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IASC-CI: Improved Ant Based Swarm Computing for Classifying Imagery

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Abstract-**The social insect metaphor for working out arrays of predicaments has become promising vicinity in latest years focusing on indirect or direct interactions among various agents. Swarm Computing has a multidisciplinary character as its study provides insights that can help humans manage complex systems that offer an alternative way of designing intelligent systems which emphasises on the emergent collective intelligence of groups of simple agents. Classification is the computational procedure [3] [5] that sort the images into groups according to their similarities. Numerous methods for classification have been developed and exploring new methods to increase classification accuracy has been a key topic. Ant Colony Optimization (ACO) [2] [6] is an algorithm inspired by the foraging behaviour of ants wherein ants leaves the volatile substance called pheromone on the soil surface for the purpose of foraging and collective interaction via indirect communications. This paper focuses on improved Methodology of Swarm Computing for classifying imagery exploring various techniques such as IASC (Improved Ant based Swarm Computing), DWT [15] (Discrete Wavelet Transform) and SVM [1] (Support Vectors Machines) for edge detection [14][15][19], feature extraction[10], feature selection [12], and finally image classification [5][6].**

Keywords- **Classification, Imagery, Feature Extraction, Feature Selection, Pheromone, Swarm Computing, Discrete Wavelet Transform, State Vector Machine, Improved Ant based Swarm Computing, Ant Colony Optimization, Edge Detection, Image Classification.**

I. INTRODUCTION

Swarm Computing [5] system has the capability to operate in a coordinated manner with no any coordinator or exterior controller. In scrupulous the discipline focuses on joint behaviour those upshots from local interactions with each other and with the surroundings. Instance of systems studied by Swarm Computing is colonies of ant and termites, school of fish, flocks of birds, herds of land animals. The problems vary ranging from a Travelling Salesman Problem (TSP) [9][13]to Edge detection[18][19] to Image classification [3][5][6].

Image of elevated dimensions can be produced with the advancement in image capturing appliances; the crucial setback in Image processing field is to reveal constructive information by assembling the images into significant categories. Several methods for classifying imagery is available in the literature such as traditional, statistical, knowledge based, neural networks, and other artificial intelligence methods. However, the above mentioned methods still generate flaws as the complexities of images increases.

Edge detection [18][19] is one of the imperative ingredients of image processing. It is effectively implicated in the pre-processing stage of image analysis and identifies the outline of an image thus providing important details about it. So, it significantly lessens the content to process for the high-level processing assignments like object recognition and image segmentation. The most important step in the edge detection, on which the success of production of true edge map depends, lies on the determination of threshold.

DWT [15](Discrete Wavelet Transform) is the multi-resolution description of an image, a mathematical tool for hierarchically decomposing an image where the decoding can be processed sequentially from a low resolution to the higher resolution. In ACO, as colonies ant reacts speedily and effectively with the environment. They find shorter path to the best food source, assign workers to various tasks, and defend their territory from enemies. Ant colonies make these possible by countless interactions between individual ants. This coordination among the ants doesn't stem from 'centre of control' rather each ant acts only on the local information. The goal of SVM is try to tackle the nearest distance between a point in one class and a point in the other class being maximized and illustrate a hyper plane [1] to classify two categories as apparently as possible. SVM (Support Vectors Machines) has shown its ability in various fields of pattern recognition, the aim of SVM in this paper is to prove its potential along with Advanced Ant Based Swarm Computing technique to classify images.

In this paper, intention of image classification inspired from Ant colonies is fulfilled using Improved Ant Colony Optimization named as IASC (Improved Ant based Swarm Computing). For Edge Detection [16][18][19] Improved Ant based method has been implemented, further for Feature extraction and feature selection, DWT is employed and a traditional base classifier SVM [1] along with Improved Ant based method is used to further classify imagery.

A. Discrete Wavelet Transform (DWT)

Discrete Wavelet Transform (DWT) is a mathematical tool for hierarchically decomposing an image [17]. It is useful for processing of non-stationary signals. The transform is based on small waves, called wavelets, of varying frequency and limited duration. Wavelet transform provides both frequency and spatial description of an image. Unlike conventional Fourier transform, temporal information is retained in this transformation process. Wavelets are created by translations and dilations of a fixed function called mother wavelet.

DWT is the multi-resolution description of an image the decoding can be processed sequentially from a low resolution to the higher resolution [15]. The DWT splits the signal into high and low frequency parts. The high frequency part contains information about the edge components, while the low frequency part is split again into high and low frequency parts. The high frequency components are usually used for feature extraction since the human eye is less sensitive to changes in edges [14].

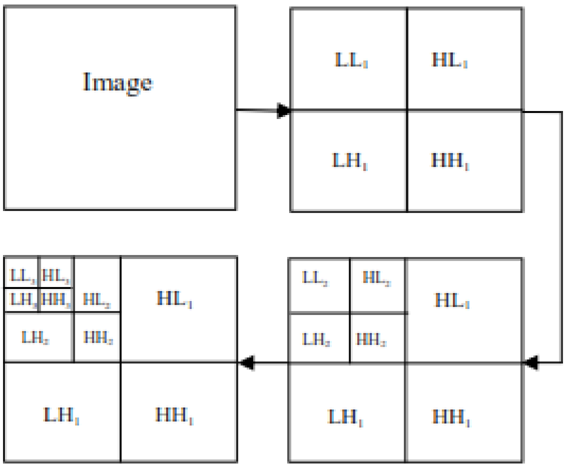


Figure 1: The three-level DWT decomposition[15].

