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# A NOVEL CONTENT BASED IMAGE RETRIEVAL MODEL BASED ON THE MOST RELEVANT FEATURES USING PARTICLE SWARM OPTIMIZATION

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***Abstract:*** Content Based Image Retrieval (CBIR) is the application of computer vision techniques to the image retrieval problem, that is, the problem of searching for digital images in large databases. Content-based image retrieval (CBIR) depends on extracting the most relevant features according to a feature selection technique. The integration of multiple features may cause the curse of dimensionality and the consumed time in the retrieval process. The proposed model includes the following steps: (i) Feature Extraction from images database using color coherence vector (CCV) and Gabor filter algorithm to extract the color and texture features (ii) Feature Discrimination using maximum entropy method for replacing numerical features with nominal features that represent intervals of numerical domains with discrete values using Class Attribute Interdependence Maximization (CAIM) algorithm (iii) Feature Selection using Particle Swarm Optimization (PSO) algorithm for extracting the most relevant features from the original features set. CBIR based applications are used in Internet and law enforcement markets for the purpose of identifying and censoring the images.

***Keywords:*** Content-based image retrieval, Feature Discrimination, Feature Selection, Ant Colony Optimization (ACO) algorithm

## INTRODUCTION

Content Based Image Retrieval (CBIR) is the application of computer vision techniques to the image retrieval problem, that is, the problem of searching for digital images in large databases. CBIR systems retrieve relevant images in a database using visual content of the images. Researchers are mainly developed based on the high-level semantic analysis of the image content along with the visual content of the image such as colors, textures, and shapes. Color features include the color histogram, the color coherence vector, the color co-occurrence matrix, vector quantization, and color moments. Texture features are derived from the gray-level co-occurrence matrix, the Tamura feature, and wavelet coefficients, and Gabor filter-based features. Once image features are extracted, another problem arouse that is which features are relevant in the retrieval process. Having more features implies more discriminative power in classification. In addition, high dimensionality of data may cause the ‘‘curse of dimensionality” problem.

Feature reduction refers to the study of methods for reducing the number of dimensions describing data. Its general purpose is to employ fewer features to represent data and reduce computational cost, without deteriorating discriminative capability. Since feature reduction can bring lots of advantages, such as avoiding over fitting, resisting noise and strengthening prediction performance. Feature transform constructs new features by projecting the original feature space to a lower dimensional one. Principal component analysis and independent component analysis are two widely used feature transform methods. Although feature transform can obtain the least dimension, its major drawbacks are that its computational over-head are high and the output is hard to be interpreted for users.

Feature selection is the process of choosing a subset of the original feature spaces according to discrimination capability to improve the quality of data. The present paper proposes a suggested image retrieval model based on extracting the most relevant features from the whole features according to a feature selection technique. The extracted features are color and texture features using the invariant features, color coherence vector and Gabor wavelets.

The color coherence vector (CCV) is an indication of how similar colors are oriented in the image. A color coherence vector (CCV) stores the number of coherent versus incoherent pixels with each color [2]. Regions which have a collection of similar color pixels are termed as coherent regions. The CCV computes the present number of coherent and incoherent pixels. Vastly different images can have the same color histograms. The CCV will differentiate the images on the basis of how many regions are present that have a sizeable contiguous color patches. In order to compute the CCV, we specified the number of bins in which the colors can be classified. Then, for each pixel the neighboring pixels are compared and the region of coherence is marked. If the size of this region is above a threshold, then the region is marked coherent, else it is marked non-coherent. Thus, by dividing the entire blocks of color into either coherent or incoherent, we get information regarding the scattering of color information.

The Gabor wavelet is widely adopted to extract texture features from the images for the image retrieval process. Basically, Gabor filters are a group of wavelets, with each wavelet capturing energy at a specific frequency and a specific orientation. The scale and orientation tunable property of Gabor filter makes it useful especially for texture analysis [3]. Gabor filters are a group of wavelets capturing energy at a specific frequency and a specific direction. The expansion of a signal using this basis provides a localized frequency description, therefore, capturing local features/energy of the signal.

