Improved Chan-Vese Image Segmentation Model for Visible-Infrared Image Fusion Using PCA

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ABSTRACT

The Chan-Vese method, which is based on level sets, principally employs region information for sequential evolutions of active contours of concern towards the object of interest, with the goal of minimising the fitness energy functional associated with the process. Orthodox gradient descent methods have been widely used to solve such optimization problems, but they have the flaw of becoming trapped in local minima and typically need an excessive amount of time to converge. This paper provides a Chan-Vese model with a modified gradient descent search strategy, dubbed the Delta-Bar-Delta learning algorithm, that reduces susceptibility to local minima and increases convergence rate. The suggested search method, when combined with the Chan-Vese model, outperforms classic gradient descent and previously proposed alternative adaption algorithms in this context, according to simulation findings. In this research, we present a novel and robust hierarchical GSA K-means clustering approach for segmenting fused images using the Principal Component Analysis method. Image fusion is a method of combining two or more pictures into a single image. The conventional Chan-Vese (CV) technique has been completely implemented to segment pictures using the iterative K-means clustering algorithm, which partitions an image into K number of groups. However, if the clusters' beginning points aren't chosen correctly, the approach frequently produces erroneous segmentation results. The Gravitational Search Algorithm (GSA) is used in this study to reformulate the issue and solve the new Chan-Vese picture segmentation formulation in such a way that it is invariant to the original cluster position. Extensive testing has been carried out on two-cluster and, in each case; the results of this proposed HGSA_K-means process show the improved achievement to segment the fused images..

Keywords *- Chan-Vese segmentation, Hierarchical based GSA_K-means (HGSA_K-mean), Image Fusion, Image segmentation, K-means algorithm, PCA, gradient descent search, level set method, Delta-Bar-Delta algorithm.;*

I. Introduction

The Chan-Vese (C-V) model [24] is used to segment active regions in images by wrapping around [24, 26] an initial active contour [27] along the steepest descent direction of energy using the gradient descent search (GDS) approach

[21]. The Chan-Vese image segmentation model is well-developed and often quoted. The Chan-Vese model formulation normally necessitates the solution of a partial differential equation (PDE) in order to acquire the contour route formed during the computation using level set formulation [24, 26]. As a result, the Euler-Lagrange equations are used to calculate the corresponding energy gradients. In this regard, the GDS technique is a useful tool since it can be used to minimise non-convex functions and is simple to apply because it involves the calculation of first order derivatives. However, it usually converges to the first local minimum it meets, with a modest rate of convergence. For the purpose of simplicity, we assume that the conclusions of relevant prior research are correct, namely, that the C-V energy fitting functional [24] is non-convex and non-unique in nature, and that it may have several local minima. obtained using the Euler-Lagrange equations. To avoid becoming trapped in local minima, this paper introduces a modified gradient search approach that assures better and faster convergence of the C-V algorithm towards its global minimum, resulting in correct segmentation results, when compared to well-known heuristic searches. The current study focuses on the effectiveness of a GDS version called the Delta-Bar-Delta rule (DBR), developed by Jacobs [23], which uses a learning parameter update rule in addition to the weight update rule in each iteration. Although the update rules are similar to those of the RPROP [21] technique, they are considerably different. To achieve even quicker convergence, we present a modified version of the DBR algorithm, dubbed MDBR, which uses a modified version of the DBR algorithm to update learning rate parameters and the momentum technique to update weights. The proposed Chan-Vese-MDBR algorithm has been used to segment both scalar and vector valued images, and its superiority has led to the development of the basic GDS model, as well as the recently proposed momentum (MOMENTUM), resilient back propagation (RPROP), and conjugate gradient (CONJUGATE) based learning methods. The following is the outline for this paper:. The proposed Chan-Vese-MDBR algorithm has been used to segment both scalar and vector valued images, and its superiority has been demonstrated in comparison to other popular level set based image segmentation algorithms, such as the well-known basic GDS model and the recently proposed momentum (MOMENTUM), resilient back propagation (RPROP), and conjugate gradient (CONJUGATE) based learning methods. The following is the outline for this paper: The basics of PCA-based image fusion are described in Section 2, and the C-V model is given in Section 3. In section 4, we go through the fundamentals of K-meanIn spite of robustness, IR image is not a good choice for identifying object because of change in environmental temperature sensitivity [6]. The motive of *image fusion* is to extract maximum number of information from input images i.e. VI and IR image. In between lots of pixel-level image fusion techniques (including Wavelet based image fusion, *Pyramid transform method* [7], *Weighted average method* [12], [13] *Principal Component Analysis* [10] is used.

Chan-Vese (CV) model is a very standard contour based approach in the field of *image segmentation*. This algorithm uses region-based information in its level set based formulation and tries to minimize an energy fitting functional associated with it by solving *Partial Differential Equation* (PDE). Though this model can segment internal objects very well, it still suffers from the problem of getting stuck at local minimum due to the fitness functional being a non-convex and non-unique one. Often different initial contours give varied segmentation results [11].

