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RESEARCH ARTICLE

Optimizing and Reconstruction of SAR Images Using Glowworm Swarm Optimization (GSO)

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Abstract- Image segmentation is the process of partitioning a digital image into multiple segments. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. In the existing System expectation–maximization (EM) algorithm is an iterative method for finding maximum likelihood or maximum a posteriori (MAP) estimates of parameters in statistical models, where the model depends on unobserved latent variables. The EM iteration alternates between performing an expectation (E) step, which creates a function for the expectation of the log-likelihood evaluated using the current estimate for the parameters, and maximization (M) step, which computes parameters maximizing the expected log-likelihood found on the E step. The glowworm swarm optimization (GSO) is a swarm intelligence optimization algorithm developed based on the behavior of glowworms (also known as fireflies or lightning bugs). The behavior pattern of glowworms which is used for this algorithm is the apparent capability of the glowworms to change the intensity of the luciferin emission and thus appear to glow at different intensities. The GSO algorithm makes the agents glow at intensities approximately proportional to the function value being optimized. The second significant part of the algorithm incorporates a dynamic decision range by which the effect of distant glowworms are discounted when a glowworm has sufficient number of neighbors or the range goes beyond the range of perception of the glowworms.

Keywords- Image Processing, Image segmentation, Expectation Maximization, Glowworm swarm Optimization (GSO)

I. INTRODUCTION

Image processing is any form of signal processing for which the input is an image, such as a photograph or video frame and the output of image processing may be either an image or, a set of characteristics or parameters related to the image. Image processing basically includes the following three steps.

- Importing the image with optical scanner or by digital photography.
- Analyzing and manipulating the image which includes data compression and image enhancement and spotting patterns that are not to human eyes like satellite photographs.
- Output is the last stage in which result can be altered image or report that is based on image analysis.

An image may be defined as function (x,y), x & y are spatial (plane) coordinates and amplitude of 'f' at any pair of coordinates (x,y) is called Intensity or gray level of image at point. A digital image consists of finite number of elements, with particular location and values are called as **Picture Elements, image Elements, pels and Pixels.** Three types of computerized process are: Low-level, Mid-level, High-level processing. Low level includes pre-processing which reduces noise, contrast enhancement, image sharpening etc. Mid-level processing includes segmentation, description, classification of an individual objects. High level processing includes recognizing objects. Sources of Digital Images are electromagnetic (EM) energy spectrum. The spectral bands are grouped according to energy per photon ranging from the gamma rays (highest energy) to the radio waves (lowest energy).

1.1 STEPS IN DIGITAL IMAGE PROCESSING

Digital and Analog are the two methods involved in image processing. Image processing combined with many steps. The fundamental steps in digital image processing shown in Fig 1 involves many stages

- Image acquisition
- Image Enhancement
- Color Image Processing
- Image Restoration
- Image Segmentation
- Representation and description
- Recognition and interpretation

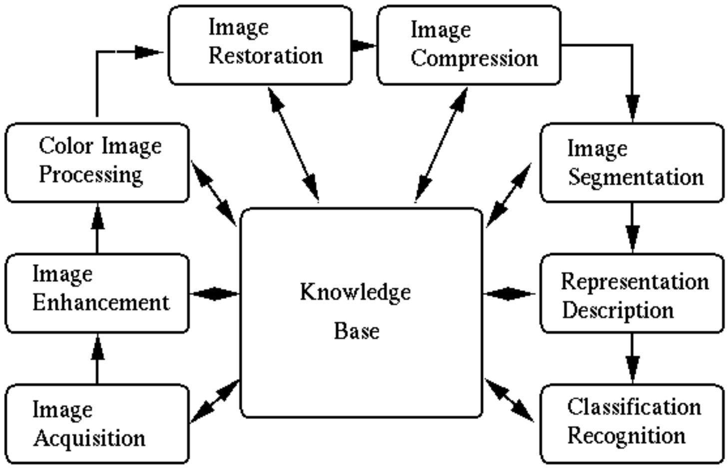

Fig1 Steps in image processing

- **Image acquisition**: To acquire a digital image. That acquisition could be simple as being given an image that already in digital form. In this stage involves preprocessing, such as scaling.
- **Image enhancement**: This is the process of manipulating an image so that the result is more suitable than the original for specific application.
- **Image Restoration**: It is an area that also deals with improving the appearance of an image. Which is subjective, image restoration is objective, in that technique tends to based on mathematical or probabilistic models of image degradation.
- **Color Image Processing**: It is an area that has been gaining in importance because of the significant increase in the use of digital images over the Internet.
- **Image segmentation**: To partitions an input image into its constituent parts or objects.
- **Image Compression**: It deals with reducing the storage required to save on image or the bandwidth required to transmit.
- **Image description:** To extract features that result in some quantitative information of interest or features that are basic for differentiating one class of objects from another.
- **Image recognition**: To assign a label to an object based on the information provided by its descriptors.
- **Image interpretation**: To assign meaning to an group of recognized objects.