In two dimensional applications, for each level of decomposition, we first perform the DWT in the vertical direction, followed by the DWT in the horizontal direction. After the first level of decomposition, there are 4 sub-bands: LL1, LH1, HL1, and HH1. For each successive level of decomposition, the LL sub band of the previous level is used as the input. To perform second level decomposition, the DWT is applied to LL1 band which decomposes the LL1[15] band into the four sub bands LL2, LH2, HL2, and HH2. To perform third level decomposition, the DWT is applied to LL2 band which decompose this band into the four sub-bands – LL3, LH3, HL3, HH3. This results in 10 sub-bands per component. LH1, HL1, and HH1 contain the highest frequency bands present in the image tile, while LL3 contains the lowest frequency band. The three-level DWT decomposition is shown in Fig.1.

DWT is currently used in a wide variety of signal processing applications, such as in audio and video compression, removal of noise in audio, and the simulation of wireless antenna distribution [8]. Wavelets have their energy concentrated in time and are well suited for the analysis of transient, time-varying signals. Since most of the real life signals encountered are time varying in nature, the Wavelet Transform suits many applications very well.

The continuous wavelet transform (CWT) of a finite energy signal x (t) (x (t) $\in L^2$ (R)) is defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet functions ψ:

$$WT_x(a,\tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t)\, \psi^{*}\left(\frac{t-\tau}{a}\right) dt \qquad [1]$$

$$WT_x(a,\tau) = \langle x(t), \varphi_{a\tau}(t) \rangle \qquad [2]$$

Where, $WT_x(a,\tau)$ is a function of scale and position (Wavelet coefficients).

Calculation of wavelet coefficient at every possible scale may not always be feasible thereby in practice only some discrete scales and positions are chosen while using DWT.

B. Ant Colony Optimization(ACO)

Ant Colony Optimization [2][7] is a comparatively new population based move toward problem solving that takes idea from the social behaviour of the ants. ACO is an iterative algorithm wherein at each iteration; a number of artificial ants build the solution by walking from vertex to vertex on the graph with the constraint of not visiting any vertex that she has visited on her walk. At the end of an iteration, on the basis of the quality of solutions constructed by the ants, the pheromone values are modified in order to bias ants in future iteration to construct solution similar to the best ones previously constructed. Different ants take up different paths to accomplish the food source [9] [13] and leave the substance (Chemical) on the soil i.e. pheromone based on the reality that higher concentration of pheromone is dropped on shorter paths and smaller concentration on stretched paths. Here, the collective behaviour of the ants provides intelligent way outs for finding the shortest path from the nest to the food source. If a single ant finds a shorter path and deposits higher concentrations on the way to food source then all the other ants gets magnetized toward the higher concentration and hence following the shorter path.

Artificial ants are like real ants [9] [13]with some major differences:1) Artificial ants have memory, 2) They aren't completely blind, 3)They live in a discrete time environment.

However they have some adopted characteristics from the real ants, like 1) They probabilistically prefer path with a larger amount of pheromone, 2)Shorter path is true path, larger is the rate of growth in the pheromone concentration, 3)They communicate to each other by means of the amount of pheromone laid on each path.

The underlying mechanism for real ant system is illustrated in Figure 1 [9] [13] [17] [18][19]. Ants communicate with each other using pheromones. In species that forage in groups, a forager that finds food marks a trail on the way back to the colony; this trail is followed by other ants (Figure 2 (a)), these ants then reinforce the trail when they head back with food to the colony. When the food source is exhausted, no new trails are marked by returning ants and the scent slowly dissipates. This behaviour helps ants deal with changes in their environment. For instance, when an established path to a food source is blocked by an obstacle (Figure 2 (b)), the foragers leave the path to explore new routes (Figure 2 (c)). If an ant is successful, it leaves a new trail marking the shortest route on its return. Successful trails are followed by more ants (Figure 2 (d)), reinforcing better routes and gradually finding the best path.

Figure 2 (a): Ants moving from nest (source) towards its food (Destination) [9] [13] [17] [18][19].

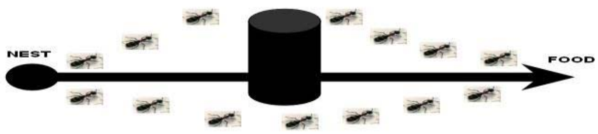


Figure 2 (b): An obstacle placed on the way between nest and food [9] [13] [17] [18][19].

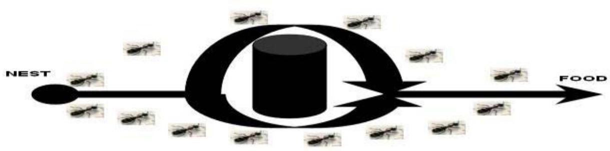


Figure 2 (c): Ants randomly choosing the path [9] [13] [17] [18][19].

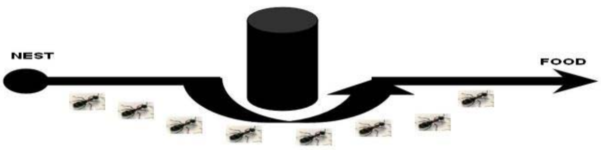


Figure 2 (d): Shortest path chosen by maximum ants based on pheromone deposits [9] [13] [17] [18][19].

C. Support Vector Machine(SVM)

Support vector machine (SVM) is supervised [1] model that is associated with learning algorithm which used to analyze data and recognize patterns used for segmentation and classification. Support vector machine is the representation of the examples as points in space. SVM [1] can also be used to perform non-linear classification using kernel trick, which implicitly mapped their inputs into high-dimensional feature.