A unique method developed by Gibou and Fedkiw [1], [4] was developed that solves the CV model by using the *K-means clustering* algorithm. Although this method [3] was found to be much faster than the standard CV model and did not require the need for level sets, it still suffers from the problem of getting stuck at local minimum if the initial cluster points are not appropriately selected. This error increases as the number of classes into which the image has to be segmented increases.

In this work, evolutionary algorithms have been used in conjunction with the K-means algorithm to take care of this problem.

Successful implementations have been done using the Gravitational Search Algorithm (GSA) [3] to segment images into two-class, three-class and four-class effectively. The model is seen to outperform the model suggested by Gibou and Fedkiw [4].

The paper is organized as follows: In Section 2, basic CV model is described. This part presents the basic K-means algorithm and GSA algorithm. The proposed *HGSA_K-means* based CV model is proposed in Section 3. Section 4, demonstrates the segmentation results of VI-IR fused images using this proposed novel method. Section 5 is GSA algorithm. Section 6 Performance comparisons of this new robust model with the standard K-means based CV model have also been highlighted in this section. Performance and result carried in Section 7. Finally, Section 8 concludes the present work.

II. PCA Based Image Fusion

The main idea behind PCA is to convert a large number of uncorrelated variables (known as Principal Components) into a smaller number of correlated variables [12].

Principle Component Analysis is a mathematical technique for converting a large number of (potentially) linked variables into a smaller number of uncorrelated variables known as principal components. The original variables are linearly combined in each main component. Variables are not split into dependent and independent variables and are handled equally.The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible. Sometimes, the original data representation will be redundant for some reasons, i.e. some variables will have a variation smaller than the measurement noise and thus will be irrelevant, and sometimes the original data is too big that it cannot be expressed because of lack of time. By Solving Eigen value problem, PCA is performed. Principal Component Analysis is a way to reduce features to some extent. It was introduced by Karl Pearson in the year of 1901. PCA is considered an exploratory technique that can be used to gain a better understanding of the interrelationships between variables. It is a powerful process for extracting structure from possibly high dimensional data sets. It is a statistical technique which uses orthogonal transformation to convert a set of observations of possibly correlated variables called principal component. The number of original variables is greater than or equal to the number of principal components. The analysis is such a way that the first principal component always has the largest possible variance and the second principal component always having the second largest possible variance, and so on. If the data set is jointly normally distributed, it is guaranteed that principal components should be independent. Depending on the field of signal processing application, it is also called the discrete Karhunen-Loeve transform (KLT). It is readily performed by solving an Eigen value problem or by using iterative algorithms which estimate principal components. PCA can produce with lower-dimensional picture, a projection of this object when viewed from its most informative point of view [20].

By Solving Eigenvalue problem, PCA is performed. This is an orthogonal linear transformation, which transforms data to a new coordinate system. The greatest variance occupies the first coordinate. In the second coordinate, the second greatest variance lies [13]. First coordinate is termed as first principal component and so on. Covariance matrix (C) of data (D_t) is diagonalizable and defined as: [14]

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$$C = \frac{1}{m}\sum_{i=1}^{m} D_i D_i^T \qquad (1)$$

Where, $D_t \in \Re^n$ t = [1, 2, m] and $\sum_{i=1}^{m} D_t = 0$.

To spot on the features and reduce the noise, SVD based PCA fusion algorithm is applied both on VI and IR images.

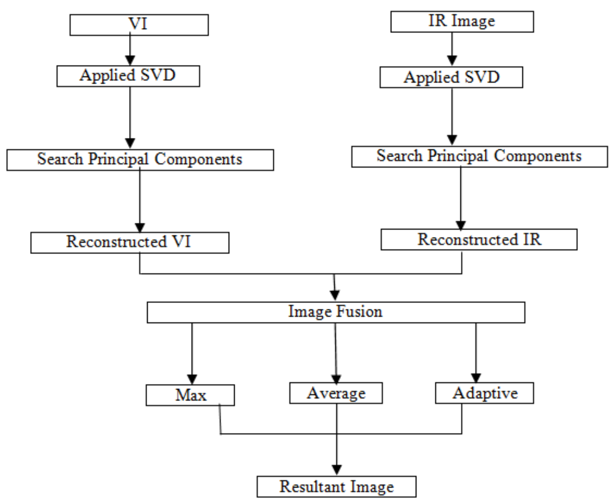


Fig. 1: PCA based image fusion

Figure 1 demonstrates the fusing algorithm using PCA. Figure 2 shows that VI and IR image is fused. And it can be shown that the fused image carries maximum information than these two inputs. Table 1 shows about the mutual information between fused image and input images.