These are all the fundamental steps in digital image processing. Image segmentation is main step in image processing. In this research work only focused on image segmentation.

1.3 IMAGE SEGMENTATION

In computer vision, segmentation refers to the process of partitioning a digital image into multiple segments. The goal of segmentation is to simplify and change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color intensity, or texture. Adjacent regions are significantly different with respect to the same characteristics. When applied to a stack of images, typical in Medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like marching cubes

SEGMENTATION TECHNIQUES

Image segmentation is to subdivide an image into constituent regions or objects. Image segmentation reduces huge amount of unnecessary data while retaining only importance data for image analysis. Segmentation techniques are listed below;

1. Histogram Based Methods
2. Edge Detection Methods
3. Region Growing Methods
4. Clustering Based Methods

1.3.1 Histogram Based Method

Histogram-based methods are very efficient when compared to other image segmentation methods because they typically require only one pass through the pixels. In this technique, a histogram is computed from all of the pixels the image, and the peaks and valleys in the histogram are used to locate the clusters in the image. Color or intensity can be used as the measure. A refinement of this technique is to recursively apply the histogram- seeking method to clusters in the image in order to divide them into smaller clusters. This is repeated with smaller and smaller clusters until no more clusters are formed.

One disadvantage of the histogram-seeking method is that it may be difficult to identify significant peaks and valleys in the image. In this technique of image classification distance metric and integrated region matching are familiar. Histogram-based approaches can also be quickly adapted to occur over multiple frames, while maintaining their single pass efficiency. The histogram can be done in multiple fashions when multiple frames are considered. The same approach that is taken with one frame can be applied to multiple, and after the results are merged. Peaks and valleys that were previously difficult to identify are more likely to be distinguishable. The histogram can also be applied on a per pixel basis where the information results are used to determine the most frequent color for the pixel location. This approach segmentation based on active objects and a static environment, resulting in a different type of segmentation useful in Video tracking.

1.3.2 Edge Detection Method

Edge detection is a well-developed field on its own within image processing. Region boundaries and edges are closely related, since there is often a sharp adjustment in intensity at the region boundaries. Edge detection techniques have been used as the base of another segmentation technique. The edges identified by edge detection are often disconnected. To segment an object from an image however, one needs closed region boundaries. Edge is nothing but boundary between two images. Edge detection technique refers to the identification and locating the sharp discontinuities in the image.

1.3.3 Region Growing Method

The first region growing method was the seeded region growing method. This method takes a set of seeds as input along with the image. The seeds mark each of the objects to be segmented. The regions and iteratively grown by comparing all unallocated neighboring pixels to the regions. The difference between a pixel's intensity value and the region's mean, is used as a measure of similarity. The pixel with the smallest difference measured this way is allocated to the respective region. This process continues until all pixels are allocated to a region.

Seeded region growing requires seeds as additional input. The segmentation results are dependent on the choice of seeds. Noise the image can cause the seeds to be poorly placed. Unseeded region growing is a modified algorithm that doesn't require explicit seeds.

1.3.4 Clustering based methods

Image segmentation can be performed effectively by clustering image pixels. Partitioning of data into meaningful subgroups and it can be applied. Clustering analysis [2] either requires the user to provide the seeds for the regions to be segmented or uses non-parametric methods for finding the salient regions without the need for seed points. Clustering is the commonly used applications for image segmentation. Clustering based image segmentation is based on clustering analysis. This thesis work focused on clustering techniques.

1.4 EXPECTATION-MAXIMIZATION ALGORITHM

An Expectation-Maximization (EM) algorithm [14] is used for finding maximum likelihood estimates of parameters in probabilistic models, where the model depends on unobserved latent variables. In order to find maximum likelihood estimate it is necessary find probability density function and log likelihood. The EM algorithm is an efficient iterative procedure to compute the Maximum Likelihood (ML) estimate in the presence of missing or hidden data. Each iteration of the EM algorithm consists of two steps:

E-step: In the expectation, or E-step, the missing data are estimated given the observed data and current estimate of the model parameters. This is achieved using the conditional expectation, explaining the choice of terminology.

M-step: In the M-step, the likelihood function is maximized under the assumption that the missing data are known. The estimates of the missing data from the E-step are used in lieu of the actual missing data.