When given a set of points which belong to either of two classes, a linear SVM finds the hyper plane leaving the largest possible fraction of points of the same class on the same side, while maximizing the distance of either class from the hyper plane. In simple form, a support vector machine constructs a hyper plane or set of hyper planes in high or infinite-dimensional spaces, which can be used for classification, regression or other tasks. Intuitively a good separation is get by the hyper plane that has the nearest training data point of any class. The hyper plane in the higher-dimensional space is defined as a set of points whose dot product with a vector in that space is constant. The vector defining the hyper plane can be choosing to be linear combinations with parameter α_i of image of feature vectors that occur in the database. With this choice of a hyper plane, the points x in a feature space that are mapped into the hyper plane [1] are define by the relation:

$\sum \alpha_i K(x_i, x) = constant$, If K(x , y) becomes small as y grows further away from x, each term in the sum measure the degree of closeness of the test point x to the corresponding database point x.

1) Optimal separating hyper plane

Let $(x_i, y_i)_{1\leq i \leq N}$ be a set of training examples, $x_i \in R^n$ and belongs to class labeled by $y_i \in \{-1, 1\}$. The aim is to carry out the equation of a hyper plane which divides the set of examples such that all the points with the same label are on the same side of the hyper plane. This means find w and b such that

$$y_i(\mathbf{w} \cdot \mathbf{x}_i + b) > 0,\ i = 1, \ldots, N \qquad \textbf{[3]}$$

If a hyperplane is present satisfying equation (3), the set is said to be linearly separable. In this case, it is always possible to rescale w and b such that

$$\min_{1\leq i \leq N} y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \geq 1,\ i = 1, \ldots, N$$

So that the closest point to the hyperplane has a distance of 1/||w||. Then equation (3) becomes

$$y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \geq 1 \qquad \textbf{[4]}$$

Among the separating hyperplanes, the one for which the distance to the closest point is maximal is called Optimal Separating Hyperplane (OSH). Since the distance to the closest point is 1/||w||, determining the OSH amounts to solve the following problem:

Minimize, ½ w.w; under constraint **[3]** **[5]**

The quantity 2/||w|| is called the margin and thus, the OSH is the separating hyperplane which maximizes the margin. The margin can be seen as a measure of difficulty of the problem: the smaller the margin is, the more difficult the problem is. The larger the margin is, the better the generalization is expected to be (as given in Figure 3 below).

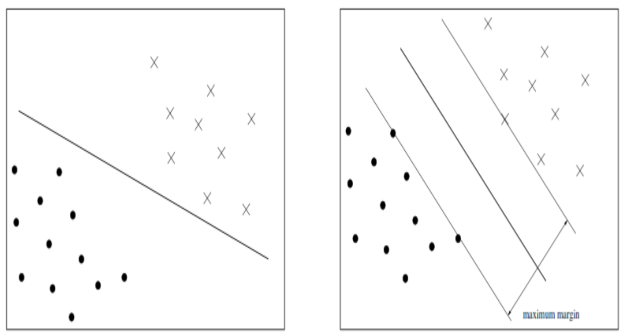


Figure 3: Hyperplanes separate [1] correctly the training examples. The Optimal Separating Hyperplane on the right hand side has a larger margin and is expected to give better generalization.

Since w^2 is convex, minimizing equation (5) under linear constraints (4) can be achieved by the use of Lagrange multipliers. Let us denote the N non negative Lagrange multipliers associated with constraints (4) by $\alpha = (\alpha_1, \alpha_2 \dots \alpha_n)$. Minimizing equation (5) amounts to finding the saddle point of the Lagrange function:

$$L(\mathbf{w}, b, \boldsymbol{\alpha}) = \frac{1}{2}\mathbf{w} \cdot \mathbf{w} - \sum_{i=1}^{N} \alpha_i [y_i(\mathbf{w} \cdot \mathbf{x}_i + b) - 1] \quad \textbf{[6]}$$

To find this point, one has to minimize this function over w and b and to maximize it over the Lagrange multipliers $\alpha_i \geq 0$.

The hyperplane decision function is written as:

$$f(\mathbf{x}) = sgn\left(\sum_{i=1}^{N} \alpha_i y_i \mathbf{x}_i \cdot \mathbf{x} + b\right) \quad \textbf{[7]}$$

2) Linearly non-separating case

If the data are not linearly separable, the problem of finding the OSH becomes meaningless. To allow the possibility of examples violating (4), one can introduce slack [1] variables ($\xi_1, \xi_2, \dots\dots, \xi_n$) with $\xi_i \geq 0$ such that

$$y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \geq 1 - \xi_i,\ i = 1, \dots, N \quad \textbf{[8]}$$

The purpose of the variables ξ_i is to allow misclassified points. Points which are misclassified have their corresponding $\xi_i > 1$, so that $\sum \xi_i$ is an upper bound on the number of training errors. The generalized OSH is then regarded as the solution of the following problem: Minimize

$$\frac{1}{2}\mathbf{w} \cdot \mathbf{w} + C \sum_{i=1}^{N} \xi_i \quad \textbf{[9]}$$

Subject to constraints (8) and $\xi i \geq 0$. The first term is minimized to control the capacity learning = as in the separable case; the purpose of the second term is to keep under control the number of misclassified points. The parameter C is chosen by the user, a larger C corresponding to assigning a higher penalty to errors. In analogy with what was done for the separable case, the use of the Lagrange multipliers leads do the following optimization problem: maximize

$$W(\boldsymbol{\alpha}) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{N} \alpha_i \alpha_j y_i y_j \mathbf{x}_i \mathbf{x}_j \quad \textbf{[10]}$$

Subject to: $\sum_{i=1}^{N} \alpha_i y_i = 0$ and $0 \leq \alpha_i \geq C$. The only difference from the separable case is that now the α_i have an upper bound of C.

