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EFFICIENT METHOD FOR IMAGE CLASSIFICATION USING ACO

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ABSTRACT: Classification of objects in an image finds its application in many real-time systems such as video surveillance systems etc. The basic operation is to detect the object present in the image frame. The processes involved are i) Extracting the object features and ii) Feeding the features into a classifier. External factors such as illumination, brightness etc., have profound effect on the process of classification. These conditions can lead to misdetection of objects. Similarly, the selection of features for classification affects the classification efficiency. Hence optimized feature detection, efficient feature extraction and a supportive classifier selection is mandatory for accurate classification. An absolute combination of suitable optimization solution, feature for classification and a matching classifier is presented in this work.

KEYWORDS: ACO, Pheromone, heuristics, Bayesian classification.

INTRODUCTION

In one aspect, Image Classification subsequently intends to object detection, involving the identification of the objects present in the image. The object in the image is determined by its characteristics such as shape, texture, colour, position gradient etc. Efficient extraction of features from these characteristics is essential in order to avoid misconception of objects. Additionally, classifier selection also must be done in such a manner that it matches the optimized criteria.

The stages of classification presented in this work are:

Optimized Feature Detection

Feature Extraction

Object Classification

An image obtained by any source is subjected to several degradation. The features of the objects in such degraded images cannot be directly determined. It may lead to faulty detection. External factors responsible for the image degradation during their acquisition include illumination variances, fluctuations in brightness and contrast levels, abrupt noises, source defects etc. In order to overcome these acquisition defects, image restoration can be done. But performing restoration followed by feature detection formulates a highly computational process. Hence Optimization can be done prior to feature detection. This produces acceptable solutions for a wide variety of images with varying attributes.

Ant Colony Optimization is the technique used to detect features from images affected by varying external factors[1]. There are few key parameters that decide the throughput of the ACO algorithm. By carefully balancing those parameters, considerable optimization can be effected. ACO is used mainly because of its enhanced efficiency compared to other optimization techniques[2]. It is a probabilistic method and has higher predictive accuracy.

The feature selected for classification is the shape of the object. Shape provides a perfect feature class for classification and also vulnerable to small errors. Even meager changes in this feature can lead to misdetection of objects. Hence optimization becomes essential. This simple shape feature is obtained by detecting the edges of the object under consideration. Edge detection is performed by ACO thus producing an optimized output[3].

Bayesian Classifier is used to classify the object based on the edge features. Similar to all classifiers Bayesian Classifier also uses two stages Training phase and Testing phase[4]. Bayesian Classifier works on the principle of conditional probability, given the training sequence it predicts the test sequence. The classifier is initially trained with the features extracted. The training dataset must be large enough to classify all the objects based on the determined feature , shape. During the testing phase the Classifier determines the prior probability based on the training set and this prior probability helps the classifier to segregate the test data to a particular class of defined object.

In the proposed work algorithms for Ant Colony Optimization, Feature extraction and Bayesian Classification are dealt in congruent manner. Finally the result for each stage along with the final classified output is shown.

Ant Colony Optimization

Edge is an important feature in an image and carries important information about the objects present in the image. Edge detection aims to localize the boundaries of objects in an image and significantly reduces the amount of data to be processed. Ant colony optimization (ACO) is a nature inspired optimization algorithm that is motivated by natural foraging behavior of ants. It is a heuristic method that imitates the behavior of real ants to solve discrete optimization problems[2]. The real ants communicate by means of a chemical substance called pheromone which they deposit on the ground in order to mark some preferred path that should be followed by other ants of the colony.

Ant Colony Optimization for Edge Detection

Ant colony optimization (ACO) is a population-based metaheuristic that mimics the foraging behavior of ants to find approximate solutions to difficult optimization problems. The proposed method establishes a pheromone matrix that represents the edge information at each pixel based on the routes formed by the ants dispatched on the image. The movement of the ants is guided by the local variation in the image's intensity values.

In ACO algorithm for edge detection, ants move through a search space, the graph which consists of nodes and edges. The pixels in the digital image can be considered as the nodes of a graph[5]. The movement of ants from a pixel to another pixel is probabilistically dictated by the transition probabilities. The transition probability reflects the likelihood that an ant will move from a given pixel to another. The transition probability depends upon the heuristic information and pheromone information. All pixels of the image are initialized with small value of pheromone. The heuristics information in most of the ACO based methods for edge detection is determined by local statistics at the pixel position. When an ant visits a pixel, it will deposit certain amount of pheromone. The more ants visit a pixel, the more pheromone deposition will be there on that pixel. In the end, edges can be detected by analyzing the pheromone distribution in the image. The whole procedure of the ACO is summarized as follows [5].