Properties of EM algorithm

The EM algorithm has several appealing properties, some of which are:

- Numerically with each iteration likelihood is increasing
- Under fair general conditions, it has reliable global convergence
- The cost per iteration is generally low, which can offset the larger number of iteration need for the EM algorithm compared to other competing procedures
- It can be used to provide the estimated of missing data

Drawbacks of EM algorithm

- EM algorithm slowly converging
- Easy to fall local maxima
- Fixing initial centroids

1.5 OPTIMIZATION ALGORITHM

An optimization algorithm is an algorithm for finding a value x such that f(x) is as small (or as large) as possible, for a given function f, possibly with some constraints on x. Here, x can be a scalar or vector of continuous or discrete values. An algorithm terminates in a finite number of steps with a solution. An algorithm is a special case of an iterative method, which generally need not coverage in a finite number of steps. Instead, an iterative method produces a sequence of iterates from which some subsequence converges to a solution.

1.5.1 GLOWWORM SWARM OPTIMIZATION (GSO)

The glowworm swarm optimization (GSO) is a swarm intelligence optimization algorithm developed based on the behavior of glowworms (also known as fireflies or lightning bugs). The behavior pattern of glowworms which is used for this algorithm is the apparent capability of the glowworms to change the intensity of the luciferin emission and thus appear to glow at different intensities.

- The GSO algorithm makes the agents glow at intensities approximately proportional to the function value being optimized. It is assumed that glowworms of brighter intensities attract glowworms that have lower intensity.
- The second significant part of the algorithm incorporates a dynamic decision range by which the effect of distant glowworms are discounted when a glowworm has sufficient number of neighbors or the range goes beyond the range of perception of the glowworms.

The part 2 of the algorithm makes it different from Firefly algorithm where there is no "sufficient number o neighbors" limit and there is no perception limit based on distance. This two "cognitive limits" allows swarms of glowworms to split into subgroups and converge to high function value points. This property of the algorithm allows it to be used to identify multiple peaks of a multi-modal function and makes in part of Evolutionary multi –model optimization algorithms family.

It starts by placing a population of n glowworms randomly in the search space so that they are well dispersed. Initially, all the glowworms contain an equal quantity of luciferin Io. Each iteration consists of a luciferin-update phase followed by a movement phase based on a transition rule.

Luciferin-update phase: The luciferin update depends on the function value at the glowworm position. During the luciferin-update phase, each glowworm adds, to its previous luciferin level, a luciferin quantity proportional to the fitness of its current location in the objective function domain.

Movement phase: During the movement phase, each glowworm decides, using a probabilistic mechanism, to move toward a neighbor that has a luciferin value higher than its own. That is, glowworms are attracted to neighbors that glow brighter.

Neighborhood range update rule: We associate with each agent i a neighborhood whose radial range $r_i^{\ d}$ is dynamic in nature ($0< r_i^{\ d} < r_s$). The fact that a fixed neighborhood range is not used needs some justification. When the glowworms depend only on local information to decide their movements, it is expected that the number of peaks captured would be a functions of the redial sensor range.

1.6 OBJECTIVE OF THE RESEARCH

The main objective is to partition an image into meaningful regions and is an important step before an image recognition process. Optimal initial value fix the GMM EM algorithm propose GSO instead of GMM. In the initial stage, the GSO is executed for a short period for automatic clustering, forming spherical or close to spherical shape clusters. The result from GSO is used as the initial seed of the EM algorithm. The EM algorithm will be applied for refining and generating the final result.

II. LITERATURE REVIEW

2.1 Expectation-Maximization algorithm

Mohamed Ali Mahjoub et al.[4], introduce a Bayesian image segmentation algorithm based on finite mixtures. An EM algorithm is developed to estimate parameters of the Gaussian mixtures. The finite mixture is a flexible and powerful probabilistic modeling tool. It can be used to provide a model-based clustering in the field of pattern recognition. The obtained results have shown a significant improvement of our approach compared to the standard version of EM algorithm

Y. Ramadevi et al.[5], Image segmentation is to partition an image into meaningful regions with respect to a particular application. This paper discusses the interaction between image segmentation and object recognition in the framework of Expectation-Maximization (EM) algorithm. Threshold is image processing technique for converting grayscale or color image to a binary image based upon a threshold value.

GAO Yan-Yu et al.[6], Automatic image annotation, which aims at automatically identifying and then assigning semantic keyword to the meaningful objects in a digital image, is not a very difficult task for human but has been regarded as a difficult and challenging problem to machines. Propose a hierarchical annotation scheme considering that generally human visual identification to a scenery object is a rough-to-fine hierarchical process.

