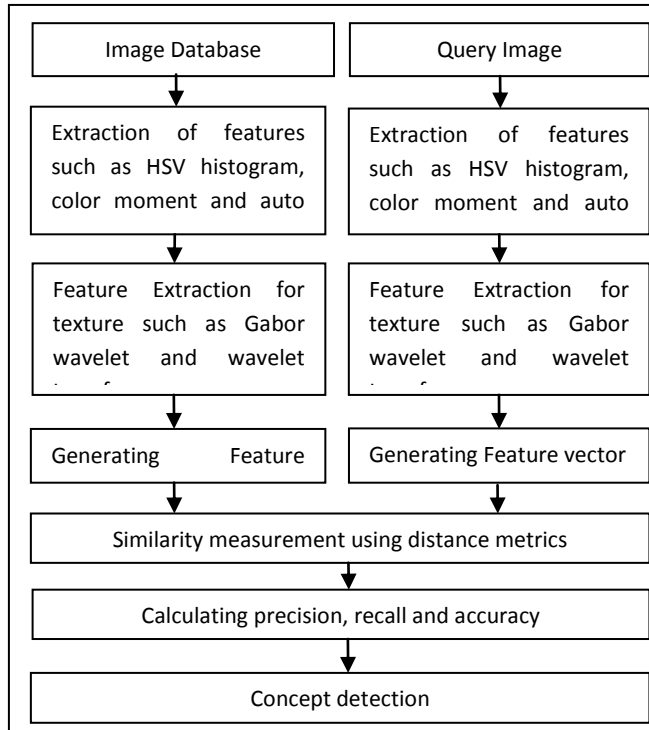
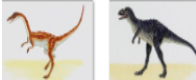


Fig. 4 Block diagram of visual concept detection using distance metrics.

Fig. 5 Sample images of Wang's database.

Class	Sample images	Class	Sample images
Africa		Elephant	
Beach		Flower	
Monument		Horse	
Bus		Mountain	
Dinosaur		Food	

B) Recall

Recall is the fraction of the total amount of relevant instances that were actually retrieved and is defined as follows:

$$\text{Recall} = \frac{\text{Number of relevant image retrieved}}{\text{Total No.of relevant image in database}} \quad (7)$$

C) Accuracy

Accuracy represents how close a measurement comes to its true value and is defined as follows:

$$\text{Accuracy} = \frac{\text{correctly predicted class}}{\text{total testing class}} \times 100 \quad (8)$$

Performance analysis of the proposed techniques of the system is divided into two sections. In the first technique, SVM is used for classification. The system is evaluated by dividing the database into different training and testing ratios such as 60:40, 70:30 and 80:20. In the first case i.e 60: 40 ratio, 600 images are been used for training and remaining 400 images for testing. Likewise images are divided for 70:30 and 80:20 ratios. Figure.6, figure.7 and figure.8 shows the confusion matrix been generated by using SVM for all different ratios. Confusion matrix is defined as a table layout of rows and columns that gives the value of positives and negatives. It also shows if they are true or false.For instance, in the confusion matrix in figure.5, for class buses 29 images are correctly classified and the remaining 1 image is wrongly classified into monuments class. Also accuracy for each class is represented as well.

Table.1 shows the values obtained for precision, recall and accuracy for different training and testing database ratios using SVM technique. As seen in the table, maximum accuracy is achieved if numbers of training images are increased.

In this second technique distance metric is used for concept detection of images. It is used to recognize similarity among the data. A distance metric employs distance functions that tell us the distance between the elements in the database.

	Africa	Beach	Mount	Buses	Dinosa	Elepha	Flower	Horses	Mount	Food
Africa	87.50% (27)	5.00% (2)	5.00% (2)	2.50% (1)	2.50% (1)	5.00% (2)	2.50% (1)	0	2.50% (1)	7.50% (3)
Beach	7.50% (3)	82.50% (25)	5.00% (2)	2.50% (1)	0	17.50% (7)	0	0	5.00% (2)	0
Monuments	12.50% (5)	15.00% (6)	85.00% (22)	10.00% (4)	0	5.00% (2)	0	2.50% (1)	0	0
Buses	0	0	10.00% (4)	90.00% (26)	0	0	0	0	0	0
Dinosaurs	0	0	0	0	100.00% (40)	0	0	0	0	0
Elephants	10.00% (4)	5.00% (2)	2.50% (1)	0	0	77.50% (31)	0	0	5.00% (2)	0
Flowers	0	5.00% (2)	0	0	0	0	95.00% (38)	0	0	0
Horses	0	0	0	0	0	5.00% (2)	0	95.00% (38)	0	0
Mountains	0	20.00% (8)	7.50% (3)	0	0	2.50% (1)	0	0	70.00% (28)	0
Food	20.00% (8)	2.50% (1)	2.50% (1)	0	0	0	2.50% (1)	0	2.50% (1)	70.00% (28)

Fig. 6 Confusion matrix for 60:40 ratios.