II. Proposed Work

The entire work of classifying imagery is defined using the following steps:

1. Edge detection using Advanced Ant based Swarm Computing (AASC).
2. Database creation for Imagery.
3. Feature extraction and feature selection using DWT.
4. Image classification using traditional base classifier SVM along with Advanced Ant based Swarm Computing (AASC).

The proposed work focuses on applying methods of Improved Ant based Swarm Computing (IASC), Discrete Wavelet Transform (DWT) [15] and Support Vector Machine (SVM) [1] to images. Firstly the foreground region from the image is extracted to get the region of interest from the input imagery. There after IASC algorithm is applied to input image, which gives the edges of image (Edge Detection) [19]. The features obtained and selected are based on wavelet of image using DWT which are stored with image type (category) in the database created. DWT basically finds the 3 level energy of an image by finding the mean value of the image which is nothing but the energy of the image at that particular level wherein the energy is stored in an array to be saved in the database. Now new input imagery is given as an input to IASC for obtaining features of the image. Now this new features of images are compared to features stored in database to obtain class of image. Each of the images from different category is re-ranked based on the histogram and Eigen value features. Support Vector Machine and IASC are used to obtain the class of image from the database and classification of the image based on features. Finally, re-ranked list is displayed highlighting the best matching image from the selected category which matches the query image.

A) Improved Ant based Swarm Computing (IASC) [19]

ACO-based advances to edge detection and classification of imagery utilizes a decision rule based on Ant System (AS) being leading algorithm based on foraging act of ants i.e. ACO. Continually since its development, quite a few accompaniments have been made to traditional ACO and from amongst which ACS is one. This paper emphasizes on a technique called IASC resulting from facets of ACS where one of the significant aspects is formation of decision rule, the pseudorandom proportional rule.

Several modifications have been proposed on the existing ACO algorithms to generate IASC: Firstly, Initialization process: assigned to pheromone matrix, weights assigned [2] [4] to calculate the heuristic function ACS based rule for Construction process, modified decision process based on selection of threshold value calculated using Otsu's method [4] and finally using the calculated threshold, pheromone matrix is used to classify each pixel either as an edge or a non-edge.

An M × N 2-D image can be represented as 2-D matrix [19] with image pixels as its elements. In the representation used, each pixel in the image represents both a node and an edge in the graph. A pixel represents a node because locations in the graph are associated with pixel locations: ants move from one pixel to another. At the same time, it also represents an edge because the heuristic information is determined from the local variation of the image's intensity values and hence, is associated with a pixel location in the image. The components of the pheromone and transition matrices are associated with pixels in the image. The algorithm consists of three main steps. The first is the initialization process. The second is the iterative construction-and-update process, where the goal [19] is to construct the final pheromone matrix. The construction and-update process is performed several times, once per iteration. The final step is the decision process, where the edges are identified based on the final pheromone values.

1) Ant Based Initialization Process:

Each of the ants is assigned a random position in the image. The initial value of each element in the pheromone matrix is set to a constant, which is small but non-zero. The heuristic information matrix is constructed. In the initialization process, each of the K ants is assigned a random position in the M image. The initial value of each element in the pheromone matrix is set to a, which is small but non-zero. Also, the heuristic information matrix is constructed based on the local variation of the intensity values. The heuristic information is determined during initialization since it is dependent only on the pixel values of the image. The initial value of each component of pheromone matrix τ (0) is set a fixed value τinit as 1/(M1M2).

Till date no standard method has been explained to initialize the pheromone matrix, so an initial value has been assigned for the pheromone matrix which will allow the ants to explore other pixels that may be considered as edge pixels.

2) Heuristic Function Calculation:

Heuristic information [4][5][19] which is used to determine the probability using which ants moves from one pixel to another. In the proposed method we have used weights to for calculating the heuristic value. As the ant moves farther the weight is reduced. This gives addition information about the neighbourhood to calculate transition probability. In this step modification done is in formation of new clique and addition of two new kernel functions. In the construction process, selected ant will move on the image for L movement-steps & this process will be repeated in each construction step and till each ant moves on image. The selected ant moves from node (l, m) to its neighbouring node (i, j) according to the transition probability [4][5]that is defined as follows:

$$p^{(n)}_{(l,m),(i,j)} = \frac{\left(\tau^{(n-1)}_{i,j}\right)^{\alpha}\left(\eta_{i,j}\right)^{\beta}}{\sum_{(i,j)\in\Omega_{(l,m)}}\left(\tau^{(n-1)}_{i,j}\right)^{\alpha}\left(\eta_{i,j}\right)^{\beta}}, \quad [11]$$

Where, $\tau^{n-1}_{i,j}$ is the pheromone value of the node (i, j), $\Omega_{(l,m)}$ is the neighbourhood nodes of the node (l, m), η_{ij} represents the heuristic information at the node (i, j). The fixed value α and β represent the influence of the pheromone matrix and the heuristic matrix, respectively.

There are two essential issues in the construction process. The first issue is the determination of the heuristic information η_{ij} in (12). In this paper, it is proposed to be determined by the local statistics at the pixel position (i, j) as

$$\eta_{(i,j)} = 1/Z V_c\left(I_{(i,j)}\right) \quad [12]$$

where $Z = \sum_{i=1:M1}\sum_{j=1:M2} Vc\,(I_{i,j})$, which is a normalization factor, $I_{i,j}$ is the intensity value of the pixel at the position (i, j) of the image I, the function Vc ($I_{i,j}$) is a function of a local group of pixels c (called the clique), and its value depends on the variation of image's intensity values on the clique c (as shown in figure 3).