Mohammed A-Megeed Salem et al.[7], Multi-resolution analysis is an established part of human vision system. It builds different representation of an image which a spatial resolution adapted to the size of objects of interest and to its level of relevance.

Xian-Bin Wen, Hua Zhang and Ze-Tao Jiang[8] A valid unsupervised and multiscale segmentation of synthetic aperture radar (SAR) imagery is proposed by a combination GA-EM of the Expectation Maximization (EM) algorithm with the genetic algorithm (GA). This approach benefits from the properties of the Genetic and the EM algorithm by combination of both into a single procedure.

Qinpei Zhao et al.[9], As EM starts with a random (potentially poor) solution, the final result of EM highly depends on the initialization. To avoid the sensitivity to initialization, RSEM randomly picks a component and relocates it to a random position. The parameters of the components will be modified accordingly. The procedure of randomization breaks up the configuration of the previous step, which can overcome the problems of EM.

Xuchao Li, Suxuan Bian [10], An unsupervised image segmentation algorithm is proposed, which combines spatial constraints with a kernel fuzzy c-means (KFCM) clustering algorithm. In order to overcome the shortcomings, the contents of image is characterized by Gaussian mixture model, and the parameters of model are estimated by modified expectation maximization (EM) algorithm, which overcomes the classical EM algorithm drawbacks that easily trap in local maxima and be susceptible to initial value.

Tao Song et al.[11], Recent research discloses that the putamen in human brain has close relationship with some neurological diseases, and the most commonly used methodology in such studies is magnetic resonance (MR) imaging. In order to measure the volume of putamen in MR image, accurate detection is highly desirable.

M.A. Balafar et al.[12], Edge-preserving neighborhood is used to improve an already exist extension for Fuzzy C-Mean (FCM). In the defined neighborhood, a window is centered on the pixel. Then, each sample, in the window, is considered the neighbor of the pixel if there is not any edge between the sample and the pixel.
Iasonas Kokkinos et al.[13], formulate the interaction between image segmentation and object recognition in the framework of the Expectation-Maximization (EM) algorithm. Consider segmentation as the assignment of image observations to object hypotheses and phrase it as the E-step, while the M-step amounts to fitting the object models to the observations.
Wafe Boussellaa et al.[15], new enhanced text extraction algorithm from degraded document images on the basis of the probabilistic models. The observed document image is considered as a mixture of Gaussian densities which represents the foreground and background document image components.
Ahmed Rekik et al.[16], presents an optimal and unsupervised satellite image segmentation approach based on Pearson system and k-Means Clustering Algorithm Initialization. Such method could be considered as original by the fact it utilized K-Means clustering algorithm for an optimal initialization of image class number on one hand and it exploited Pearson system for an optimal statistical distributions' affectation of each considered class on the other hand.
Sankar K. Pal.[17], The problem of segmentation of multispectral satellite images is addressed. An integration of rough-set-theoretic knowledge extraction, the Expectation Maximization (EM) algorithm, and minimal spanning tree (MST) clustering is described. EM provides the statistical model of the data and handles the associated measurement and representation uncertainties.

2.2 Glowworm Swarm Optimization algorithm

K.N. Krishnand, D.Ghose [18], Glowworm swarm optimization (GSO), a novel algorithm for the simultaneous computation of multiple optima of multimodal functions. The algorithm shares a few features with some better known swarm intelligence based optimization algorithms, such as ant colony optimization and particle swarm optimization, but with several significant differences.
Piotr Oramus [19], Glowworm Swarm Optimization algorithm is applied for the simultaneous capture of multiple optima of multimodal functions. The algorithm uses an ensemble of agents, which scan the search space and exchange information concerning a fitness of their current position.
Y, Yang et al.[20], Solving system of nonlinear equations is an important question in scientific calculations and engineering technology field. The problem of solving nonlinear equations is equivalently changed to the problem of function optimization, and then a solution is obtained by artificial glowworm swarm optimization algorithm, considering it as the initial value of Hooke-Jeeves method, a more accurate solution can be obtained.
Jiakun Liu et al.[21], In basic GSO algorithm foundation, introduce a conception of definite updating search domains at glowworm position stochastic updating stage to control the change of glowworm position.
Zhengxin Huang, Yongquan Zhou [22], Cluster analysis has become an important technique in exploratory data analysis, pattern recognition, machine learning, neural computing, and other engineering fields. . Two new cluster analysis methods based on glowworm swarm optimization (GSO) algorithm are proposed. The first algorithm showed hoe GSO can be used to self-organization cluster analysis. The second algorithm is hybrid the GSO clustering analysis with the K-means algorithm to accelerate classification. Two clustering algorithms are tested on three data sets; experimental results show that the two kind of clustering algorithm has higher clustering results

III. PROPOSED METHODOLOGY FOR IMAGE SEGMENTATION

3.1 EXISTING METHODOGY

In analyzing the images, accuracy and the results of segmentation become an important factor. According to the input images the accuracy and the results of segmentation to complete the process of segmentation may vary. There are many types segmentation methods are available but here use Expectation-Maximization (EM) algorithm with Gaussian Mixture Models (GMM) based on clustering methods.