## RELATED WORKS

A color coherence vector (CCV) stores the number of coherent versus incoherent pixels with each color. By separating coherent pixels from incoherent pixels, CCV's provide finer distinctions than color histograms [2].Color histograms also have some limitations.

Color coherence as the degree to which pixels of that color are members of large similarly-colored regions. We refer to these significant regions as coherent regions, and observe that they are of significant importance in characterizing images. Color coherence measure classifies pixels as either coherent or incoherent. Coherent pixels are a part of some sizable contiguous region, while incoherent pixels are not. A color coherence vector represents this classification for each color in the image.

In computing, a CCV is similar to the computation of a color histogram. We first blur the image slightly by replacing pixel values with the average value in a small local neighborhood (currently including the 8 adjacent pixels). This eliminates small variations between neighboring pixels. Then the color space is discretized, such that there are only n distinct colors [2] in the image.

Gabor wavelet is widely adopted to extract texture features from the images for retrieval and has been shown to be very efficient. Gabor filters are a group of wavelets, with each wavelet capturing energy at a specific frequency and specific orientation. The scale and orientation tunable property of Gabor filter makes its especially useful for texture analysis. The use of Gabor filters in extracting textured image features is motivated by various factors. The Gabor representation has been shown to be optimal in the sense of minimizing the joint two-dimensional uncertainty in space and frequency. These filters can be considered as orientation and scale tunable edge and line (bar) detectors, and the statistics of these micro-features in a given region are often used to characterize the underlying texture information. Gabor features have been used in several image analysis applications including texture classification and segmentation, image recognition, image registration, and motion tracking.

Support Vector Machines is built on the structural risk minimization principle to seek a decision surface that can separate the data points into two classes with a maximal margin between them. This allows for formulating the classifier training as a constrained optimization problem.

The Genetic Algorithms (GA) is efficient methods for function minimization. In descriptor selection context, the prediction error of the model built upon a set of features is optimized. The genetic algorithm mimics the natural evolution by modeling a dynamic population of solutions. The members of the population, referred to as chromosomes, encode the selected features. The encoding usually takes form of bit strings with bits corresponding to selected features set and others cleared. Each chromosome leads to a model built using the encoded features. The parameters steering the crossover, mutation and survival of chromosomes should be carefully chosen to allow the population to explore the solution space and to prevent early convergence to homogeneous population occupying a local minimum. The choice of initial population is also important in genetic feature selection. In this paper, proposed system uses Maximum Entropy method for feature discrimination and Ant Colony Optimization (ACO), which is used to find the optimal solution for feature selection process.

## PROPOSED SYSTEM

In this paper, a suggested image retrieval model is proposed based on extracting the most relevant features from the whole features according to a feature selection technique. The extracted features are color and texture features using the invariant features, color coherence vector and Gabor wavelets. These features are discriminated by using CAIM method for replacing the numerical features with nominal features that represent intervals of numerical domains with discrete values. These features pass to a feature selection technique for extracting the most relevant features and dropping the irrelevant ones using PSO algorithm. The relevant features can not only achieve maximum recognition rate but can also simplify the calculation and reduce the consumed time in the retrieval process. The overall process of the system is shown in Fig.1.

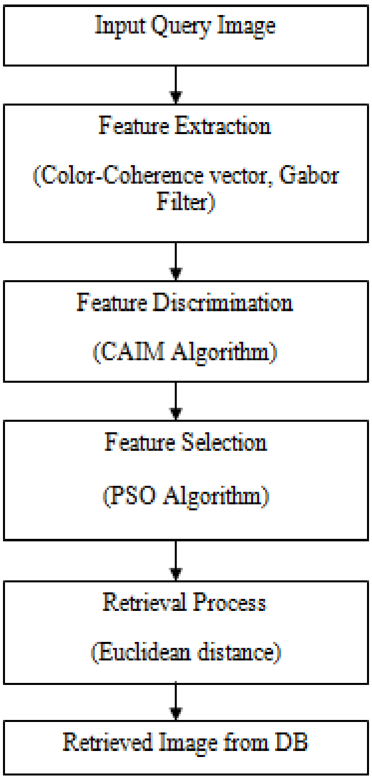


Figure.1 Overall Process of the System

### *Feature Extraction*

#### *Color Extraction:*

The features which are extracted in this paper are color and texture representation. The color coherence vector (CCV) is an indication of how similar colors are oriented in the image. Regions which have a collection of similar color pixels are termed as coherent regions. The CCV computes the present number of coherent and incoherent pixels. Vastly different images can have the same color histograms. The CCV will differentiate the images on the basis of how many regions are present that have a sizeable contiguous color patches. Thus, by dividing the entire blocks of color into either coherent or incoherent, we get information regarding the scattering of color information. The algorithm of color coherence vector (ccv) is given as,

