Content Based Image Retrieval using Support Vector Machine based on ACOGA

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Abstract - The conventional CBIR is not perfectly suitable for retrieving the images from the large image dataset. The basic problem is generated from conventional CBIR method are: First, whenever users perform the image search on Google, since unnatural and unsupported data is retrieve from www. Second, it is very time consuming, due to this reason perfect result is not obtained in given time duration. Basically Content-based image retrieval is use for retrieving the similar images from image dataset on basis of sample query image. To overcome the above problem, the propose scheme improving the performance of image classification and retrieval accuracy of images. The SURF method is used to find the image frame descriptors. These descriptors is reflects texture feature of various images. Optimize the descriptor in the ROI (Region of interest) of Images using ACO (Ant Colony Optimization) and GA (Genetic Algorithm) Technique. Optimize image descriptors are classified in different classes of image dataset using Support vector machine. SVM is use for image retrieval for maintain accuracy. This supervised learning approach use the concept of image optimizer for improves the performance of retrieved images. The performance of proposed method SVM-ACOGA (Support Vector Machine – Ant Colony Optimization with Genetic Algorithm) method is improved instead of comparable CBIR method.

Keywords: Content Based Image Retrieval, World Wide Web, Ant Colony Optimization with Genetic Algorithm.

1. INTRODUCTION

Content-based image retrieval (CBIR) is used to find application in various areas of a geographic information system (GIS), video surveillance and medicine. All these applications reduce user involvement with high degree of accuracy . CBIR engine's myriad has been proposed in the literature**.** Though several of the methods perform considerably well**,** the semantic gap remains to be bridged. Most of the common methods include region-based techniques which are theoretically exhaustive and the success of the methods depends on the segmentation techniques used**.** various relevance-based techniques have also been planned but the retrieved results may depend on individual observation of relevance**.** This spawns the need for a simple and proficient retrieval system with no user participation**.** There are many methods being used for the retrieval of images based on visual features such as color, texture and shape. Learn about the semantic content of the image. Complicated, time- consuming image processing technique is used by these successful method**..** For example, if we want to study the split regions of the image, then acceptable color or texture segmentation algorithms should be used to separate the all the same regions for advance analysis to classify them based on the facial appearance Yet after such complicated semantic analysis, the improvements in the results were not so considerable additionally, simple image-matching policies frequently lead to poor exactness in image retrieval**.** So, with model-based classification technique of a CBIR system may guide to improved results**.**

2. SYSTEM MODEL

Here, a simple CBIR system is modeled which will use facial appearance that can be acquired from the image in a quick mode. An attempt is made to prove that the correctness of a simple CBIR system can be made competitively equal to that of a complicated CBIR system**,** if the simple and more considerable features of the image are chosen for coding in the image feature dataset. To develop the image retrieval accuracy**,** a support vector machine (SVM) and ant colony optimization with genetic algorithm (ACOGA) based retrieval model is used. Four phases is used for development process of this project **–** image feature extraction, training the SVM network, Optimize feature point through ACOGA and similar the query image with database images using the formerly trained network**.** Wavelet histograms (WH) are used For the first phase. SVM neural network is used for the second phase, and for the retrieval part, the formerly trained network as well as simple distance evaluate is used. By fuzzy set theoretic approach, The clusters of points around considerable curvature regions are extracted**.** To evaluate the connection between images, a few invariant color features are computed from these points. A set of related and non-redundant features is chosen using the common information-based minimum redundancy–maximum relevance framework. By using fuzzy entropy-based measure, The relative importance of each feature is evaluated The combination of the local color, texture and to provide a strong feature set for image retrieval, the universal shape features have been used .The set of regions, represent image roughly equivalent to objects characterized by color, texture, shape and location. Images are classifies into semantic categories by the system for enhancing the retrieval. The system is accurately strong to image alterations.

3. PREVIOUS WORK

An image retrieval scheme which makes use of visually considerable point features has been presented before By a fuzzy set theoretic approach, clusters of points around considerable curvature regions are extracted. Some invariant color features are computed from these points to estimate the comparison between images. A set of relevant and non-redundant features is preferred using the common information-based minimum redundancy–maximum relevance framework. In fact, SVMs are not only a good classification technique but also a good feature selection method. The problem of feature selection is well known in machine learning. Data over fitting arises when the number of features is large and the number of training samples is comparatively small. This case is very common especially in image classification. The prospective of the SVM is illustrated on a 3D object identification task using the Coil database and on a image classification task using the Corel database. The images are represented by two method either matrix of their pixel values (bitmap representation) or by a color histogram. In both, method the planned system does not involve feature removal and performs acknowledgment on images regarded as points of a space of high measurement. We also point an addition of the basic color histogram which keeps added about the information restricted in the images.