ACO Algorithm

1. Initialize the positions of all ants as well as pheromone matrix (same size as image).
2. For the construction step, move the ant K for L steps according to the probability transition matrix.
3. Update the pheromone matrix.
4. Make the binary decision to decide if there is an edge or not based on final pheromone matrix.

Feature Extraction Algorithm

In this chapter, we introduced a robust feature extraction concept that returns the object edge information that can be further used for classification. The resultant shape is obtained as a distance vector, calculated between the centroid of the object and its outer edge.

This section deals with the procedure to generate the features associated with the objects in the image that is to be classified.

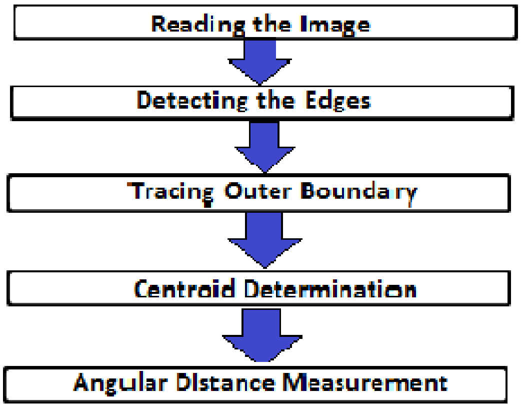


Fig.1. Feature Extraction Flow Diagram

The initial step is to take an image in which an object has to be identified. Different sets of images are taken involving variety of shapes. The colour image that is taken is converted into a grey-scale image as only the shape of that image is required. The input set we have taken includes car, human face, motor bike and bag.

After converting to gray scale format high frequency components present in the image are identified using the ACO edge detection, methods.

After obtaining the edges of the object, its outer boundary is traced out through scanning process. Scanning is done in horizontal, vertical and angular directions to increase the continuity of the boundary pixels. In the process of scanning the entire image is scanned from its outer boundary and the first occurrence of the edge or high intensity value is noted. In case of only horizontal and vertical scanning certain hidden portions in the image may be overridden leading to discontinuities in the traced outer boundary, hence we go also for angular scanning. Different scanning processes are given in Figure 3.3

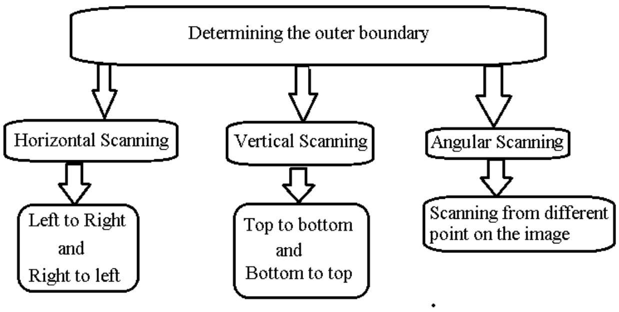


Fig.2. Flow of the Scanning Process

The angular scanning is performed from various points such as image corners and boundary mid points. The traced outer boundary gives the exact outline of the object under consideration.

After determining the outline, the centroid for object is identified. Centroid position is calculated only for the given object and not for the entire image. It is calculated by first calculating the mean row of the object. The mean row is obtained by averaging the row where the first occurrence of the high intensity pixel is obtained in top to bottom vertical scanning and the row where the first occurrence of the high intensity pixel is obtained in bottom to top vertical scanning. After determining the mean row the mean centroid pixel is determined by averaging the column pixel in the mean row where the first occurrence of the high intensity value is obtained in left to right scanning and the column pixel in the mean row where the first occurrence of the high intensity value is obtained in right to left scanning.

After determining the centroid coordinates, distance feature is extracted. It is obtained in an angular fashion, creating a distance vector for the corresponding angular measurement with respect to the centroid. This angle estimation is made with help of the two-point form of the line equation as in equation (1)

(y-y1) = m(x-x1) .... (1)

where m is the slope and is given in (2) on below and x1,y1 are centroid coordinates.

m= tan(θ) …. (2) where Θ is the angular coordinate.

Similarly, the processed image is scanned and those pixels that satisfy the line equation and having the high intensity value is noted. The Euclidian distance between the centroid pixel and the outline pixel is noted for every 5 degree increment with respect to the centroid pixel, thus creating an array of 72 vectors.

The Euclidian distance is measured as:

$\mathbf{D = \sqrt{((y2-y1)^2+(x2-x1)^2)}}$…. (3)

Where x1,y1,x2,y2 are the pixel co-ordinates.

Completely connected outline is necessary for the object in order to obtain the correct values of distance vectors.