More specifically, for the pixel Ii,j under consideration, the function $V_c(I_{i,j})$ is

$$\begin{aligned} V_c(I_{i,j}) = f\big(&|I_{i-2,j-1}-I_{i+2,j+1}| + |I_{i-1,j-2}-I_{i+1,j+1}| \\ &+ |I_{i-1,j-1}-I_{i+1,j+1}| + |I_{i-1,j}-I_{i+1,j}| \\ &+ |I_{i-1,j+1}-I_{i-1,j-1}| + |I_{i-1,j+2}-I_{i-1,j-2}| \\ &+ |I_{i,j-1}-I_{i,j+1}|\big) + |I_{i,j-1}-I_{i,j+1}| \end{aligned} \quad [13]$$

To determine the function f(x) in [13], the following four functions are considered in this paper; they are mathematically expressed as follows and illustrated in Figure 2, respectively.

$$f(x) = \lambda x, \quad \text{for } x \geq 0, \quad [14]$$

$$f(x) = \lambda x^2, \quad \text{for } x \geq 0, \quad [15]$$

$$f(x) = \begin{cases} \sin(\pi x|2\lambda) & 0 \leq x \leq \lambda \\ 0 & else \end{cases} \quad 16]$$

$$f(x) = \begin{cases} \dfrac{\pi x \sin(\pi x|\lambda)}{\lambda} & 0 \leq x \leq \lambda \\ 0 & else \end{cases} \quad [17]$$

The parameter λ in each of above functions [14]-[17] adjusts the functions' respective shapes.

The second issue is to determine the permissible range of the ant's movement [19] (i.e., $\Omega_{(l,m)}$ in [11]) at the position (l, m). In this paper, it is proposed to be either the 4-connectivity neighbourhood or the 8-connectivity neighbourhood, both of which are demonstrated in Figure 5.

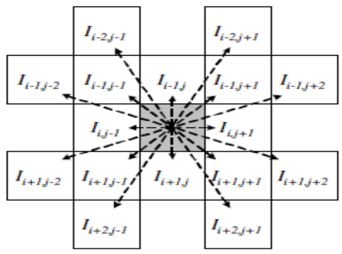


Figure 4: A local configuration [4][5] [19] at the pixel position Ii,j for computing the variation Vc(Ii,j) defined in [13]. The pixel Ii,j is marked as gray square.

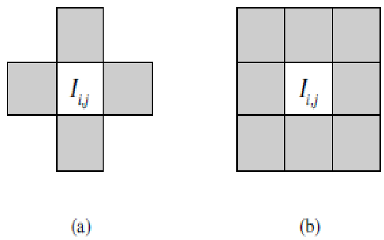


Figure 5: Various neighbourhoods (marked as gray regions) of the pixel Ii,j : (a) 4-connectivity [4][5] [19] neighbourhood; and (b) 8-connectivity neighbourhood.

3) Ant Based Decision Process:

Finally, a modified decision process and the modification is in the selection of new threshold. Here pheromone matrix is used to classify each pixel either as an edge or a non-edge. The decision is made by applying a threshold T on the final pheromone. The threshold T is computed based on Otsu technique [4] as specified earlier. The initial threshold $T^{(0)}$

is selected as the mean value of the pheromone matrix. The entries of the pheromone matrix are classified in two parts as:

(a) Those entries of pheromone matrix whose value is less than $T^{(0)}$

(b) Those entries of pheromone matrix whose value is larger than $T^{(0)}$

Then the new threshold is calculated [12][14] by taking the square of two mean values of each of the two categories and then taking their average. The complete process is repeated again and again until the threshold value becomes constant (in terms of user defined tolerance).

III. Experimental / Simulation Result

Experiments were carried outed using numerous ordeal illustrations. The proposed method i.e. AASC based edge detection, DWT based feature extraction and selection and SVM and finally Improved ACO based classification were implemented using Matlab R2011a. The program is run on a PC with an Intel (R) Core (TM) i5: 2400CPU @ 3.10 GHz; 4 GB RAM and 32 bit Operating System.

Parameters, its significance, values for each parameter [19] used for experiments are summarized in following table:

Table 1 Parameters used in Experiments

Paramets	Significance
τ_{init}	Initial pheromone value
N	No. of iterations
L	No. of construction steps
K	No. of ants
α	Influence of pheromone
β	Influence of heuristic value
ψ	Pheromone decay coefficient
ρ	Pheromone evaporation coefficient

Table 2 Parameters value used in Experiments

Parameter s	Value
τ_{init}	$1/M_1M_2$
N	1-25
L	50
K	256
α	1
β	1
ψ	0.05
ρ	0.1

Table 3 Output Parameters generated via Experiments

Parameters
Execution / Processing Time (Time Required)
Figure Of Merit (FOM)
Kappa value
Peak to Signal Noise Ratio (PSNR)

Several images has been considered and tested. In the experimental / simulation results, three images: Designer Door, Bath Room, Living Room, has been projected as Image 1, Image 2 and Image 3 respectively.

Several edge detectors and classifier is available in the literature. In the simulation result given below, we have highlighted the proposed methodology of Image Classification known as: Improved Ant based classifier in terms of Execution / Processing Time (time required), Figure Of Merit (FOM), Kappa value and Peak to signal Noise Ratio (PSNR).