To solve combinatorial optimization problem by using Ant Colony and Genetic programming algorithms. Hybrid algorithm is planned. Evolutionary procedure of Ant Colony Optimization algorithm adapts genetic operations to get better ant movement towards solution state. The algorithm coverage to the best possible final solution, by accumulating the most efficient sub-solutions.

4. PROPOSED METHODOLOGY

The proposed method is SVM-ACOGA (Support Vector Machine – Ant Colony Optimization with Genetic Approach). To classify and retrieve the image descriptor, SVM technique which is the supervised machine learning approach is used ACOGA (Ant Colony Optimization with Genetic Approach) used for optimize the descriptor, from which descriptor difficulty is reduced. This method increases the exactness of Precision – Recall curve. Hence, we are explain the planned CBIR (Content Based Image Retrieval) based on ACOGA (Ant Colony Optimization with Genetic Approach) method. The potential of the SVM-ACOGA is illustrate on a 3D object acknowledgment task using the Coil database and on an image classification and recovery task using the Corel database. The images are represents by a matrix of their pixel ethics (bitmap representation) or using a color histogram. In both cases, the planned system requires feature removal and performs appreciation on images regarded as points of a space of high measurement. We also use an addition of the basic color histogram which keeps further about the information enclosed in the images. The algorithm of proposed method is explained in two phase, which is as below:

Phase I (Algorithm of SVM):

Step 1: candidateSV = {nearest pair from different labels}

Step 2: while there are violating nodes do

Step 3: Find a node-violator Candidate_SV = candidate_SV S violator

Step 4: if any αp < 0, addition of c to S then candidate_SV = candidate_SV \ p

Step 5: continue till all nodes are pruned

Step 6: end if

Step 7: end while

Phase II (Algorithm of ACOGA):

ACOGA have two main sections: initialization and a main loop, In the second sections Gp is used. For user distinct number of iterations. The main loop runs. These are described below:

Step 1: Initialization:

a. Set primary parameters that are system: variable, states, function, input, output, input trajectory, output trajectory.
b. Set primary pheromone trail value. c. every ant is separately placed on primary state with vacant memory.

Step 2: While termination conditions not meet do

a. Put up Ant Solution: Each ant constructs a path by consecutively applying the evolution function the prospect of moving from state to state depend on: as the attractiveness of the shift, and the trail level of the shift. b. Apply Local Search

c. Best Tour check: If there is an upgrading, update it.

d. Update Trails: - dissolve a fixed quantity of the pheromone on each road. - For every ant execute the "ant-cycle" pheromone update. - emphasize the best tour with a set number of "elitist ants" performing the "ant-cycle".

e. produce a new population by apply the following operation, based on pheromone trails. The operations are applied to persons selected from the population with a prospect based on strength

• Darwinian simulated

• Structure-Preserving Crossover

• Structure-Preserving Mutation

End While

5. SIMULATION/EXPERIMENTAL RESULTS

We can retrieve more images through the planned technique SVM-ACOGA. The input query image with dissimilar sizes, each image is resize into normal size and practically to SIFT method then build up descriptor in row vector. In a parallel way image dataset (approx 20000) descriptors is pile up in mat file and apply ACOGA. Now, achieve the best point of descriptor, these descriptor point are use for similar with query descriptors and regain best images. The kernel function is implements with guide the data with SVM. generally we apply Radial Basis Function (RBF) and Polynomial kernel. Here, we talk about these kernels in following type. We achieve the following results:

In this case, we apply distance metric as 1 for implementing Manhattan distance metric and 2 for implementing Euclidean distance metric. This distance metrics affect the SVM classifier. The Kernel function is used in two way, we use Radial Basis Function (RBF) and Polynomial Kernel with special kernel parameters. In image classification, Recall is expressed as the random number of associated documents fetched by a initial find process categorized by the random number of already consisting relevant files, whereas precision value is expressed as the random number of associated files and documents fetched by a search divided by the complete number of files and documents fetched by that find process. In image retrieval domain, the precision value for a label is the total number of true positives categorized by the complete number of elements marked as involving to the positive label. Basically, recall in this desired context is defined as the total number of true positives value divided by the total number of data points that actually involve to the positive label. We consider that Manhattan Distance Metric (MDM), now analysis is performs on basis of PR-curve and Confusion Matrix with two different kernel mode such as Radial Basis Function (RBF) and Polynomial.