The distance vectors so obtained is fed to a classifier that detects the exact object.

Classification

Classification is the core operation in object detection. There are different types of classifier used for this purpose. The main function of the classifier is to segregate the test sample to the predefined class. The predefined class is created by training the classifier with large number of training samples.

Basically 2 steps are involved in a classifier:

1. Training the classifier using the training samples.
2. Classifying the test sample.

Bayesian Classifier

Bayesian Classifier is used to determine the class to which the test sample belongs. It is based on the conditional probability P(X/Y), where X and Y represents the random sequence. It is the probability of occurrence of the event X given the event Y has occurred [7].

Since ACO is a probabilistic method of determining the features of the object to be classified, Bayesian Classifier suits well for classifying the objects based on the features extracted by the ACO.

Resutls

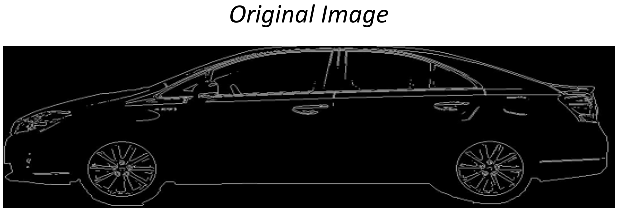
The results of complete execution of the algorithm discussed above are shown below

Parameter Variation Result

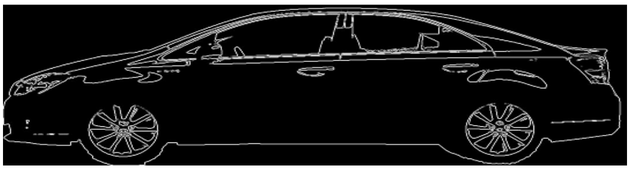
The below set of images show the effect of the variation in the ACO parameter for detecting the edges in the image.

The parameters taken here for consideration are the number of iterations in the algorithm and the number of ant cells used.

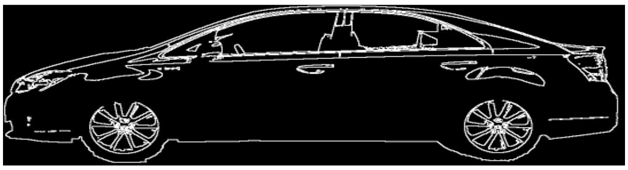
Original Image



2 Iterations, 300 ants



2 Iterations, 500 ants



3 Iterations, 500 ants

Fig.3. ACO Parameter Variation – Car

Fig.3. shows the parameter variation results. After analysis it is clear that for the below specified parameter values, the edges detected are near to exact.

Number of Transition Steps : 100 - 150

Number of Iteration : 2 - 3

Number of Ants : 400 – 500

The determination of these parameters are crucial in getting the most efficient results. They play an important role in reducing the load of the classifier thereby pruning the number of the training set required for the same.

FEATURE EXTRACTION RESULTS

From the edges detected after applying ACO, The feature of distance vector is extracted in following steps :

1. Outline determination
2. Boundary Box creation
3. Resizing to a common value (250 x 250)

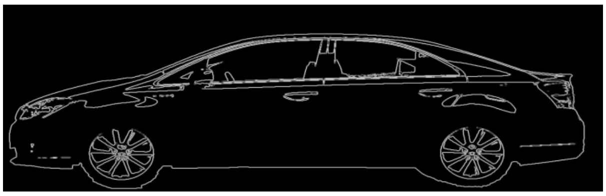
Finally from the resized image the distance vector is calculated. The calculation procedure for the distance vector is shown in the Feature Extraction segment.

For the analysis we have taken two sets of images, one from a Car set and another with a different shape of a motorcycle. When the distance vector is calculated for these two sets, they vary widely giving thereby easy to understand the best-case effect of the proposed methodology.

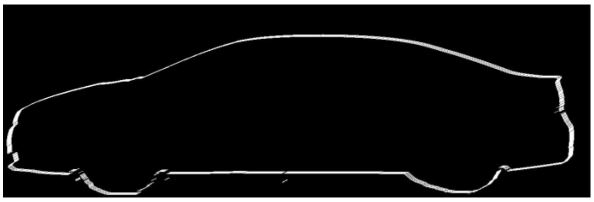
The outputs of the sample images are shown below :

Image 1:

Original Image



ACO Output

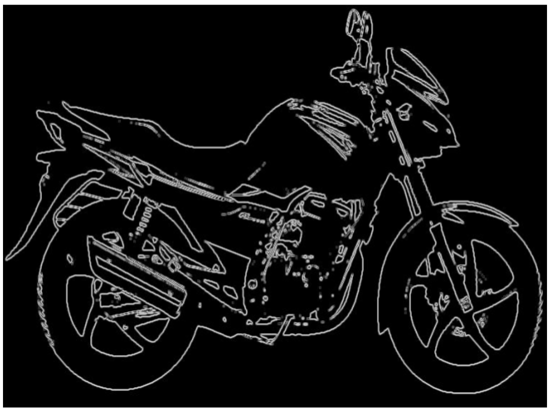


Outer Boundary

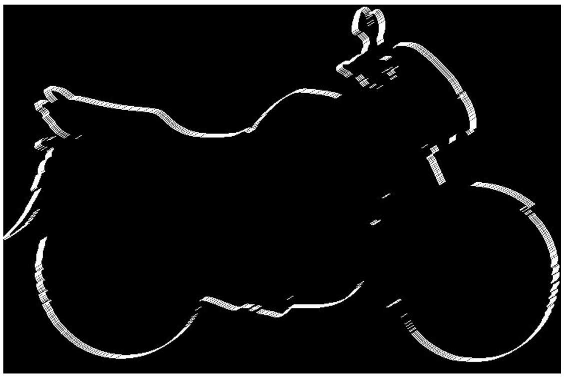
Fig.4. Feature Extraction Stages – Car model

Image 2:

Original Image



ACO Output



Outer Boundary

Fig.5. Feature Extraction Stages – Bike model

CLASSIFICATION RESULT

The distance vector obtained is stored as a matrix. For training the classifier nearly 250 different images of car and bike models are chosen and their distance vectors are saved in the same mat file thus creating a matrix of size 250 X 72.

	1	2	3	4	5	6	7	8	9
1	44	0	43.8406	63.6396	73.7902	44	0	44	6
2	38	85.3815	48.0833	39.5980	69.3181	38	0	38	3
3	63	104.3552	86.2670	65.0538	125.2198	63	0	63	6
4	45	69.5701	65.0538	50.9117	87.2067	45	0	45	5
5	38	0	56.5685	70.7107	107.3313	38	0	38	7
6	39	94.8683	36.7696	94.7523	71.5542	39	0	39	9
7	29	120.1666	25.4558	52.3259	38.0132	29	60.8276	29	5
8	48	60.0833	22.6274	100.4092	33.5410	48	60.8276	48	10
9	47	0	42.4264	65.0538	120.7477	47	0	47	6
10	27	120.1666	52.3259	26.8701	76.0263	27	103.4070	27	2

A predefined class is specified for the corresponding row vector.

The graphs corresponding to the distance vector of car and bike variants are shown below:

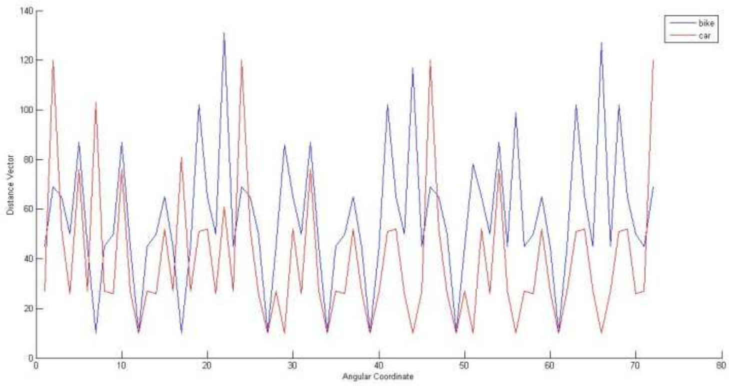


Fig.6. Distance Vector variation

Test image values are fed as a row vector of 72 values. In order to get a more accurate result, the number of training set can be increased. Once all the training set has been fed to the classifier, the Bayesian parameters are well set in the classifier. Now if the vector corresponding to the actual object is presented to the classifier, based on the training parameters the corresponding class is predicted.

CONCLUSION

A classification technique that uses an optimized method for feature detection and lucid approach for feature extraction is developed. Ant Colony Optimization technique, with its greater average predictive accuracy than other optimization and data mining techniques, proves to determine the features in the image with near accuracy. It optimizes the external illumination variations and provides a standard result . The feature extraction technique that extracts the distance vectors from the edges detected from the ACO, provides a simple and elegant solution. The classification of the object from the distance vector created is effected with the help of the Bayesian Classifier. This probabilistic model gives better classification results with less error.

Various input dataset spanning across different classes of images are given as input to the algorithm. The outputs obtained at each step of the algorithm is captured. Input images include objects belonging to different class but has close outline resemblance. The effective working of the algorithm is checked with such input images and it is verified to be executing without any misconception errors.

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