` (a) (b)

(c)

Fig 2 (a) IR image, (b) VI, (c) Fused image

TABLE **1.** Mutual Information in Fused Image

Mutual Information between Visible image and Fused image (100X100)	100%
Mutual Information between IR image and Fused image (100X100)	81.83%

III. The CV Algorithm

The CV model [1] assumes that the image is formed by two regions of approximately homogenous intensities. The evolving contour C, tries to segment the image domain Ω into two regions i.e. Ω_1 and Ω_2 (inside and outside C). The fitting energy associated with the CV model in the level-set representation [1], [3] is given by:

$$F_{CV}(C_1, C_2, \phi) = \lambda_1 \int_\Omega \left|u_0 - C_1\right|^2 H(\phi)dxdy + \lambda_2 \int_\Omega \left|u_0 - C_2\right|^2$$
$$(1 - H(\phi))dxdy + \mu \int_\Omega \partial_0(\phi)\left|\Delta\phi\right|dxdy + v \int_\Omega H(\phi)dxdy$$

(2)

Where, ϕ is the level set function, H and ∂_0 are the Heaviside and one-dimensional Dirac functions and the constants C_1 and C_2 [1] are, respectively, the mean intensity values within the regions Ω_1 and Ω_2. H_z And ∂_z are the regularized versions of H and ∂_0 respectively. The other terms in Eq. (1) denote the length and area of the curve C [1]. The $F_{CV}(C_1, C_2, \phi)$ can be minimized with respect to ϕ by solving the gradient flow equation [11].

$$\frac{\partial \phi}{\partial t} = -\frac{\partial F_{CV}(C_1, C_2, \phi)}{\partial \phi} \quad (3)$$

The PDE that needs to be solved to evolve the level set function [8] is given by:

$$\frac{\partial \phi}{\partial t} = \partial_z(\phi)\left[-\lambda_1(u_0 - C_1)^2 + \lambda_2(u_0 - C_2)^2 + \mu div\left(\frac{\nabla \phi}{|\nabla \phi|}\right) - v\right] \quad (4)$$

IV. K-means Clustering Algorithm

The main concept of clustering is to make a group of similar data in to cluster that comprises of almost similar members [5]. All the members in a group are different in comparison with other members in that group. K indicates the number of clusters and the value of K is positive. In this work, the value of K is set to 2. The training of this algorithm completes, when there is no such change in any cluster.

Table 2. K-means clustering Algorithm [15]

1. Inputs: number of K and dataset for intrusion detection.
2. Outputs: Set of clusters K whish minimize square-error criterion
3. Initialization: Select K elements for data randomly and initialize K clusters.
4. Repeat step 2, when number of cluster structure changes.
5. Cluster determination: To which source data belongs. Add element to the cluster with minimum (Using Euclidean distance) Distance (P_i, Q_i)
6. Mean calculation: Mean of cluster. Using step 3, change in cluster centroid to mean obtained.

V. GSA

GSA optimization algorithm is based on law of gravity [16]. Newton defined it as, "Every particle in the universe attracts every other particle with a force that is directly proportional to the product of the masses of the particles and inversely proportional to the square of the distance between them."

System having G masses in which the j^{th} mass's position is defined as:

$$S_j = (s_j^1, s_j^2, \ldots\ldots, s_j^d, \ldots\ldots, s_j^g),\ j = 1, 2, \ldots., G \quad (5)$$

where, s_j^d is j^{th} mass's position in d^{th} dimension and in the search space, g is total numbers of dimensions. The calculated mass of each agent:

$$O_j^t = \frac{fit_j(t) - worst(t)}{\sum_{k=1}^{G} fit_k(t) - worst(t)} \quad (6)$$

Where, O_j^t is the mass and $fit_j(t)$ is fitness value of agent j at t. And $worst(t) = \max fit_k(t),\ k \in \{1, \ldots, G\}$ (7)

Table 3. GSA K-means approach Algorithm [17]

1.Scaled dataset 2.For K =2. Using Euclidean distance Centroid determination of each cluster 3.For producing 2 centroids 4.Determine number of agents Define G' constant Compute fitness function Stopping condition is [0,100] 5.Resultant GSA K-means

VI. Proposed HGSA_K-means based CV model

Proposed GSA-K-means based CV model is presented here. In this approach, the fitting functional energy of the CV model is used to assign masses to the agents in the search space. The algorithm is described below:

The basic method is as follows: Suppose the motive is to segment the image into three-parts. After the first step, the image has been divided into two clusters – one object and its complementary background. The intensity variation across the captured object and its complementary background is compared, and the one having the larger variation becomes the target for the next step of the hierarchy. The intensity with the smaller intensity variation is not used for the next step of segmentation. Thus the image will be divided into three distinct parts using the modified proposed CV model. Figure 3 describes the Binary tree structure of hierarchical segmentation algorithm.

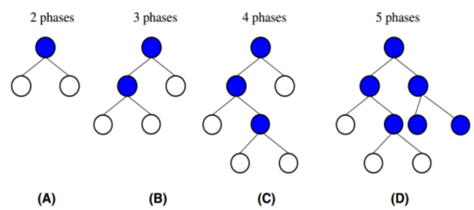


Fig.3. Binary tree structure of hierarchical segmentation

The procedure is represented as a binary tree with the regions being represented as nodes and children of each node being created by a single step of the two-cluster GSA_K algorithm. The set of the leaves of this tree constitutes the final segmentation of the original image into a number of clusters equal to the number of leaves.