	Africa	Beach	Mount	Buses	Dinosa	Elepha	Flower	Horses	Mount	Food
Africa	86.67% (26)	6.67% (2)	0	0	0	13.33% (4)	0	0	0	13.33% (4)
Beach	6.67% (2)	76.67% (23)	10.00% (3)	0	0	3.33% (1)	0	3.33% (1)	0	0
Monuments	6.67% (2)	10.00% (3)	63.33% (19)	13.33% (4)	0	0	0	0	6.67% (2)	0
Buses	0	0	3.33% (1)	96.67% (29)	0	0	0	0	0	0
Dinosaurs	0	0	0	0	100.00% (30)	0	0	0	0	0
Elephants	16.67% (5)	3.33% (1)	3.33% (1)	0	0	63.33% (19)	0	0	10.00% (3)	3.33% (1)
Flowers	0	0	0	0	0	0	100.00% (30)	0	0	0
Horses	3.33% (1)	10.00% (3)	3.33% (1)	0	0	0	0	83.33% (25)	0	0
Mountains	0	13.33% (4)	13.33% (4)	0	0	3.33% (1)	0	0	66.67% (20)	3.33% (1)
Food	16.67% (5)	0	0	3.33% (1)	0	0	0	0	0	80.00% (24)

Fig. 7 Confusion matrix for 70:30 ratios.

	Africa	Beach	Mount	Buses	Dinosa	Elepha	Flower	Horses	Mount	Food
Africa	80.00% (16)	0	0	5.00% (1)	0	0	5.00% (1)	0	0	10.00% (2)
Beach	5.00% (1)	85.00% (17)	5.00% (1)	0	0	0	0	0	5.00% (1)	0
Monuments	10.00% (2)	0	80.00% (16)	10.00% (2)	0	0	0	0	0	0
Buses	0	0	10.00% (2)	90.00% (18)	0	0	0	0	0	0
Dinosaurs	0	0	0	0	100.00% (20)	0	0	0	0	0
Elephants	5.00% (1)	0	0	0	0	90.00% (18)	0	5.00% (1)	0	0
Flowers	0	0	0	0	0	0	100.00% (20)	0	0	0
Horses	10.00% (2)	0	0	0	0	0	0	90.00% (18)	0	0
Mountains	0	10.00% (2)	0	0	0	10.00% (2)	0	0	80.00% (16)	0
Food	20.00% (4)	0	0	10.00% (2)	5.00% (1)	0	0	0	0	65.00% (13)

Fig. 8 Confusion matrix for 80:20 ratios.

Table.1. Values of precision, recall and accuracy for different training and testing database ratios using SVM.

Ratio	Precision	Recall	Accuracy
60:40	8.40	9.04	78.25%
70:30	8.89	9.02	79.67%
80:20	9.15	9.53	86.00%

There are several distance metrics which can be used. For our analysis, 12 different distance metrics are used. Table.2, 3 and 4 depicts the values of precision, recall and accuracy for 60:40, 70:30 and 80:20 training and testing database ratios. The tables show comparison of different distance metrics. Out of all different metrics, relative deviation provides better results.

Table.2. Comparison of precision values for different training and testing database ratios.

Distance metrics	Precision		
	60 : 40	70 : 30	80 : 20
Manhattan	8.82	8.93	9.01
Euclidean	8.89	8.94	9.17
Std. Euclidean	8.84	9.06	9.01
Mahalanobis	9.04	9	9.17
Cityblock	8.89	8.87	9.11
Minkowski	8.77	9.09	8.91
Chebyshev	8.9	9.02	9.1
Cosine	8.93	9.08	9.01
Correlation	8.81	8.98	9.05
Spearman	8.86	9.06	9.02
Normalized Euclidean	8.95	8.98	9.11
Relative Deviation	8.77	9.09	9

Table.3. Comparison of recall values for different training and testing database ratios.

Distance metrics	Recall		
	60 : 40	70 : 30	80 : 20
Manhattan	9	8.91	9.16
Euclidean	8.93	9.07	9.16
Std. Euclidean	9.24	9.3	9.15
Mahalanobis	9.11	9.06	9.16
Cityblock	8.93	8.94	9.03
Minkowski	9.11	9.12	9.48
Chebyshev	8.94	9.05	9.01
Cosine	9.02	8.9	9.33
Correlation	8.77	9.07	8.87
Spearman	8.94	9.3	9.16
Normalized Euclidean	9.24	9.02	9.03
Relative Deviation	9.11	9.12	9.48



Fig.9 GUI implementation for relative deviation distance metric

Distance metrics	Accuracy (%)		
	60 : 40	70 : 30	80 : 20
Manhattan	79.40	79.09	83.00
Euclidean	79.75	81.33	83.50
Std. Euclidean	81.80	83.00	83.67
Mahalanobis	82.28	81.67	83.50
Cityblock	79.25	79.00	82.50
Minkowski	80.00	82.33	83.00
Chebyshev	79.75	81.33	82.50
Cosine	80.00	81.00	83.50
Correlation	77.25	80.67	81.00
Spearman	79.00	83.00	83.67
Normalized Euclidean	81.50	80.67	82.50
Relative Deviation	80.00	82.33	83.00

Table.4. Comparison of accuracy values for different training and testing database ratios.

CONCLUSION

The prime purpose of the proposed system is to detect concept of an image. This work shows the implementation of two concept detection techniques. SVM and distance metrics are used to detect the concept. The performance is evaluated using precision, recall and accuracy. The methodology establishes an efficient feature extraction technique to extract various colors and texture attributes. All these features are merged to generate a feature vector which aids for classification of images.

In the first technique which uses SVM for classification provides better results as compared to the second method i.e using distance metrics. By evaluating the values of precision, recall and accuracy it is observed that out of all the distance metric techniques used, relative deviation provides better results. For 80:20 training and testing database ratio, accuracy achieved is 83 percent for relative deviation. Whereas for the same ratio of training and testing database using SVM technique the accuracy achieved is 86 percent.

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