The EM (Expectation-Maximization) algorithm is a very popular model based clustering algorithm in many areas of application, in particular for clustering problems, its practical usefulness is often limited by its computational efficiency, In fact, one of the common criticisms of the EM algorithm is, compared to other optimization methods that it converges only at a linear rate. The convergence can be especially slow if the proportion of unobserved to observe information is large. Another drawback of EM is that every iteration it passes through all of the available data. Thus, if the size of the data is very large, even one single iteration of EM can become computationally intense.

Fitting parametric density models such as Gaussian mixture models (GMM) by using the Expectation – Maximization (EM) algorithm can be interpreted as model-based clustering methods where each mixture component is viewed as a cluster. Due to its capability of discovering clusters of arbitrary ellipsoidal shapes, the GMM-EM algorithm is a superior version of K-means. However, as the number of dimensions increases, significant difficulties arise in the estimation of covariance matrices for GMMs.

Furthermore, due to their objective of interest being a non-convex optimization problem. K-means and GMM-EM easily get trapped in local minima, and are very sensitive to initializations. The common practice is to run algorithm many times from different initial values and to employ several local search heuristics.

3.2 PROPOSED METHODOLOGY

GMM-EM algorithm may converge to a local maximum of the observed data likelihood function, depending on starting values. It is very sensitive to initialization. In order to eliminate local maxima problem of GMM-EM clustering the idea of proposed method developed. Glowworm swarm optimization algorithm used for finding the initial seed of Expectation-Expectation (EM) algorithm instead of Gaussian Mixture Model (GMM)

3.2.1 Glowworm swarm Optimization (GSO) clustering algorithm

Propose glowworm swarm optimization (GSO) instead of GMM. In GSO, swarm of agents is initially randomly distributed in the search space. The agents in GSO are thought of as glowworms that carry a luminescence quality called luciferin along with them. The glowworms emit a light whose intensity is proportional to the associated luciferin and interact with other agents within a variable neighborhood. The glowworm identifies its neighbors and computers its movements by exploiting an adaptive neighborhood, which is bounded above by its sensor range. Each glowworm selects using a probabilistic mechanism, a neighbor that has a luciferin value higher than its own and moves toward it. These movements based only on local information and selective neighbor interactions enable the swarm of glowworm to partition into disjoint subgroup that converge on multiple optima of a given multimodal function.

It starts by placing a population of n glowworm randomly in the search space so that they are well dispersed. Initially, all the glowworms contain an equal quantity of luciferin. $\int_{o.}$ Each iteration consists of a luciferin-update phase followed by a movement phase based on a transition rule.

GLOWWORM SWARM OPTIMIZATION (GSO) ALGORITHM

Set number of dimensions=m
Set number of glowworm=n
Let s be the step size
Let x_i (t) be the location of glowworm I at time t
Deploy_agents_randomly;
for i=l to n do $\int$i (0)n=$\int$n
r^i_d (0)=r0
Set maximum iteration number = iter_max;
Set t=l;
While (t<iter_max) do;
{
For each glowworm *i* do: % Luciferin-update phase
$li(t) = (l-p)\, l_i(t-l) + \gamma J(x_i(t))$;
For each glowworm *i* do: % Movement-phase
{
$N_i(t) = \{ j: d_{ij} < rid(t): l_i(t) < l_j(t)\}$;
For each glowworm j=N_i (t) do:
P_{ij} (t) =
J=Select_ glowworm (P);
$Xi(t+l) = Xi(t) + S\left(\frac{xj(t)-xi(t)}{\| xj(t)-xi(t) \|}\right)$
$r^i_d(t+l) = \min\{r_s, \max\{0, rid(t)+\beta)n_t - |N_i(t)\}\}$;
}
t ←t+l ;

A full parameters analysis is found in Krishnanand and Ghose [11], show that the choice of these parameters has some influence on the performance of the algorithm. In, terms of the total number of peaks captured, Author suggests the parameters selection as shown in Table 1. Thus, only *n* and r_s need to be selected. These parameters value brings more convenience to people to apply the GSO algorithm (Table I).