VII. The GDS method and the Delta-Bar-Delta algorithm

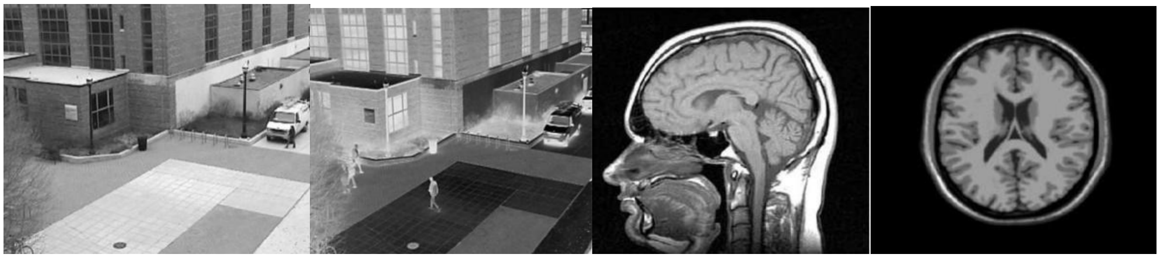
In the steepest descent implementation of the traditional adaptation, the GDS moves in the negative direction of the gradient, locally minimizing the cost function. The basic GDS algorithm in the form of a standard line search optimization method [21].

The modified GDS method highlighted in our work shows another way in which the descent direction and length can be optimally calculated for faster and better convergence than the basic GDS model. Some new methods such as momentum (MOMENTUM), Resilient Back propagation (RPROP) [21] and conjugate gradient (CONJUGATE) [22] have already been proposed which show significant improvement over the basic GDS algorithm.

Jacobs developed an improved learning algorithm, called the Delta-Bar-Delta (DBR) algorithm, a modified version of the Delta-Delta algorithm, where the learning rule comprises both a weight update rule and a learning rate update rule [23].

VIII.Implementation and Results

This proposed method is implemented in Matlab (version R2013a, using Core 2 Duo CPU, 2.66 GHz, 3GB RAM). In this work, hierarchical setup is used to continuously segment the images following the Chan-Vese Image segmentation model. For this approach, HGSA_k-means clustering based CV model is used for image segmentation. This work follows directly from the previous work.



(a) (b) (c) (d)

Fig.4. Sample PCA fused images (a, b, c, d) on which the experiment has been done

Table 4. Two-class segmentation of the sample images

Image		G-F		HGSA-k		Image		G-F		HGSA-k	
		C1	C2	C1	C2			C1	C2	C1	C2
(a)	1	21	159	21	159	(c)	1	35	137	35	137
	2	21	159	21	159		2	71	201	35	137
	3	14	151	21	158		3	20	114	35	137
	4	47	192	21	159		4	35	137	35	137
	5	14	150	21	159		5	35	137	35	137
(b)	1	19	146	19	146	(d)	1	5	125	5	125
	2	19	146	19	146		2	41	175	5	125
	3	64	225	19	146		3	1	109	5	125
	4	19	146	19	146		4	42	235	5	125
	5	65	228	19	146		5	5	126	5	125

For, G-F model, no of iterations of k-means = 125, for proposed model, k-means-iteration = 5, N = 5, max-it=5

Table 4 gives the cluster values (C1 and C2) obtained from the G-F and GSA-k model for five test runs on the sample images of figure 4. It is quite evident from the results obtained that the values of C1 and C2 from the G-F model varies quite a bit, whereas, for this proposed GSA-k model, C1 and C2 almost always converge to the same values. This has been further illustrated in figure 4 which highlights the standard deviation of the data obtained for Table 4.

Our proposed algorithm has been used to segment different sample images both for scalar and vector-valued cases. The performances of our proposed method are compared with the traditional GDS algorithm, and the recently proposed MOMENTUM, RPROP [21] and CONJUGATE methods [22] based adaptation of level sets for image segmentation. The lower the fitness function reached indicates the superiority of a learning algorithm in approaching the optimum and the lower the computation time taken indicates better convergence rate achieved. In addition, the segmentation results are also compared with the ground truth to calculate the segmentation performance by using the Dice Coefficient (DC). Fig. 5 and fig.6 show the segmentation performance of a sample gray image by the above mentioned competing algorithms. The implementation is done such that, if the fitness function remains unchanged for 50 iterations, the algorithm stops. From fig. 2, the MDBR based method is shown to be the fastest while it also achieves accurate segmentation results. Table 5 presents the corresponding comparative performances, in quantitative form. From Table 1it can be easily observed that MDBR algorithm achieves the lowest fitness function value, consumes least computation time and reaches the minimum fitness function value within the fewest number of iterations. The DC value achieved is also quite competitive, greater than 0.99, compared to the other adaptation algorithms. Next, fig. 7 and fig. 8 show corresponding segmentation performances for a color images. Here also, MDBR could successfully segment the given image within the quickest time, using fewest numbers of iterations. The efficiency of our proposed MDBR algorithm can be further illustrated by several examples of gray-scale and color image segmentations shown in fig. 9 and fig. 10.