*INPUT:* Color image
*OUTPUT:* The values of coherent and incoherent pixels are displayed using color coherence vector
*STEPS:*

a. Color image is given as input
b. The image is divided into eight regions
c. Regions having a collection of similar color pixels are coherent regions
d. The neighboring pixels are compared and the region of coherence is marked
e. If the size of this region is above a threshold, then the region is marked coherent, else it is marked non-coherent.

***Texture Extraction:***

Gabor wavelet is used to extract texture features from the images for retrieval and has been shown to be very efficient. Gabor filters are a group of wavelets, with each wavelet capturing energy at a specific frequency and specific orientation. The scale and orientation tunable property of Gabor filter makes its especially useful for texture analysis.

*INPUT:* Color image
*OUTPUT:* Texture image
*STEPS:*

a. Color image is given as input
b. Color image is converted into grey scale image
*c.* Then the image is extracted into texture representation using gabor filter function,

*K = exp (2*pi*theta*sqrt(-1)*(xprime+ yprime));*
*G (round ((i+1)*filterSize), round ((j+1)*filterSize)) = exp ((i^2+j^2)/ (sigma^2))*K;*

***Feature Discrimination:***

The discrimination process is an essential step for the proposed feature selection technique. Once image features are extracted, the feature discrimination technique [4] must be performed to transform continuous values into discrete ones in accordance with certain thresholds. The discrimination process converts continuous features into discrete ones by yielding intervals in which the feature value can reside instead of singleton values, and by associating a discrete numerical value with each interval. Class Attribute Interdependence Maximization (CAIM) algorithm is used for discrimination process. The goal of the CAIM algorithm is to maximize the class-attribute interdependence and to generate a (possibly) minimal number of discrete intervals.

***Feature Selection:***

Feature selection is the process of choosing a subset of the original feature spaces according to discrimination capability to improve the quality of data. This paper proposes a suggested image retrieval model based on extracting the most relevant features from the whole features according to a feature selection technique [6]. The goal of feature selection technique is to select the best features from the original ones. It can not only achieve maximum recognition rate but can also simplify the calculation of the image retrieval process. The goal of feature selection technique is to select the best features from the original ones. Particle Swarm Optimization (PSO) is used for feature selection technique. PSO is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. The result of PSO is shown in Fig.4.

***Retrieval Process:***

The features' vectors are saved in the database with a pointer to the model image to which they are belonging. In the retrieval process, a query image is presented to the system and the features of the image are extracted. Each individual feature vector from the query image is compared using the Euclidean distance measure [8] with all the other features' vectors stored in the database of the model images.

## RESULTS AND DISCUSSIONS

The first images database was downloaded from www.google.com. This images database consists of 1000 images. These images are grouped into 10 clusters, each cluster contains 100 images. The feature extraction technique was applied on the proposed images database for extracting the color and texture features. A color coherence vector (CCV) stores the number of coherent versus incoherent pixels with each color. Coherent pixels are a part of some sizable contiguous region, while incoherent pixels are not. A color coherence vector represents this classification for each color in the image. CCV's prevent coherent pixels in one image from matching incoherent pixels in another. Color image is given as input.The color image is divided into regions and then the coherent and incoherent pixels are differentiated using color coherence vector. For each pixel the neighboring pixels are compared and the region of coherence is marked. Threshold value is set, if the size is above threshold value then the region is marked as coherent else it is marked as incoherent, which is shown in Fig.2.