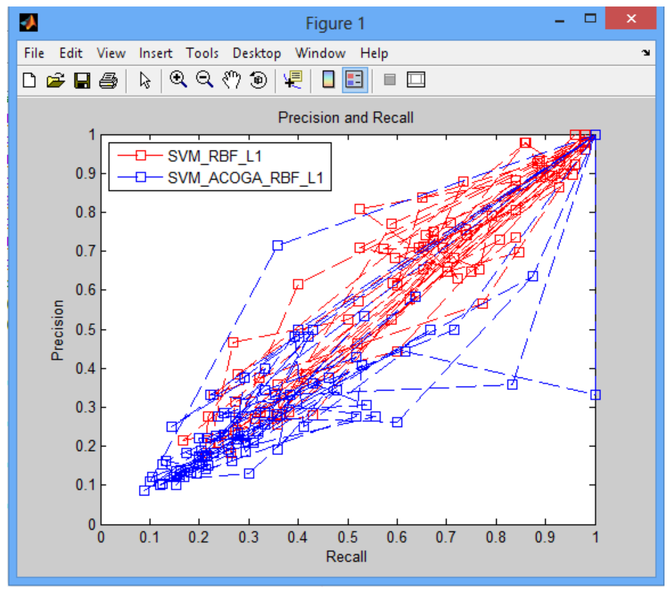

Figure 1: PR Curve for SVM and SVM-ACOGA (RBF Kernel)

In case of MDM (Manhatten Distance Metric), The Precision and Recall of SVM is relatively high than SVM-ACOGA. So SVM method retrieves additional images as evaluate than SVM-ACOGA. Images which are retrieving from SVM are less significant with query image as evaluate than SVM-ACOGA because SVM-ACOGA has less inconsistency retrieve images.

An uncertainty matrix, is a 2D array with 2 rows and 2 columns that remove the random number of false positives value, false negatives value, true positives value, and true negatives value. This allows more comprehensive determination than simply percentage of accurate accuracy. salvage accuracy is not a consistent measurement for the real competence of a classifier, because it will co-factor support results if the dataset node is not expected. In uncertainty matrix, the row which labeled as 0,1,…,9 are considered as real class and the column which labeled as 0,1,…,9 are measured as predicted class. The uncertainty matrix shows number of similar images in every class as per query image. In next figure shows the dissimilar uncertainty matrix, these matrix is characterize in eight ways because number of distance metric is 1 (MDM), number of kernel tricks is 2 (RBF and Polynomial) and number of CBIR is 2 (SVM and SVM-ACOGA).

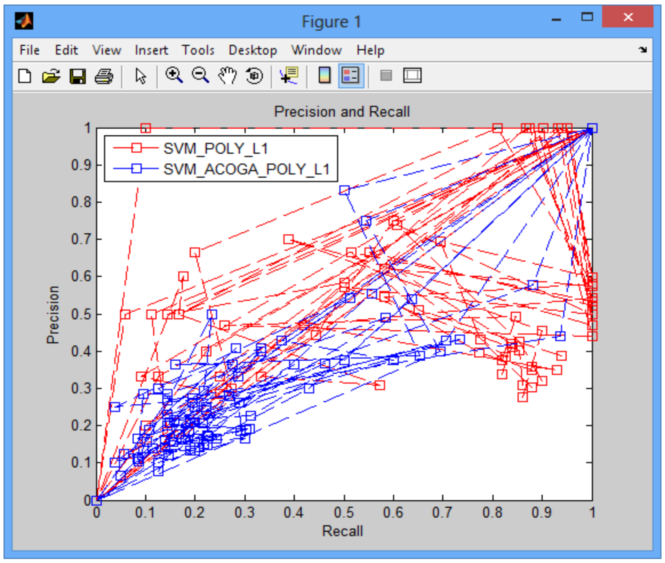

Figure 2: PR Curve for SVM and SVM-ACOGA (POLY Kernel)