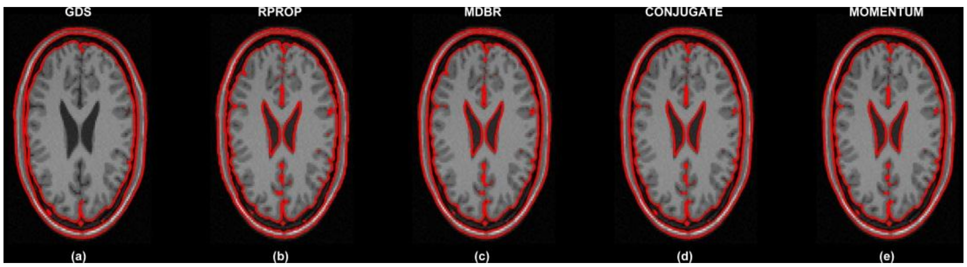


Fig.5**.** Samplegray image segmentation by GDS and its variants.

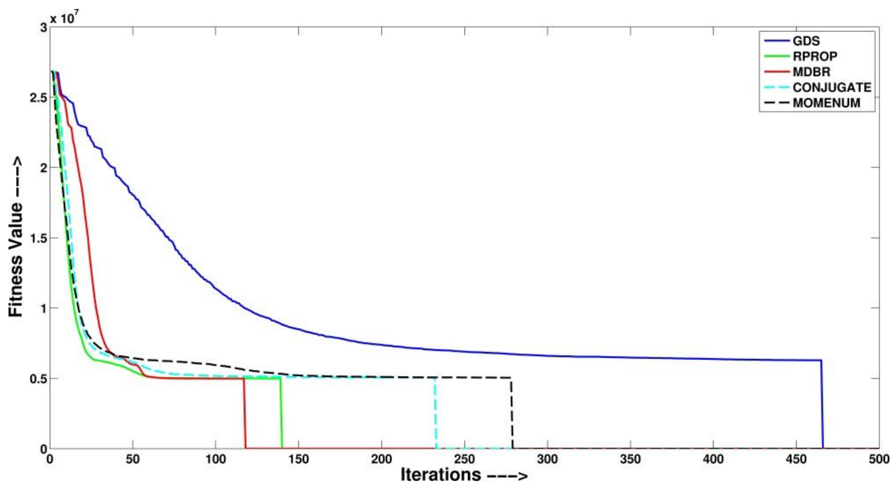


Fig.6**.**The plot of the fitness function with number of iterations n for the image segmented in fig. 1.

Table 5. Performance comparison for the different segmentation methods for the sample image of fig. 1.

Method	Number of iterations	Time taken (in seconds)	Fitness function value reached ($\times 10^6$)	DC
GDS	465	2.21	6.2863	0.9534
RPROP	139	0.74	4.9889	0.9958
MDBR	125	0.64	4.9822	0.9916
CONJUGATE	232	2.08	5.0438	0.9957
MOMENTUM	278	1.34	5.0468	0.9958

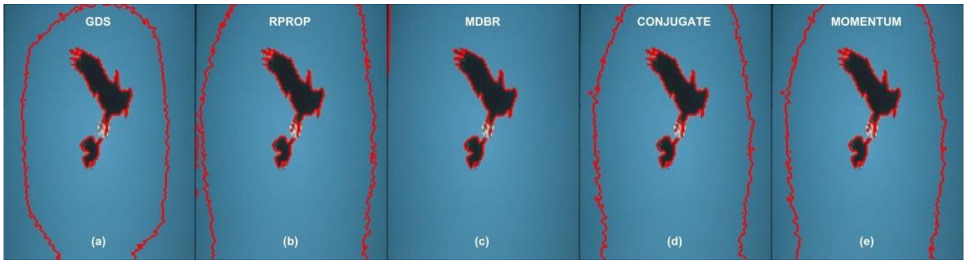


Fig.7.Sample color image segmentation by GDS and its variants.