TABLE I
THE GSO ALGORITHM PARAMETER SELECTION

P	**Γ**	**β**	n_t	**s**	l_0
0.4	0.6	0.08	5	0.03	5

Algorithm symbolic description: X_i (t) is the glowworm *i* in *i* iteration location; l*i*(t) is the luciferin of the glowworm *i* in *t* iteration; N_i (t) is the neighborhood set of glowworm *i* in *t* iteration; r^i_d (t) is the dynamic decision domain radius of glowworm *i* in *t* iteration; r_s is the upper bound of the r^i_d (t); P_{ij} (t) is the probability of glowworm *i* selects neighbour j ; n_t is the threshold of the number of agents include in the neighbourhood set; ρ is the evaporation rate of luciferin ; γ is the replacement rate of luciferin; β is the rate of change of the neighbourhood range. *J* (x_i(t)) represents the value of the objective function at agent *i*'s location at time *t.* The glowworms encode the fitness of their current locations, evaluated using the objective function, into a luciferin value that they broadcast to their neighbors. Enhance the GSO clustering by using the Schwefel Function as the objective function.

Schwele's function is deceptive in that the global minimum is geometrically distant, over the parameter space, from the next best local minima. Therefore, the search algorithms are potentially prone to convergence in the wrong direction. Function has following definition which is shown in Eqn. 1

$$f(X)= \sum_{i=1}^{n} [- Xi \sin (\sqrt{| Xi|})] \quad \text{(Eqn. 1)}$$

3.2.2 Hybrid GSO with Expectation-Maximization clustering algorithm

In the hybrid algorithm, the algorithm includes two segmentation process; the Glowworm Swarm Optimization and the Expectation–Maximization based on clustering methods. In the initial stage, the GSO is executed for a short period for automatic clustering, forming spherical or close to spherical shape clusters. The result from the GSO is used as the initial seed of the EM algorithm. The EM algorithm will be applied for refining and generating the final result. The hybrid algorithm can be summarized as in Fig 3.1:

Step 1: Start the GSO clustering process until the maximum number of iterations is exceeded;
Step 2: The result from the GSO is used as the initial seed of the EM clustering algorithm.
Step 3: Start EM process until a stop criterion is met.
The EM algorithm seeks to final the MLE by iteratively applying the following two steps. Until all pixels in the input images cluster following two steps are repeated.
3.1 Expectation step: Calculate the expected value of the log likelihood function, with respect to the conditional distribution of z given *x* under the current estimate of the parameters *(-) (t).*
3.2 Maximization step: Find the parameter which maximizes this quantity.

GSO Algorithm

IV. IMPLEMENTATION RESULT AND ANALYSIS

The proposed algorithm implemented in MATLAB (7.10) it was run under windows7 with Intel®Core i3 CPU with a RAM capacity of 2GB. Propose method to find a initial seed of EM algorithm using Glowworm Swarm Optimization is implemented in MATLAB environment.

The proposed image segmentation technique is evaluated with the help of a Berkley's image data set. The dataset used in the proposed algorithm is Berkley dataset. The Berkley dataset contained 12,000 hand-labeled segmentations of 1,000 Corel dataset images from 30 human subjects. Half of the segmentations were obtained from presenting the subject with a color image; the other half from presenting a grayscale image. The public benchmark based on this data consists of all of the grayscale and color segmentations for 300 images. The images are divided into a training set of 200 images, and a test set of 100 images. Form this large database only the natural images are taken for this proposed algorithm implementation. The human segmented image is used for comparison measurement. The resulting image is compared with the human segmented image for performance measurement.

The comparison is carried out with image segmentation using standard Expectation-Maximization, proposed Hybrid Glowworm Swarm Optimization with Expectation-Maximization. The result of segmented image is compared to the ground truth value of original image is shown in Fig 2, Fig 3, and Fig 4.

