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Segmentation of Satellite Images for Damage Assessment::Natural Calamity Images Perspective

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Abstract: *Image processing has been proved to be an effective tool for analysis in various fields and applications in engineering. Among the segmentation methods, image thresholding technique is one of the most well-known methods due to its simplicity, robustness, and high precision. The primary objective of image processing is to optimize visualization of particular thematic data set. The type of image processing method and strategy is broadly influenced by the application and its objectives. Use of satellite imagery has become an integral aspect in planning of multiple domains which include disaster management and analysis of natural calamity images. In this paper an attempt is made to develop an efficient segmentation method for satellite images of natural calamity images for damage assessment using a hybrid algorithm EGA & E-BFOA and proved to be an efficient to evaluate index parameters for damage assessment. Disaster management is one such area where the changes brought in by the disaster has to be assessed for effective rescue and rehabilitation.*
Keywords: *EGA & E-BFOA, Natural Calamity images, Image segmentation*

I. Introduction

Extraction of very minute details from Natural Calamity (NC) images is a challenging task for meteorological department of the Government. The current research is attempts to investigate the better method for segmentation of NC images and seems hopeful results have obtained by Enhanced Genetic Algorithm (EGA) & Enhanced Bacterial Foraging Optimization Algorithm (E-BFOA). Visual image interpretation can be defined as the examination of images for the purpose of identifying objects and judging their significance. Human beings are well prepared to examine images, as our visual system and experience equip us to discern distinctions in brightness and darkness, to distinguish between various image textures, to perceive depth, and to recognize complex shapes and features. Disaster management can be categorized in four phases: mitigation, preparedness, response, and recovery. Within the disaster management cycle, possibly the most critical and challenging phase is the response phase since the situation after the event is uncertain .The overall cost of a disaster after the event, both in terms of economic damage and fatalities, is minimized when the response phase is quickly and efficiently managed. Effective management of the response phase requires accurate and timely damage assessment. Damage assessment through field survey has high accuracy; however, field survey requires extensive time and man power, especially if the area affected is large Moreover, because of ground interruptions after the disaster, transportation of survey crew and the timely communication of detailed damage assessment by field surveying are challenging. Analyzing the extent of disaster using satellite imagery is an effective and viable option in damage assessment and disaster mitigation. To have effective assessment of damages the images have to be analyzed through better image processing techniques. The primary requirement for image analysis is to have effective and efficient image segmentation techniques. Image segmentation is required as a very important and fundamental operation for significant analysis and interpretation of images. For practical purposes, it must be necessary to complete damage detection as quick as possible after the occurrence of disasters in order to make use of the detection result in emergency management.