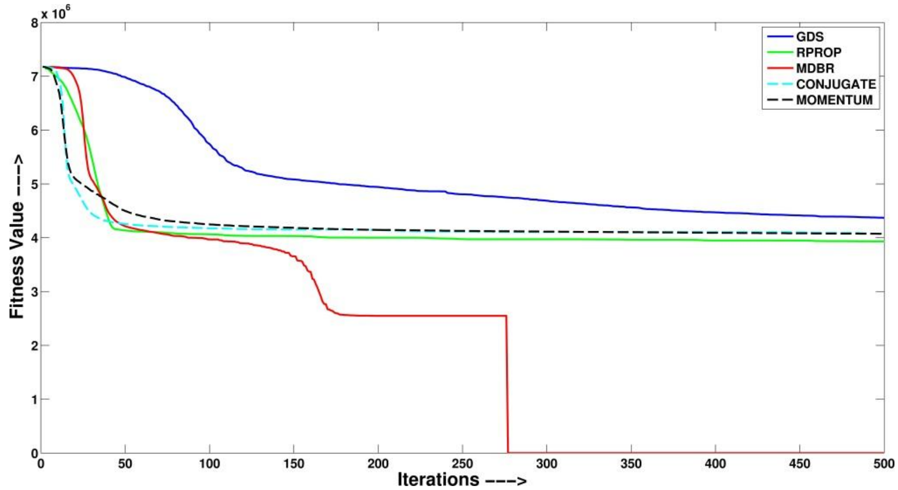


Fig.8.The plot of the fitness function with number of iterations n for the image segmented in fig.3.

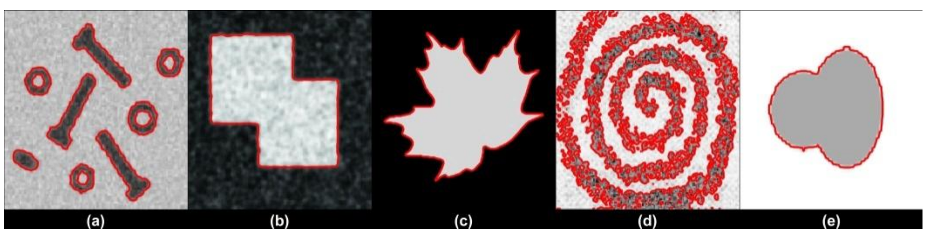


Fig.9.(a)-(e) Grayscale image segmentation and their segmentation contours marked in red. The DC values, number of iterations and computation time (in seconds) for each image are: (a) 0.9610, 148, 0.94, (b) 0.9979, 117, 0.61, (c) 0.9995, 144, 0.74, (d) 0.9607, 154, 0.95, and (e) 0.9996, 113, 0.58.

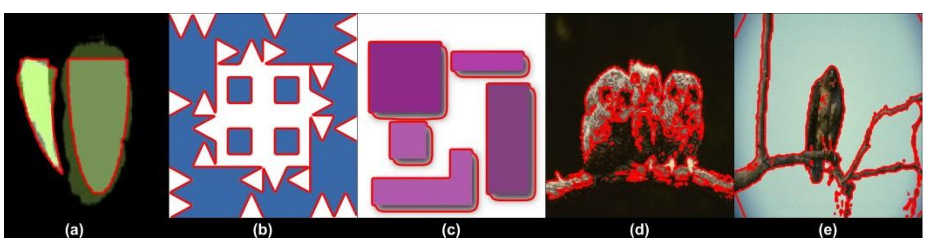
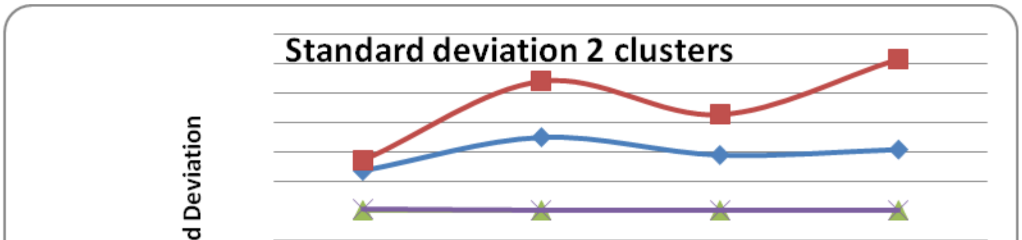


Fig.10.(a)-(e) Colour image segmentation and their segmentation contours marked in red. The DC values, number of iterations and computation time (in seconds) for each image are: (a) 0.9995, 168, 1.68, (b) 0.9970, 113, 1.16, (c) 0.9004, 126, 1.19, (d) 0.9652, 225, 2.52, and (e) 0.9644, 239, 2.51.