	0	1	2	3	4	5	6	7	8	9
0	0	0	0	0	0	0	0	0	0	0
1	0	87.23% (41)	0	0	0	0	6.38% (3)	0	4.26% (2)	2.13% (1)
2	0	6.12% (3)	65.31% (32)	4.08% (2)	6.12% (3)	0	4.08% (2)	8.16% (4)	2.04% (1)	4.08% (2)
3	0	10.87% (5)	6.52% (3)	50.00% (23)	8.70% (4)	0	8.70% (4)	6.52% (3)	6.52% (3)	2.17% (1)
4	0	4.00% (2)	0	2.00% (1)	82.00% (41)	0	4.00% (2)	0	6.00% (3)	2.00% (1)
5	0	0	0	0	0	96.00% (48)	4.00% (2)	0	0	0
6	0	0	10.00% (4)	7.50% (3)	0	0	15.00% (6)	17.50% (7)	27.50% (11)	22.50% (9)
7	0	4.88% (2)	12.20% (5)	9.76% (4)	2.44% (1)	2.44% (1)	9.76% (4)	24.39% (10)	19.51% (8)	14.63% (6)
8	0	0	9.52% (4)	9.52% (4)	4.76% (2)	0	26.19% (11)	11.90% (5)	19.05% (8)	19.05% (8)
9	0	4.76% (2)	2.38% (1)	4.76% (2)	7.14% (3)	0	14.29% (6)	30.95% (13)	21.43% (9)	14.29% (6)

Figure 3: Confusion Matrix for SVM (RBF Kernel, MDM)

	0	1	2	3	4	5	6	7	8	9
0	0	0	0	0	0	0	0	0	0	0
1	0	22.22% (10)	13.33% (6)	17.78% (8)	4.44% (2)	8.89% (4)	13.33% (6)	11.11% (5)	4.44% (2)	4.44% (2)
2	0	9.09% (4)	11.36% (5)	18.18% (8)	11.36% (5)	4.55% (2)	15.91% (7)	13.64% (6)	11.36% (5)	4.55% (2)
3	0	4.08% (2)	14.29% (7)	18.37% (9)	8.16% (4)	6.12% (3)	18.37% (9)	20.41% (10)	6.12% (3)	4.08% (2)
4	0	11.90% (5)	7.14% (3)	7.14% (3)	16.67% (7)	9.52% (4)	11.90% (5)	4.76% (2)	9.52% (4)	21.43% (9)
5	0	6.38% (3)	12.77% (6)	12.77% (6)	10.64% (5)	25.53% (12)	8.51% (4)	8.51% (4)	6.38% (3)	8.51% (4)
6	0	12.50% (5)	10.00% (4)	10.00% (4)	12.50% (5)	15.00% (6)	15.00% (6)	12.50% (5)	10.00% (4)	2.50% (1)
7	0	8.51% (4)	6.38% (3)	14.89% (7)	17.02% (8)	10.64% (5)	10.64% (5)	10.64% (5)	12.77% (6)	8.51% (4)
8	0	8.89% (4)	15.56% (7)	13.33% (6)	24.44% (11)	4.44% (2)	11.11% (5)	8.89% (4)	6.67% (3)	6.67% (3)
9	0	17.50% (7)	5.00% (2)	12.50% (5)	5.00% (2)	17.50% (7)	15.00% (6)	10.00% (4)	10.00% (4)	7.50% (3)

Figure 4: Confusion Matrix for SVM-ACOGA (RBF, MDM)

	0	1	2	3	4	5	6	7	8	9
0	0	0	0	0	0	0	0	0	0	0
1	0	90.00% (45)	4.00% (2)	2.00% (1)	4.00% (2)	0	0	0	0	0
2	0	10.00% (5)	82.00% (41)	2.00% (1)	6.00% (3)	0	0	0	0	0
3	0	34.69% (17)	22.45% (11)	10.20% (5)	28.57% (14)	0	0	2.04% (1)	0	2.04% (1)
4	0	6.00% (3)	2.00% (1)	0	92.00% (46)	0	0	0	0	0
5	0	0	20.00% (10)	0	0	74.00% (37)	0	0	2.00% (1)	4.00% (2)
6	0	30.61% (15)	32.65% (16)	0	24.49% (12)	0	2.04% (1)	4.08% (2)	0	6.12% (3)
7	0	32.61% (15)	39.13% (18)	4.35% (2)	15.22% (7)	0	0	4.35% (2)	0	4.35% (2)
8	0	27.08% (13)	29.17% (14)	6.25% (3)	25.00% (12)	0	4.17% (2)	4.17% (2)	0	4.17% (2)
9	0	38.30% (18)	19.15% (9)	2.13% (1)	27.66% (13)	0	2.13% (1)	4.26% (2)	0	6.38% (3)

Figure 5: Confusion Matrix for SVM (Poly Kernel, MDM)

In this metric, Figure 3 represents 41 images of real class 1 are properly match with predicted class 1. Figure 4 represents 10 images of real class 1 are properly match with predicted class. In a parallel way, Figure 5 represents 95 images of real class 1 are correctly equivalent with predicted class 1. Figure 6 represents 6 images of definite class 1 are acceptably equal with predicted class. hence, reliable accuracy of SVM-ACOGA is superior than SVM.