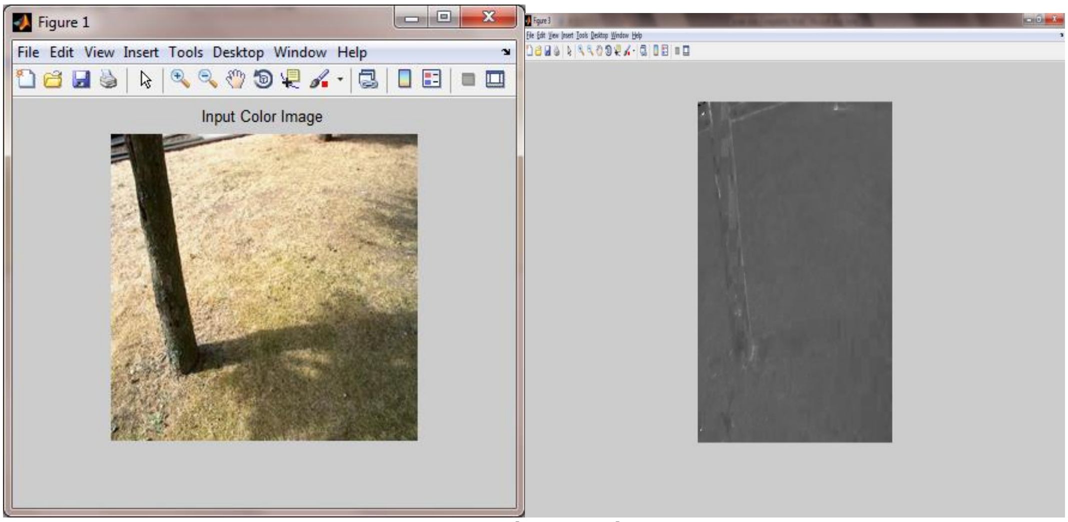

Fig 2 Input and Segmented image

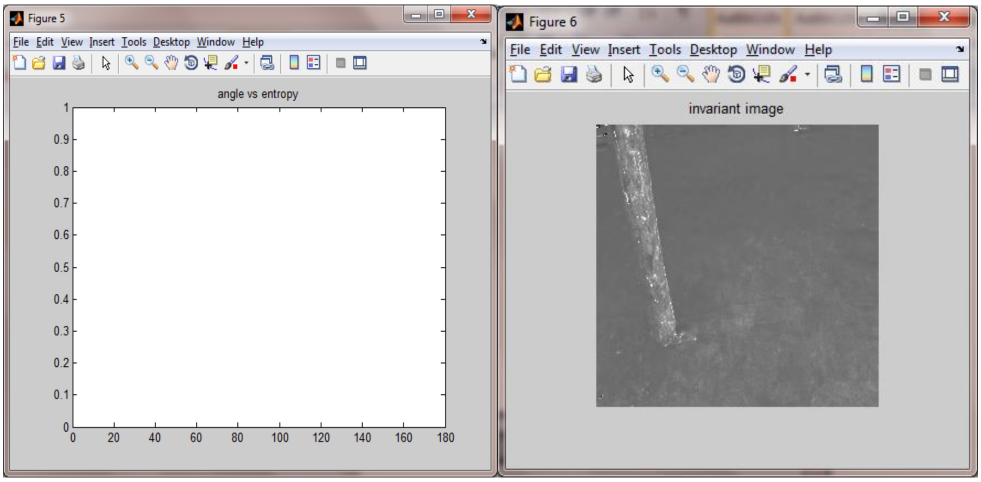

Fig 3 Entropy and Invariant Image

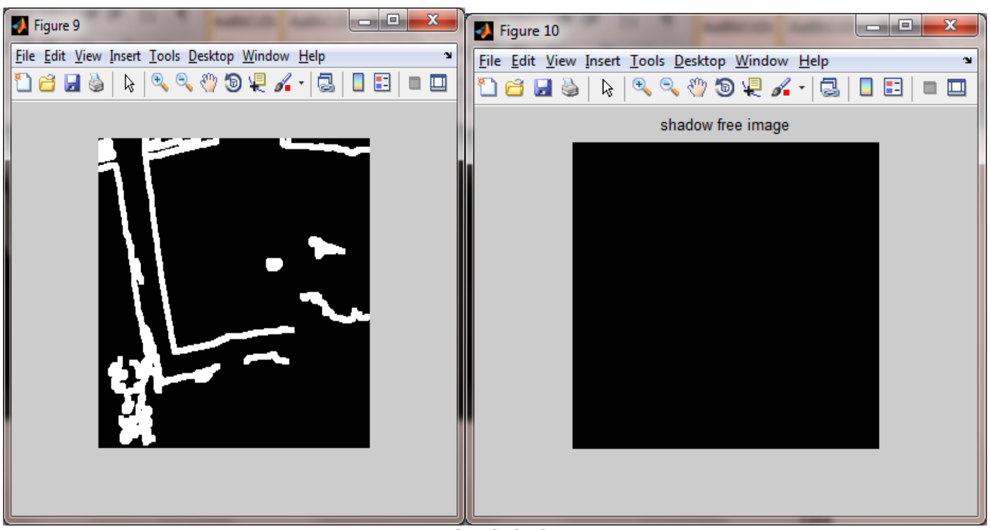

Fig 4 Segmented and Shadow Free Image

3.2.3 PERFORMANCE MEASUREMENT

The performance of images segmentation is measured by rand index measure and GCE (Global consistency Error). The following measurement is given for one sample images.