II. Earlier Work

Attempting to replicate capabilities using computer programs, it becomes obvious how powerful human‘s abilities are to derive this kind of complex information [1]. Among the first studies that applied these images for post-earthquake damage assessment was a study carried out by Saito et al [2] following the 2001 Gujarat (India) earthquake. Saito et al. [3] used visual interpretation to determine different levels of damage according to the European Macro-seismic Scale (EMS 98) from Ikonos image. This study revealed that damage sustained to high-rise building is easier to identify compared to that to low-rise buildings, with the exception of middle to high-rise buildings with soft storey collapse. Single storey buildings that had totally collapsed were clearly visible. The 2003, Boumerdes (Algeria) earthquake was the first major earthquake for which very-high-resolution satellite imagery has been extensively used for assessing damage severity [3] [4]. Yamazaki et al. [5] visually interpret damage level 3 to 5 on EMS 98 using change detection on Quick-bird images. Visually interpreted damage survey using satellite images are likely to underestimate rather than overestimate the damage [4][5]. Similar studies were conducted following the 2003 Bam earthquake. Yamazaki et al. [5] used visual inspection to determine different grades of building damage from Quick-bird images. In order to assess the accuracy, the field data collected by Hisada et al [6] was used. The comparison revealed that the best accuracy was achieved for the complete damaged buildings (EMS 98, Grade 5) and for the slightly and moderate damaged buildings (EMS 98, Grade 1 and 2). After the 2006 Yogyakarta Earthquake, the International Charter of Space and major disaster had been activated to provide satellite images of the severely damaged areas. The preliminary maps of damage distribution published on the internet by UNOSAT are a good example for rapid damage estimation by visual inspection [7]. The spectral and textural characteristics of rubble piles or damaged buildings vary significantly from intact building roofs and can therefore be detected from optical satellite images. Most change detection algorithms operate pixel-wise. Image differencing and image rationing are the most applied algorithms for post-earthquake damage assessment [8]. Using image differencing, co-registered images are subtracted. The co-registration of the images is an essential pre-processing step in order to avoid misaligned pixels. Pixel based change detection techniques have been employed for building damage detection in various studies. Olgun [9] detected building damage from SPOT images after the 1999 Kocaeli earthquake using image differencing, image rationing and the normalized differenced vegetation index (NDVI) C.J. Van Waste [10]proposed remote sensing and GIS for natural hazards assessment and disaster risk management. Norman Kerle [11] assessed the accuracy of Satellite-based damage mapping following the 2006 Indonesia earthquake. Quan-guo Li [12] analyzed spatial information technology in the investigation and identification, distribution and law, risk evaluation and zoning, loss assessment, forecasting and dynamic monitoring of the application in natural disasters. Kazuya Kaku [13] presented the vision and stepwise approach of establishment and continuous improvement of the regional program Sentinel Asia initiative.

Satellite imagery analysis can be very broadly be classified in to two namely, pixel based image classification and object based image classification. Classical pixel-based image classification automatically categorizes all pixels in an image into land cover classes or themes in a pixel by pixel manner. Usually, multispectral data are used and the spectral pattern present within the data for each pixel is used as the numerical basis for categorization. The classical pixel-based methods are minimum-distance/nearest neighbor, parallelepiped and maximum likelihood classifiers. Among the segmentation methods, image thresholding method is one of the most well-known methods due to its simplicity, robustness, and high precision. Thresholding method can be classified into two categories: The first category includes methods that find the optimal threshold using image histogram analysis. The second category includes methods that find the optimal threshold using objective functions. The goal is to find the exact threshold in images but the obstacle of all these methods is the complexity of calculation. Image Segmentation techniques can be classified [14] into the following categories: Edge-based, Threshold based, Region-based, Neural Network based, Cluster-based, and Hybrid [15] Image segmentation based on thresholding is one of the oldest and powerful technique, since the threshold value divides the pixels in such away that pixels having intensity value less than threshold belongs to one class while pixels whose intensity value is greater than threshold belongs to another class [16]. Segmentation based on edge detection attempts to resolve image by detecting the edges between different regions that have sudden change in intensity value are extracted and linked to form closed region boundaries. Region based methods [17], divides an image into different regions that are similar according to a set of some predefined conditions. The Neural Network based image segmentation techniques reported in the literature [18] can mainly be classified into two categories: supervised and unsupervised methods. Supervised methods require expert human input for segmentation. Usually this means that human experts are carefully selecting the training data that is then used to segment the images. Unsupervised methods are semi or fully automatic. User intervention might be necessary at some point in the process to improve performance of the methods, but the results should be more or less human independent. An unsupervised segmentation method automatically partitions the images without operator intervention. However, these architectures might be implemented using application specific a priori knowledge at design time, i.e. anatomical, physical or biological knowledge. Clustering is an unsupervised learning technique, where one needs to know the number of clusters in advance to classify pixels [19]. A similarity condition is defined between pixels, and then similar pixels are grouped together to form clusters.

For the current research the images are sourced from the open source data base provide by Digital Globe, a satellite imaging firm. These images are provided as a part of their effort towards rescue and rehabilitation in the aftermath of the Nepal earthquake. The images:: Image.1, Image.2 and Image.3 sourced from Digital Globe are obtained from Worldview Satellites and that are placed at an altitude of 617 KM. These images have a multi spectral resolution of 1.2 Meters. The size of the images used in this research work is as given below.