	0	1	2	3	4	5	6	7	8	9
0	0	0	0	0	0	0	0	0	0	0
1	0	12.00% (6)	24.00% (12)	0	2.00% (1)	4.00% (2)	4.00% (2)	16.00% (8)	32.00% (16)	6.00% (3)
2	0	13.33% (6)	28.89% (13)	6.67% (3)	2.22% (1)	15.56% (7)	6.67% (3)	11.11% (5)	13.33% (6)	2.22% (1)
3	0	2.13% (1)	21.28% (10)	6.38% (3)	6.38% (3)	10.64% (5)	4.26% (2)	27.66% (13)	14.89% (7)	6.38% (3)
4	0	14.58% (7)	12.50% (6)	14.58% (7)	2.08% (1)	4.17% (2)	2.08% (1)	16.67% (8)	29.17% (14)	4.17% (2)
5	0	10.42% (5)	29.17% (14)	8.33% (4)	0	10.42% (5)	4.17% (2)	8.33% (4)	25.00% (12)	4.17% (2)
6	0	10.42% (5)	16.67% (8)	12.50% (6)	14.58% (7)	8.33% (4)	6.25% (3)	10.42% (5)	18.75% (9)	2.08% (1)
7	0	12.50% (6)	12.50% (6)	10.42% (5)	6.25% (3)	4.17% (2)	10.42% (5)	8.33% (4)	31.25% (15)	4.17% (2)
8	0	14.29% (7)	18.37% (9)	10.20% (5)	10.20% (5)	2.04% (1)	4.08% (2)	14.29% (7)	22.45% (11)	4.08% (2)
9	0	8.33% (4)	27.08% (13)	4.17% (2)	6.25% (3)	12.50% (6)	6.25% (3)	8.33% (4)	20.83% (10)	6.25% (3)

Figure 6: Confusion Matrix for SVM-ACOGA (Poly, MDM)

6. CONCLUSION

The basic conclusion of my thesis work is as follows:

We have established that dynamic knowledge with support vector machines can present a dominant tool for penetrating picture databases, outperforming a number of conventional query modification schemes. SVM-ACOGA not simply achieves every time high accurateness on a broad diversity of preferred returned results, except also does it speedily and keeps high exactitude when asked to convey time after time retrieved of images**.** and, dissimilar modern systems for example SVM, it does not have need of a plain semantically layer to execute fine. here a number of attractive instructions that we aspiration to follow. The operation instant of our algorithm balance linearly with the dimension of the image database both for the significance response stage and for the recovery of the top-k images**.** This is because, for all querying around, we have to examine during the database for the twenty images that are nearby to the existing SVM border line, and in the recovery stage we have to examine the whole database for the peak k most appropriate images with admiration to the well-read conception. SVM-ACOGA is sensible for image databases that hold a little thousand images; on the other hand, we would want to find traditions for it to extent to superior sized databases. In the planned system, characteristic aggregation was formulated as a binary organization and recovery problem and solved by support vector machine-continuous orthogonal ant colony optimization (SVM-ACOGA) in a characteristic difference space. Incorporating the techniques of data concentrated effort and noise understanding classifier, a new two-step approach was projected to handle the loud positive examples. In step 1, an assembly of SVM-ACOGA skilled in a characteristic difference space is used as compromise filters to classify and remove the loud positive examples. In step 2, the noise tolerant significance estimate was performed, which coupled each retained positive example with a significance probability to additional improve the sound influence. The tentative results show that the projected system outperforms the contending characteristic aggregation based image recovery systems when loud positive examples there in the query. The most excellent output of this planned system as follows:

1. We have to decrease the time for retrieving images from dataset through ACOGA technique. This technique uses the theory of orthogonal array. therefore we find best key point descriptors in orthogonal plan matrix of descriptors.

2. We get considerably best Confusion matrix, which stand for the corresponding retrieve images from different images.

3. The SVM-ACOGA provides best exactness of reliable image retrieval from databases weigh against traditional SVM CBIR.

7. FUTURE SCOPES

The future work of current thesis work is as follows:

1. We can use K-Mean, Markov Model and ANN as a supervised learning for classify and retrieve image.

2. We can use Max-Min ACO (Ant Colony Optimization), PSO or Ranked Based ACO techniques for evaluating optimize descriptors.

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