A. Global Consistency Error

The first parameter used for evaluating the proposed segmentation technique is Global Consistency Error (GCE). This measure is a Region-based Segmentation Consistency which is computed to quantify the consistency among image segmentations of various granularities. Let S and S' be two segmentations as before. For a given point x_i (pixel), consider the classes (segments) that contain x_i in S and S_0. These sets are denoted in the form of pixels by C (S, x_i) and C (S_o, x_i) respectively. The local refinement error (LRE) is then defined at point x_i as (Eqn. 2):

$$\text{LRE }(S, S', Xi) = \frac{|C(S, Xi) \setminus C(S', Xi)|}{|C(S, Xi)|} \qquad \text{(Eqn.2)}$$

Global Consistency Error (GCE) forces all local refinements to be in the same direction and is defined as (Eqn.3):

$$\text{GCE }(S, S') \frac{1}{N} \min\{\Sigma \text{ LRE}(S, S', Xi), \Sigma \text{ LRE}(S', S, Xi)\} \qquad \text{(Eqn.3)}$$

In this formula S is a ground truth value of original image and S' is a segmentation result of original image. Pixel value of S and S' values compared to this measure.

B. The Probabilistic Rand Index (PRI)

Rand Index is the function that converts the problem of comparing two partitions with possibly differing number of classes into a problem of computing pair wise label relationships. PRI counts the fraction of pairs of pixels whose labeling are consistent between the computed segmentation and the ground truth, averaging across multiple ground truth segmentations to account for scale variation in human perception. It is a measure that combines the desirable statistical properties of the Rand index with the ability to accommodate refinements appropriately. Since the latter property is relevant primarily when quantifying consistency of images segmentation results.

$$\text{PR(stets,\{sk\})} = \frac{1}{\binom{N}{2}} \sum \qquad \text{(Eqn.4)}$$

This measure (Eqn. 4) takes values in [0,1] – 0 when S and {S1,S2,……, SK} have no similarities and I when all segmentations are identical (i.e. when S consists of a single cluster and each segmentation in {S1, S2,…., SK} consists only of clusters containing single points, or Vice versa).

TABLE II
PERFORMANCE MEASUREMENT OF INPUT IMAGES USING GMM-EM & GSO-EM

Performance	*Algorithm*	
	GMM-EM	***GSO-EM***
Probabilistic Rand Index	*0.9234*	*0.9716*
Global Consistency Error	*0.0531*	*0.0514*

The Fig. 5 (Constructed from Table II) shows a performance measurement of PRI and GCE. The proposed approach is better results compare to existing methods.

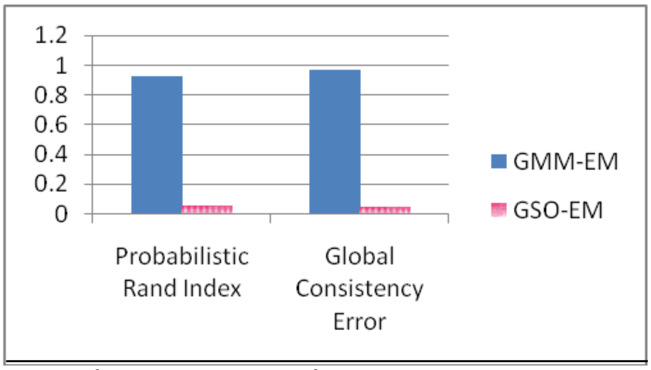

Fig.5 Performance Measurement of images using GMM-EM & GSO-EM

V. CONCLUSION

The EM (Expectation-Maximization) algorithm is a very popular model based clustering algorithm in many areas of application, in particular for clustering problems. GMM-EM algorithm may converge to a local maximum, depending on starting values. It is very sensitive to initialization. In order to eliminate local maxima problem of Gaussian Mixture Model-Expectation Maximization clustering algorithm, the idea of proposed method developed. Propose glowworm swarm optimization (GSO) instead of Gaussian Mixture Model. Hybrid glowworm swarm optimization (GSO) with Expectation-Maximization algorithm is shows a better result when compared to the GMM-EM. In future the image segmentation concept with glow worm is used to deskew the traffic image which is not in clear manner. The noise can be reduced with salt and pepper noise removal filter with Discrete wavelet Transform concept.

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