- Natural Calamity Image.1 : 748 * 421
- Natural Calamity Image.2 : 988 * 741

- Natural Calamity Image.3 : 748 * 421

III. Proposed Method

In the current research work a hybrid method comprising the application of Genetic Algorithm (GA) and Bacterial Foraging Optimization Algorithm is employed. The Genetic Algorithm (GA) is used to define the BFOA parameters. In the current research, the researcher has employed Enhanced Genetic Algorithm (EGA) to optimize the segmentation process. The most critical problem for the traditional genetic algorithm is the loss of diversity. Generally, a genetic algorithm does not verify if some elements of the population are repeated. If a control of diversity is not implemented, the best solutions become dominant in the new populations, leading to a loss of diversity [20]. This problem is partially solved using two strategies:

1. Using more and more elevated mutation rates and

2. Verifying and eliminating the repeated solutions and carrying out a recombination of the population, which normally involves randomly generating new solutions.

This last proposal is rarely used because it is computationally expensive and the substitution process is not efficient. Therefore, the loss of genetic diversity is one of the biggest problems of traditional genetic algorithms. The researcher has addressed this issue of imparting diversity and has proposed an Enhanced Genetic Algorithm (EGA) approach.

The steps involved in the implementation of the proposed Enhanced Genetic Algorithm (EGA) can be envisaged as:

Specifying the parameters like population size, recombination rate, mutation rate

- Setting up the initial population choice of selection by tournament
- Implementing the process of selection by tournament and choosing only two generating solutions
- Implementing recombination and preserving only one offspring
- Implementing mutation in the preserved offspring
- Deciding whether the improved offspring can enter the population, substituting an element after verifying the substitution test
- Checking for stopping criteria, if the stopping criterion is not satisfied, then returning to step or else ending the process and the present the results of optimization.

The Enhanced Genetic Algorithm is used to find near optimal thresholds by maximizing the intra-class variance and minimizing the inter-class variance. Initially the histogram of an image is found and the histogram gives information that will be used for evaluating fitness.

In the proposed approach the following function, F is used as a measure of the fitness of threshold i

$$F\ (\text{fitness},\ i) = S_{\text{between objects}} / S_{\text{within objects}} \qquad \text{Eq.1}$$

The variance between objects, $S_{\text{between objects}}$, is given as:

$$S_{\text{between objetcs}} = \sum_i P_i \left(m_i - m_g\right)^2 \qquad \text{Eq.2}$$

And the variance S within the objects is given as

$$S_{\text{within objetcs}} = \sum_i \frac{S_i}{S_g} \qquad \text{Eq.3}$$

Where m_i is given as:

$$m_i = \sum_{thsldi}^{thsldi+1} x *= \hbar\text{ist}\ (x) \qquad \text{Eq.4}$$

The probability of segment i, Pi, is given as:

$$P_i = \sum_{thsldi}^{thsldi+1} \hbar\text{ist}\ (x) \qquad \text{Eq.5}$$

And the global mean of the image is given as:

$$m_g = m_i \times m_g$$

The variance in segment i is given as:

$$S_i = \sum_{thsldi}^{thsldi+1} (\hbar\text{ist}\ (x) - m_i)^2 \qquad \text{Eq.6}$$

And the global variance of the image is given as:

$$S_g = \sum_x \hbar\text{ist}\ (x) \times (x - m_g)^2 \qquad \text{Eq.7}$$

Miis the mean of pixels in the segment whose threshold value is $thsldi$andthe variance in segment i is given as S_i and $S_g$global variance of the image. Swarm intelligence, as an emerging intelligent computing technology, has been the focus of attention of artificial intelligence researchers. In 2002, Passino who was inspired by the social foraging behavior of Escherichia coli, proposed the Bacteria Foraging Optimization Algorithm, which has become a new member in the coveted realm of swarm intelligence [21].