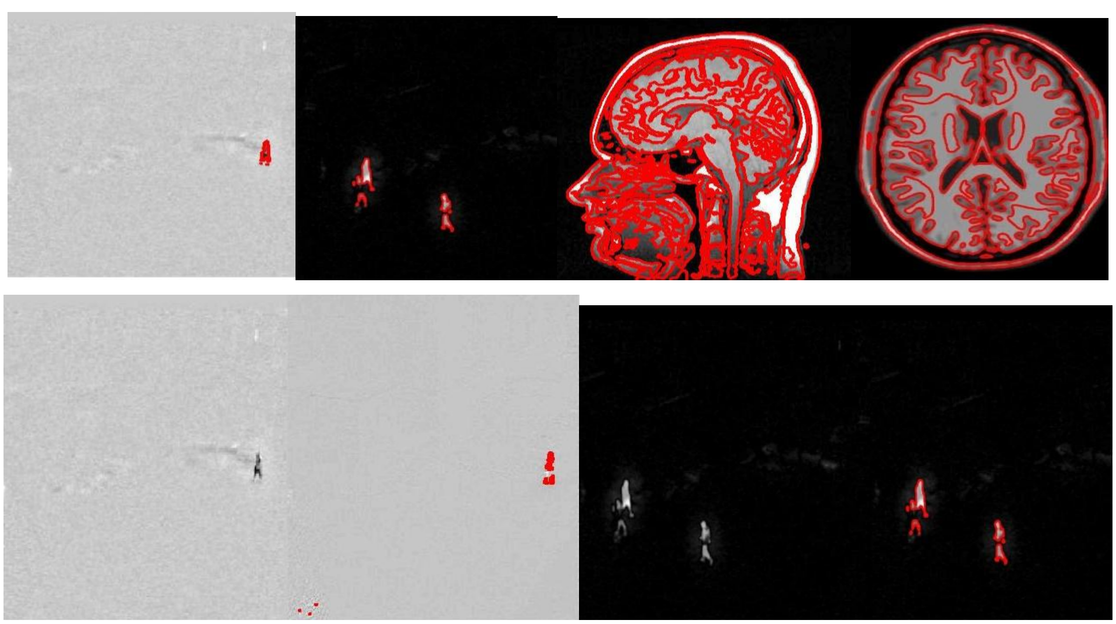


	(a)	(b)	(c)	(d)
SD_GF_c1	13.6491758	24.92388413	18.92617235	20.78942039
SD_GF_c2	17.19592975	44.10442155	32.74446518	51.60426339
SD_GSA_K_c1	0	0	0	0
SD_GSA_K_c2	0.447214	0	0	0

Fig.11: Standard Deviation of the obtained data for segmentation of image into two clusters. As can be seen clearly, for this robust proposed method SD is close enough to be zero, hence, showing good convergence to the global minimum value

Finally, Figure 12 gives the segmentation result of this HGSA_K-means proposed algorithm when applied on the sample images of figure 4 in its 2-class implementation. All of the images are of size256x256 [18], [19].

Here, it is also reported about the progression of error while detecting the clusters in the image for segmentation. As it is evident from the above observation that the percentage of error increases as the number of clusters to be increased.



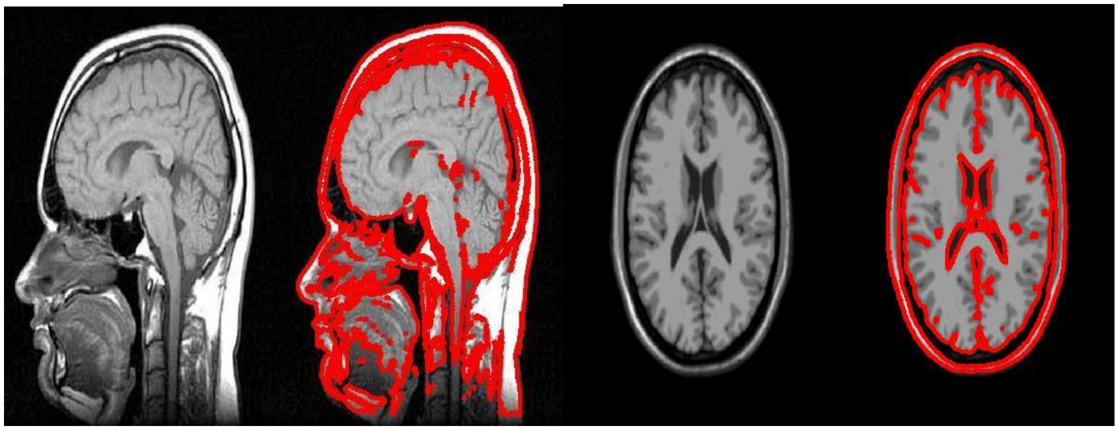
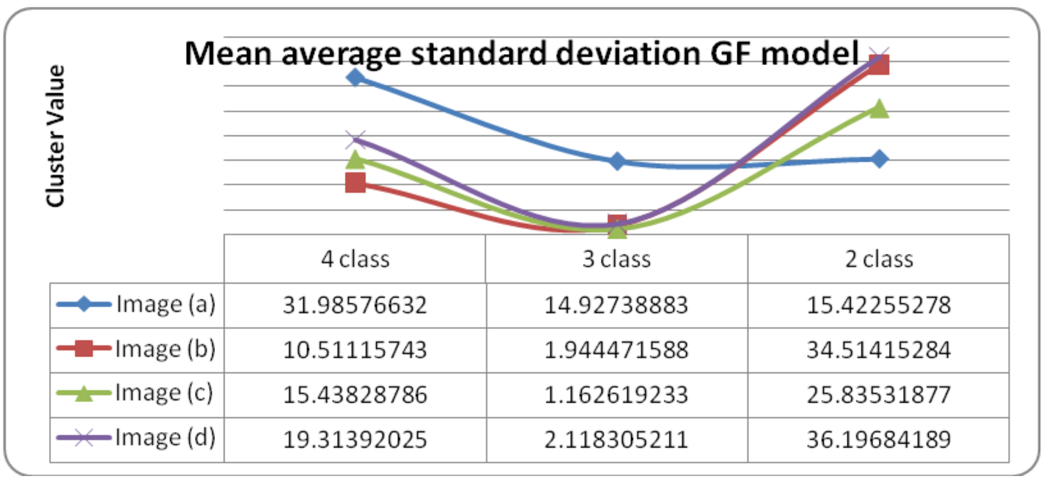
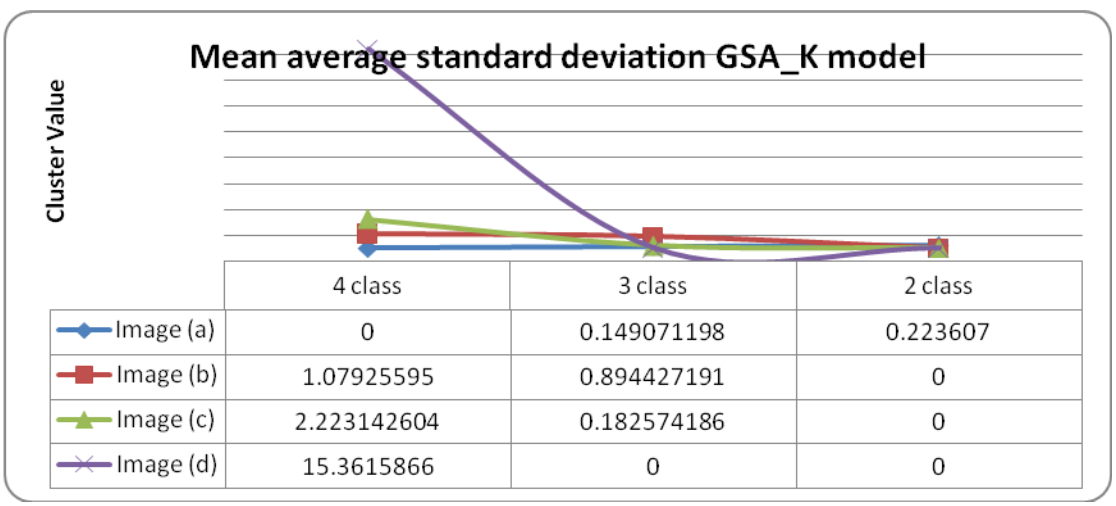