The simulation is highlighted in the following manner:

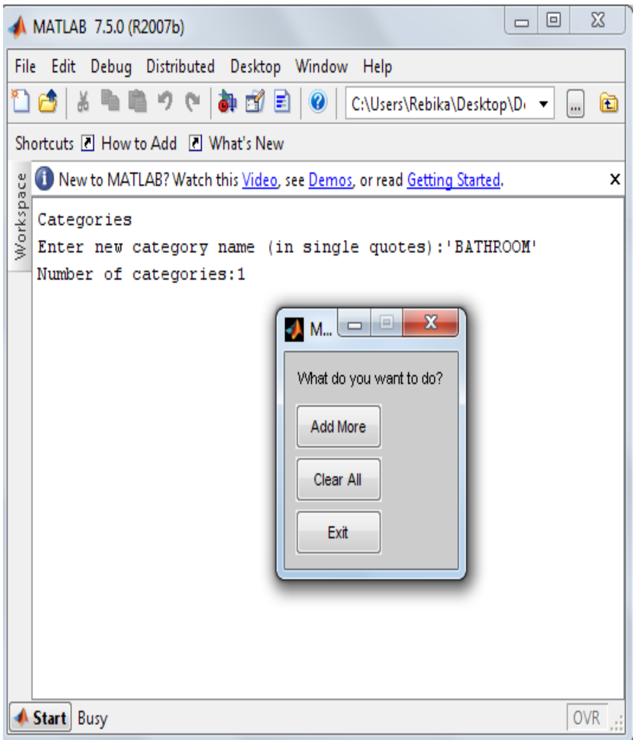
STEP 1: New database for imagery is created and several categories (Unlimited) of images are entered and stored in the database **(as shown in Result 1 & Result 2 given below).**

STEP 2: Images are inserted in each category created in the STEP 1. As and when, the images are inserted, the foreground information of image is extracted, edge is detected using Improved ACO, energy level feature of the edge detected image is evaluated and further the Eigen Value and Histogram of the image is evaluated **(as shown in Result 3 given below).**

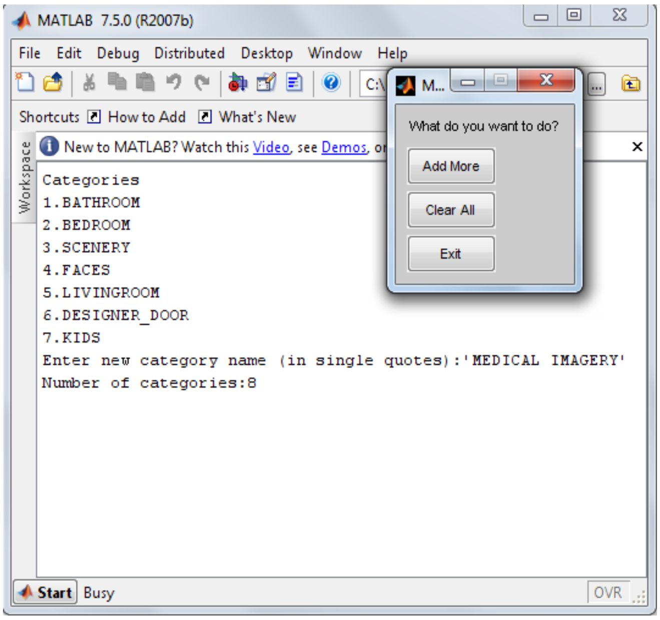
STEP 3: Subsequently, energy level of the input image is calculated, list is re-ranked, input image is compared with images from the category database and the best matching image is extracted thereby classifying the input image in that category.

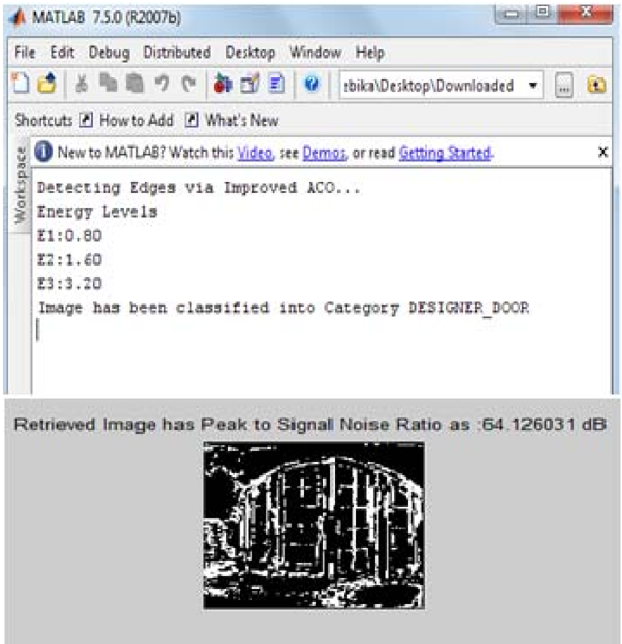
The various input images that had been inserted in the category database are shown below (Image 1, Image 2 and Image 3) along with the outcome of STEP 3.

Result 1:

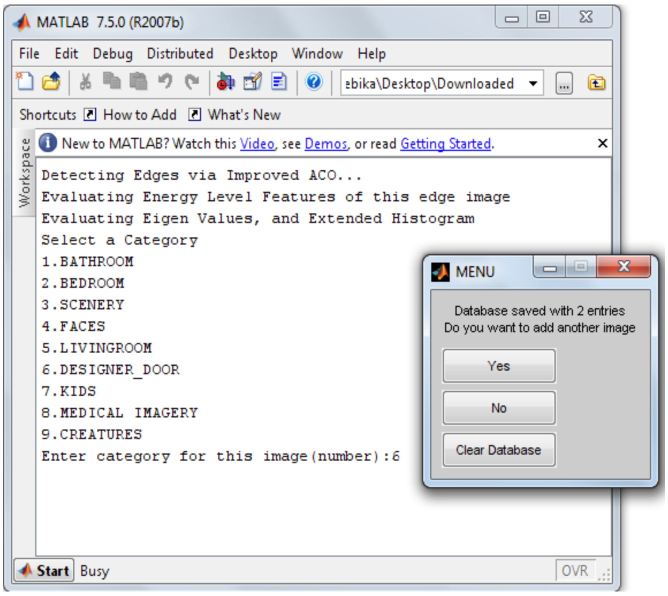


Result 2:





Result 3:



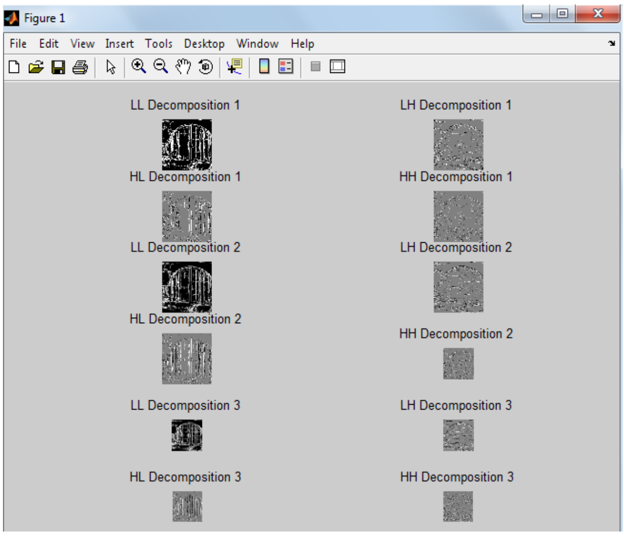


Image 1: Designer Door

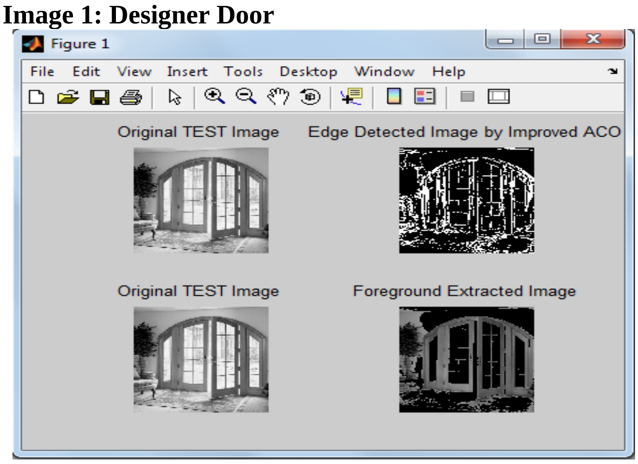
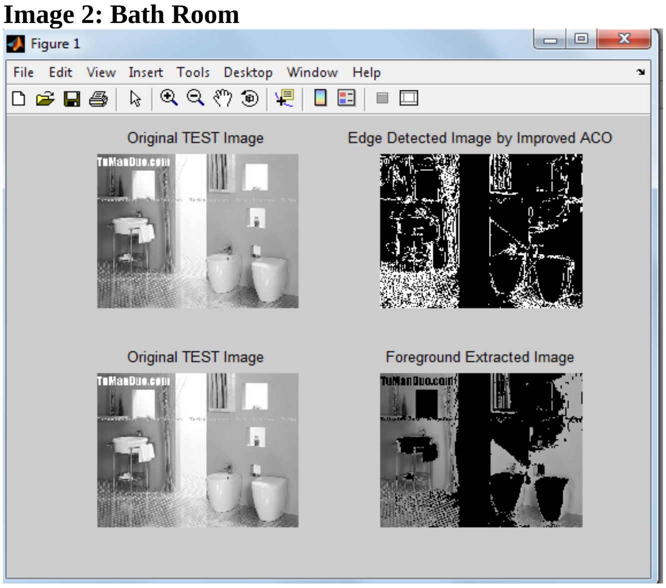
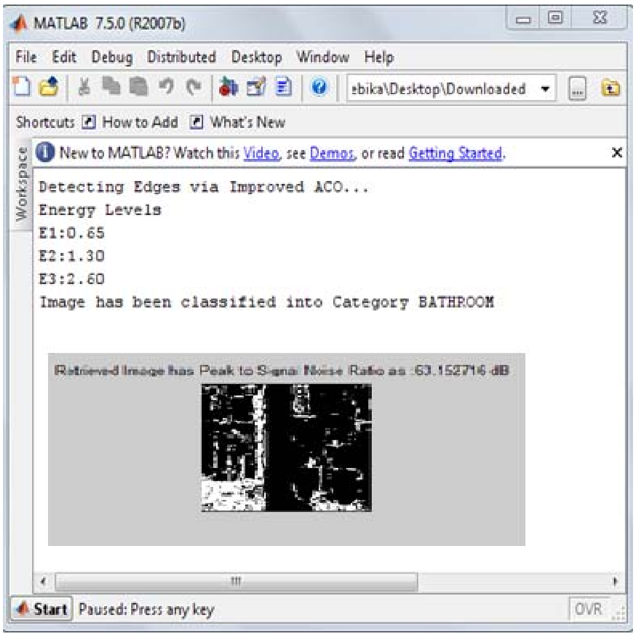
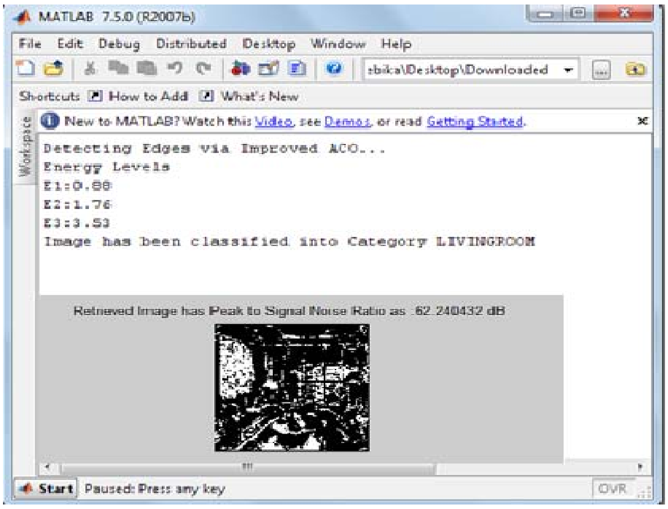
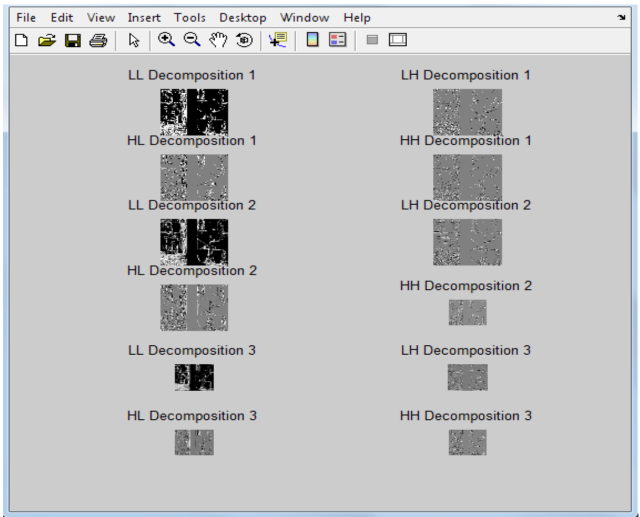