With reference to the Enhanced Genetic Algorithm, the parameters that are used for implementing the EGA are listed in the Table. A: given as below.

Table.1: Control Parameters for Enhanced Genetic Algorithm

Initial Population	20
Elite Count	2
Type of Selection	Tournament
Cross over Probability	0.2
Type of Mutation	Adaptive Feasible Mutation
Mutation Rate	0.8
Number of iterations	100

Since its inception, BFOA has drawn the attention of researchers in different fields of knowledge, in terms of its biological motivation, and elegant structure. The algorithm has been instructed in optimal search by swarm intelligence, which is produced by cooperation and competition among individuals within groups. It has advantages, such as parallel distributed processing, insensitivity to initial value, and global optimization. In the process of foraging, E. coli bacteria undergo four stages, namely, chemotaxis, swarming, reproduction, and elimination and dispersal. In search space, BFOA seek optimum value through the chemotaxis of bacteria, and realize quorum sensing via assemble function between bacterial, and satisfy the evolution rule of the survival of the fittest make use of reproduction operation, and use elimination-dispersal mechanism to avoiding falling into premature convergence [21].

In this research work EGA is exploited to choose the threshold and also to fine tune the BFOA parameters. The implementation of the segmentation approach can explained through the following steps.

- Using EGA to choose the threshold of that particular image needed to be segmented by optimizing the objective function as describe before.
- Defining the parameters of BFOA based on the fitness function evaluation through EGA.
- Initiating the process of chemotaxis by starting with a group of four neighboring pixels with an assumption that they are from the same region
- Checking the fitness value, for checking the fitness value, central pixel of first group is checked against the central pixel of second group. The L*a*b values of both the pixels are considered for computed the CMC distance between the pixels.
- If value computed is less than the threshold value then they belong to the same segment and their neighboring remaining 8 pixels also do belong to the same segment.
- If the value computed is greater than threshold then reproduction takes place in which first group of pixels is divided in to two, making two pixel heads and check their fitness. If again the value is less than threshold, then they belongs to the same segment otherwise elimination & dispersal takes place.

The different pixel group will be eliminated from this segment & is dispersed to the next segment. This is repeated process is repeated for the entire image

The Steps involved in BFOA as such is given as below.

Step 1: Initialization of BFOA parameter through EGA
Step 2: Evaluate Fitness in the form of Objective Function.
Step 3: Initiate Chemo taxis Tumble / Run
Step 4: Check for End of Chemo taxis if yes go to Step5 otherwise go to Step 2
Step 5: Start Reproduction
Step 6: Check if it is end of Reproduction as initiate, if yes go to Step 7 else go to Step 2
Step 7: Initiate Elimination and dispersion
Step 8: If end of Elimination and dispersion then go to next Step, or else go to Step 2
Step 9: Provide the optimized result.

BFOA is coded using Matlab and the initial parameters of algorithm used in this research work are as mentioned below. These parameters are adjusted with the help of EGA during the process of segmentation.

The number of bacteria : 20
Number of chemotactic steps : 10
Limit length of a swim : 4
The number of reproduction steps : 4
The number of elimination-dispersal events : 2
The number of bacteria reproductions : 2
The probability that each bacterium will be eliminated /dispersed: 0.2

IV. Results & Discussion And Performance Measures

The results of the proposed method are illustrated using satellite images of recent Nepal earthquake. The images are courtesy of Digital globe. The April 2015 Nepal earthquake (also known as the Gorkha earthquake) (22) killed more than 8,800 people and injured more than 23,000. It occurred at 11:56 NST on 25 April, with a magnitude of 7.8 .The destruction caused in the densely populated Katmandu was intense. With its unique topography and clustered layout of the city pose researchers with a daunting task in assessing damage. The fig.3.a , fig.3.b, fig.4.a , fig.4.b,fig.5.a, fig.5.b illustrate the extent of the damage caused to different structures.