Gabor wavelet is widely adopted to extract texture features from the images for retrieval and has been shown to be very efficient. Gabor filters are a group of wavelets, with each wavelet capturing energy at a specific frequency and specific orientation. The use of Gabor filters in extracting textured image features is motivated by various factors. The Gabor representation has been shown to be optimal in the sense of minimizing the joint two-dimensional uncertainty in space and frequency. Color image is given as input. Color image is converted into grey scale image. Then the image is extracted into texture representation using gabor filter function. The values of the texture image are displayed using gabor wavelet function, which is shown in Fig.3. The method used in discrimination technique is Class-Attribute Interdependence Maximization (CAIM). The goal of the CAIM algorithm is to maximize the class-attribute interdependence and to generate a (possibly) minimal number of discrete intervals. The results of discrimination technique are shown in Fig.4. The features discriminated are given as input for feature selection technique.

 

Feature Selection technique is done by using Particle Swarm Optimization (PSO). PSO is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. The selected features are displayed as output using Particle Swarm Optimization (PSO) algorithm.

The feature vectors are saved in the database with a pointer to the model image to which they are belonging. In the retrieval process, a query image is presented to the system and the features of the image are extracted as described above. Each individual feature vector from the query image is compared using the Euclidean distance measure with all the other features' vectors stored in the database of the model images. When improved positions are being discovered these will then come to guide the movements of the swarm. The process is repeated and by doing so it is hoped, but not guaranteed, that a satisfactory solution will eventually be discovered. The images are retrieved from database which is relevant to the given input image shown in Fig.6.

```
 from the active settings drop-down list. For more information, see Help.

 Click here if you do not want to see this message again.


Color =

   255     0     0
     0   255     0
     0     0   255
   255   255     0
   255     0   255
     0   255   255
   255   255   255
     0     0     0


ans =

  Columns 1 through 7

           0           0           0           0           0        2636           0

  Columns 8 through 14

           0           0           0           0        2377       21135        9065

  Columns 15 through 16
```

Figure.2. Coherent and Incoherent pixels using CCV

```
Command Window
   0.2005 + 0.0364i   0.2391 - 0.1269i   0.1348 - 0.2432i  -0.0066 - 0.2297i
   0.1959 + 0.0084i   0.2100 - 0.1555i   0.0922 - 0.2521i  -0.0374 - 0.2188i
   0.1856 - 0.0136i   0.1846 - 0.1769i   0.0582 - 0.2603i  -0.0623 - 0.2101i
   0.1698 - 0.0403i   0.1557 - 0.1961i   0.0278 - 0.2654i  -0.0844 - 0.2002i
   0.1717 - 0.0706i   0.1370 - 0.2293i  -0.0047 - 0.2839i  -0.1135 - 0.1986i
   0.1791 - 0.1011i   0.1252 - 0.2636i  -0.0306 - 0.3054i  -0.1397 - 0.2016i
   0.1888 - 0.1239i   0.1227 - 0.2906i  -0.0435 - 0.3255i  -0.1570 - 0.2090i
   0.2085 - 0.1378i   0.1314 - 0.3152i  -0.0494 - 0.3478i  -0.1704 - 0.2209i
   0.2342 - 0.1445i   0.1489 - 0.3361i  -0.0468 - 0.3701i  -0.1780 - 0.2365i
   0.2549 - 0.1400i   0.1712 - 0.3445i  -0.0336 - 0.3867i  -0.1762 - 0.2526i
   0.2676 - 0.1235i   0.1937 - 0.3392i  -0.0144 - 0.3954i  -0.1671 - 0.2661i
   0.2715 - 0.1099i   0.2070 - 0.3294i   0.0005 - 0.3948i  -0.1566 - 0.2716i
   0.2723 - 0.1042i   0.2112 - 0.3225i   0.0072 - 0.3902i  -0.1501 - 0.2711i
   0.2699 - 0.0984i   0.2131 - 0.3157i   0.0120 - 0.3866i  -0.1454 - 0.2705i
   0.2603 - 0.0866i   0.2159 - 0.3033i   0.0214 - 0.3841i  -0.1380 - 0.2725i
   0.2489 - 0.0847i   0.2116 - 0.2963i   0.0243 - 0.3813i  -0.1349 - 0.2717i
   0.2406 - 0.0870i   0.2073 - 0.2946i   0.0254 - 0.3818i  -0.1343 - 0.2726i
   0.2363 - 0.0930i   0.2034 - 0.2975i   0.0250 - 0.3841i  -0.1355 - 0.2740i
   0.2338 - 0.1002i   0.2003 - 0.3010i   0.0255 - 0.3854i  -0.1356 - 0.2750i
   0.2362 - 0.1078i   0.2006 - 0.3061i   0.0277 - 0.3874i  -0.1350 - 0.2773i
   0.2444 - 0.1113i   0.2066 - 0.3101i   0.0331 - 0.3888i  -0.1318 - 0.2804i
   0.2538 - 0.1129i   0.2139 - 0.3110i   0.0400 - 0.3868i  -0.1263 - 0.2818i
   0.2629 - 0.1130i   0.2207 - 0.3097i   0.0468 - 0.3819i  -0.1196 - 0.2811i
   0.2873 - 0.1038i   0.2444 - 0.3084i   0.0639 - 0.3833i  -0.1084 - 0.2866i
   0.3113 - 0.0862i   0.2686 - 0.3019i   0.0799 - 0.3812i  -0.0975 - 0.2894i
   0.3236 - 0.0627i   0.2857 - 0.2865i   0.0928 - 0.3721i  -0.0867 - 0.2870i
   0.3154 - 0.0374i   0.2893 - 0.2605i   0.1019 - 0.3545i  -0.0755 - 0.2783i
   0.3012 - 0.0186i   0.2846 - 0.2375i   0.1035 - 0.3385i  -0.0699 - 0.2680i
   0.2840 - 0.0076i   0.2746 - 0.2192i   0.1017 - 0.3244i  -0.0671 - 0.2583i
```