Image 2: Bath Room









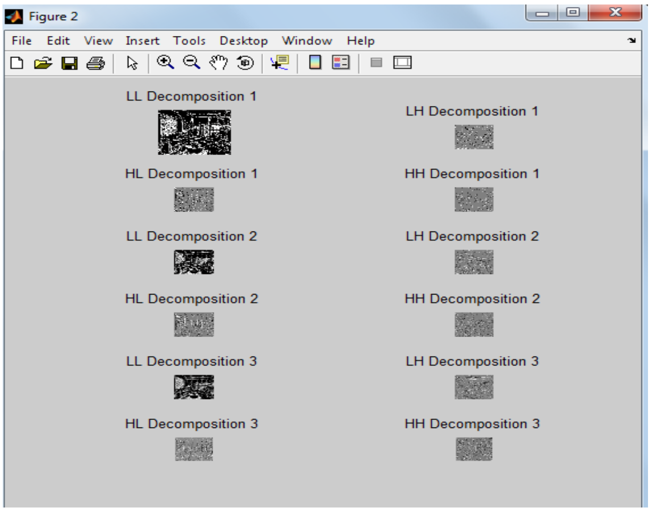
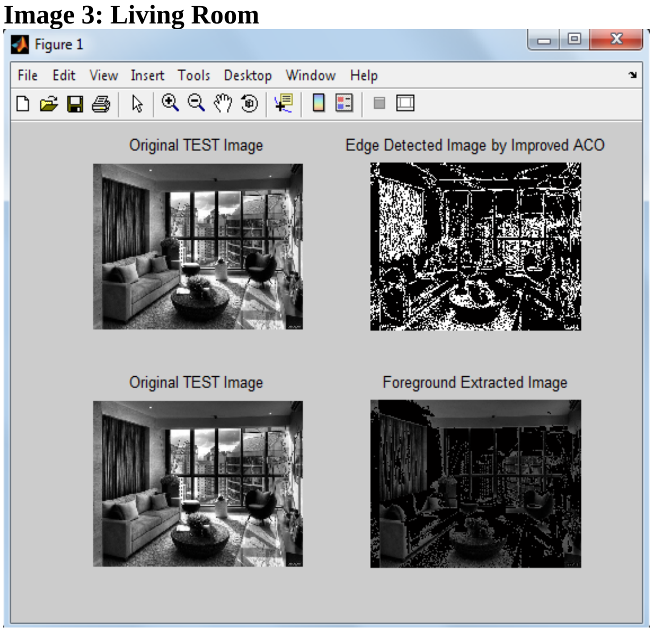


Image 3: Living Room



IV. CONCLUSION

For **Designer Door (Image 1),** the following values have been tabulated:

Parameters	By IASC-CI
Time required	1.92 seconds
Figure Of Merit	0.89
Kappa Value	19.04
PSNR	64.126 dB

For **Bath Room (Image 2),** the following values have been tabulated:

Parameters	By IASC-CI
Time required	2.32 seconds
Figure Of Merit	0.892
Kappa Value	19.081
PSNR	63.162 dB

For **Living Room (Image 3),** the following values have been tabulated:

Parameters	By IASC-CI
Time required	2.22 seconds
Figure Of Merit	0.921
Kappa Value	19.14
PSNR	62.240 dB

In this paper, an improved methodology termed as IASC-CI (Improved Ant based Swarm Computing for Classifying Imagery) has been proposed and result highlights the quality performance based on the above mentioned parameters. As per the conclusions and experiment, it leads to the following research directions:

1. Edge detection is highly dependent on the lighting conditions, density of image and noise. Therefore, an automatic detector that [19] adjusts the factors mentioned to provide better edge detection is required.
2. Threshold value is determined in this paper using Otsu's method which gives a comparatively better outcome but if multiple thresholding techniques can be available applying each one when the scene conditions are most ideal.
3. Classification has been performed in this paper using a base classifier SVM with proposed method IASC-CI. A hybrid swarm based
4. method can be developed using ACO (Ant Colony Optimization), PSO (Particle Swarm Optimization) and FPAB (Flower Pollination by Artificial Bees) to yield better outcome thereby increasing the Figure Of Merit, Processing time and accuracy.

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