Figure 3.a: Image.1 before earthquake

igure.3.b. Image.1 after earthquake

Figure.4.a: Image.2 before earthquake,

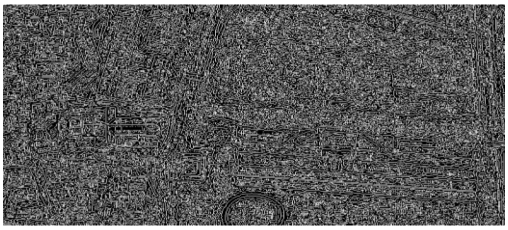
Figure.4b: Image.2 after earthquake

Figure.5.a: Image.3 before earthquake,

Figure.5.b: Image.3 after earthquake

The histogram profile of the images serves to give a trend in distribution of intensity values and help in the initial stages of the choosing the threshold.Edge detection plays a crucial role in identifying individual elements in an image. Detection of edges in an image is a very important step towards understanding image features. Edges consist of meaningful features and contained significant information. The fig.6.a,b & c describes the edges as extracted using Prewitt operator for different satellite images from pre-earthquake and fig.7.a,b & c post-earthquake event.

Figure 5.a: Satellite Image of region in Katmandu: Pre Quake



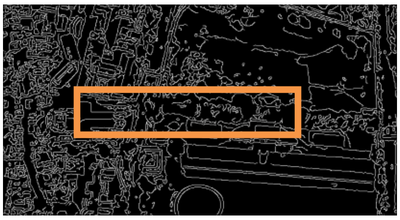


Figure.5. b Figure.5.c:

Figure.5.b: Edges of that image as detected using Prewitt operator.

Figure.5.c: Edges detected using Canny operator

Figure 6.a: Satellite Image of region in Katmandu: Post Quake

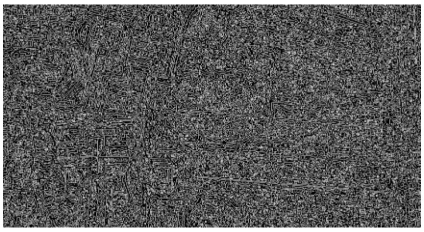


Figure.6.b: Figure 6.c:

Figure.6.b: Edges of that image as detected using Prewitt operator.

Figure.6.c: Edges detected using Canny operator

It can be clearly inferred from the fig. 5.a,b& c and fig.6.a,b & c that the edges are clearly marked and more distinguishable while using Canny edge detection operator than they are when the Prewitt operator is used. Analyzing the edges and comparing the images Fig.5.c and Fig.6.c it can be easily distinguished the presence of fewer discontinuities in image Fig.5.c than they are in image Fig.6.c. These discontinuities are because of collapsed structures. Edge detection can be a valuable tool in visual assessment of the damage. The region marked in a box in fig.5.a & c, and Fig.6.a & c, illustrates the presence of a structure; its corresponding edges and the presence of discontinues indicating the damage to the structure respectively. As a part of this research the proposed method for the segmentation of Natural calamity images is implanted and compared with Expected Maximization (EM), Fuzzy C- Means (FCM) and Bacterial Foraging Optimization Algorithm (BFOA) methods to test the performance of the proposed method. This section presents the results of segmentation as obtained using different segmentation approaches implemented as a part of this research work.