Fig. 12: Two-class segmentation of the sample images [19] of figure: 4 by this proposed algorithm. Here, k-mean-iteration=5, max-it=5; and N=5. Image size is of 256x256. Time taken 0.79 seconds



	4 class	3 class	2 class
Image (a)	31.98576632	14.92738883	15.42255278
Image (b)	10.51115743	1.944471588	34.51415284
Image (c)	15.43828786	1.162619233	25.83531877
Image (d)	19.31392025	2.118305211	36.19684189

Fig. 13: Mean average standard deviation of the GF model. Here the deviation from the nominal value is quite high which shows that this method often diverges from the global minimum value



	4 class	3 class	2 class
Image (a)	0	0.149071198	0.223607
Image (b)	1.07925595	0.894427191	0
Image (c)	2.223142604	0.182574186	0
Image (d)	15.3615866	0	0

Fig. 14: Mean average standard deviation value from the proposed model. The deviation is relatively kept under check for all the class divisions for image (a)-(c). However, for the image (d), the deviation is quite high for the 2-class image segmentation by this proposed model

As we can see from the above observations that the clustering algorithm's performance decreases steadily as the number of clusters is increased. In proposed HGSA_K method, the error percentage is very low for the 2 class cases. So it seems prudent enough to convert the multi-cluster problem into a subsequent iterative based 2-cluster problem so as to decrease this error.

The advantages of proposed method are as follows:

1. No need for level sets.
2. Good convergence towards the global minimum.
3. Faster method than the normal CV model.

At each step, only the relevant parts of the image is being used for clustering based segmentation, thereby, preventing lots of redundant calculations and saving computation time.

IX. CONCLUSION

By employing the CV model in both two-phase and multi-phase implementations, the proposed HGSA K-means CV method is successful in segmenting pictures. The convergence of the cluster values to the global minimum is virtually always assured due to the connection of the normal K-means clustering method with the GSA algorithm.

To get good segmentation results, the C-V model often employs the conventional GDS approach to develop the active contour. The MDBR algorithm, a modified form of the Delta-Bar-Delta method, is presented in this study as an enhanced level set adaptation methodology. When compared to alternative learning algorithms such as basic GDS, RPROP, MOMENTUM, and CONJUGATE, extensive segmentations of both scalar and vector-valued pictures indicate that our technique consistently achieves lower fitness function values and takes less adaption time. In future study, we want to look at using the second order partial derivatives of the cost function to speed up and improve the active contour model's convergence.

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