Figure.3. Output of texture image

 

```
Command Window
     2     3     5     5     1     4     7     5     4     6     6     7     4     4
     4     4     7     5     1     5     4     4     6     4     4     2     3     3
     5     1     5     8     1     5     7     7     1     5     6     5     4     3
     7     1     1     8     1     5     8     7     1     4     4     4     4     4
     4     1     5     5     1     5     8     7     1     3     4     4     3     5
     5     1     5     6     1     2     8     8     1     5     6     5     4     4
     4     1     1     6     1     1     8     2     6     5     6     4     2     2
     4     1     1     6     1     1     8     4     3     6     6     5     4     4
     4     3     1     6     1     3     8     4     4     5     6     6     4     4
     4     4     1     6     1     3     4     7     4     5     6     5     4     4
     4     1     7     5     1     3     7     4     6     5     6     5     3     3
     5     3     1     8     1     1     7     2     1     6     6     6     8     5
     2     1     5     5     1     3     8     1     1     6     5     8     8     8
     1     1     7     4     2     4     7     4     1     5     6     4     4     4
     4     1     2     6     1     4     7     7     1     4     4     8     8     4
     4     1     1     5     1     1     8     1     6     6     4     6     4     4
     7     3     1     8     1     3     8     2     4     5     6     5     3     3
     4     1     8     6     2     5     3     5     4     5     6     5     3     4
     7     1     5     8     1     4     8     8     4     4     4     5     4     3
     4     1     7     5     1     5     4     2     4     4     4     5     4     5
     2     3     1     6     1     3     8     2     6     5     2     5     4     4
     7     1     5     6     1     4     8     8     1     5     4     4     4     4
     4     3     1     5     1     3     2     2     5     6     6     6     8     4
     2     1     8     5     2     5     8     4     1     4     4     6     4     4
     4     1     2     5     1     3     5     4     4     6     6     5     4     5
     6     1     1     6     1     1     4     7     6     5     5     5     3     3
     5     1     5     6     1     1     4     4     1     5     6     8     4     5
     4     1     5     6     1     4     7     4     1     6     6     8     8     4
```

Figure.4. Output of discriminated values

```
     4     3     6     2
     2     2     5     5
     3     3     5     4
     1     2     3     5
     4     3     5     4
     4     2     5     4
     4     3     6     4
     4     3     6     4
     2     2     4     5
     4     2     4     5
     1     2     5     6
     4     3     6     3
     2     2     4     7
     3     2     5     5
     3     2     4     7
     4     2     5     2
     2     2     4     4

Current plot held
>> [Selected]=pso_feature(5,fea(:,1:17)',fea(:,18)')
Current plot held

Selected =

     5
     6
    10
     1
    12

fx >>
```

Figure.5. Output of the selected features

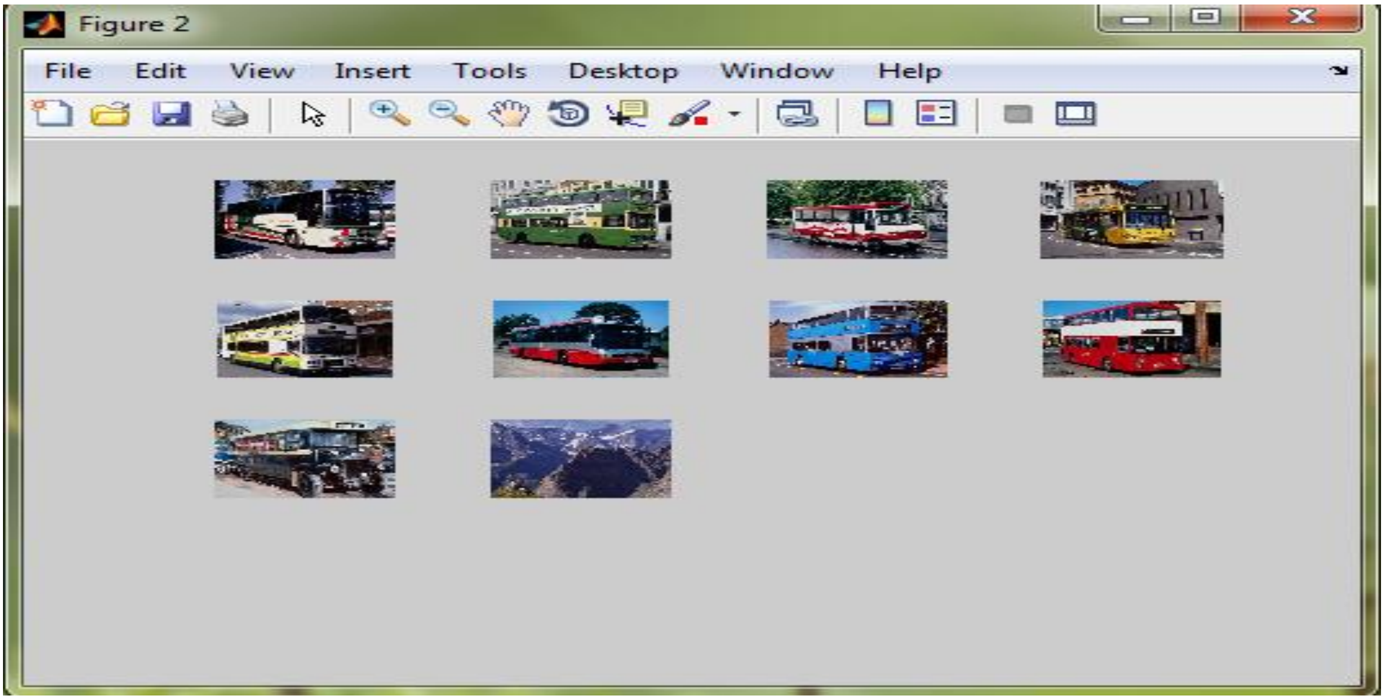


Figure.6. Output of the retrieval system

## CONCLUSION

In this paper, the color coherence vector and Gabor wavelets are used to extract color and texture feature using feature extraction technique. In discrimination process, exogenous method is used and to obtain the optimal boundaries, Genetic algorithm is used for feature selection. Therefore, we introduced a proposed feature discrimination technique using Maximum entropy method for transforming the extracted continuous features to the nominal features. The effectiveness of the proposed approach has been also analyzed by optimizing it with the Particle Swarm Optimization (PSO) algorithm. The proposed model reduces the search space for the most relevant features set and reduces the consume time in the retrieval process.

The performance improvement of the proposed method has been successfully demonstrated the effectiveness and efficiency of the proposed model when it is compared with other models using precision and recall. Further this can be improved by using unsupervised algorithms such as equal-width interval, equal-frequency interval, k-mean clustering and also by some other optimization methods.

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