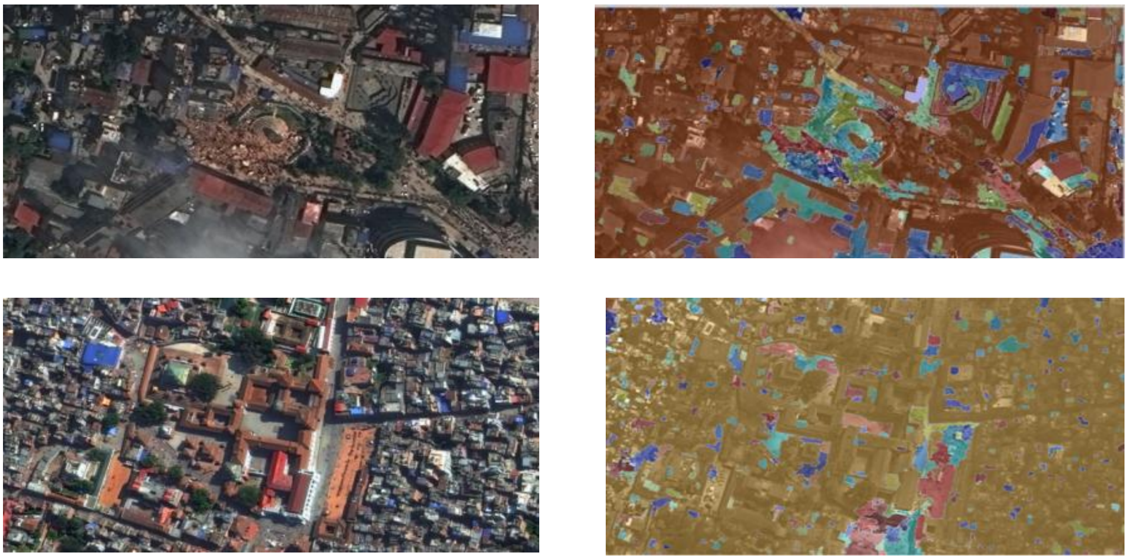


Figure.7: Structurally damaged regions marked and superimposed over the original image

The damaged regions assed are marked and superimposed on the original image and are shown in fig.. The performance of the segmentation approaches is evaluated using different performance measures and their significance is as given below:

- Probabilistic Rand Index (PRI)
- Variation of Information (VOI)
- Global Consistency Error (GCE)

Table.1:: Performance measurers with different Methods for image-1

Method	**PRI**	**VOI**	**GCE**
FCM	0.8952	0.5896	0.0695
EM	0.9123	0.4523	0.0458
BFOA	0.9517	0.2571	0.0283
EGA -EBFOA	0.9725	0.1923	0.0187

Table.2:: Performance measurers with different Methods for image-2

Method	**PRI**	**VOI**	**GCE**
FCM	0.8421	0.4397	0.0574
EM	0.8763	0.4124	0.0495
BFOA	0.9214	0.2247	0.0362
EGA- EBFOA	0.9651	0.2016	0.0296

From the From Table.1 & Table.2,it is observed that the PRI as obtained by the proposed method returns a higher value when compared with other methods of segmentation. The proposed method delivers a high PRI value for both images that have been illustrated. The high value of PRI signifies the similarity of the segmented image with that of its ground truth and it can be clearly observed that the proposed method is capable of segmenting an image that has close resemblance with ground truth.Variation of Information (VOI) is another parameter that can be used to quantify the similarity between the two segmented images. In a way it tries to quantify the difference between the images and provide an abstraction of how similar they are, the smaller the value is more similar the two segmentations are. It is observed from the Table.1 & Table.2, that the proposed method results in less VOI when compared to other illustrated methods and hence provide a segmented image that has high degree of similarity with ground truth.

The proposed method also fares better in terms of Global Consistency Error (GCE) as well which is an indication that refinement of one segmentation over another. It is visualized from Table.1 & Table.2, that the proposed method delivers in the parameter as well and returns a lower error value when compared to other methods.

Similarly a Damage Assessment Index is formulated by analyzing the number of clusters and connected components in the image before destruction and after destruction with respect to natural calamity. The damage is indexed in the scale of 1 to 10 with 1 being indicative of less or no damage and 10 indicating damage of highest degree. The fig.8, with images of the natural calamity with the different intensity levels of destruction. The damage assessment is analyzed and tabulated and is shown in the Table.3 and Table.4 respectively.

(a) (b)

Figure.8: Image of (a) High intensity damage and (b) Less intensity damage

Table.3: DAI for image shown in fig.8

Method	DAI with High Intensity	DAI with Less Intensity
FCM	4.8	4.1
EM	5.4	4.9
BFOA	5.9	5.2
EGA-EBFOA	**6.4**	**5.6**

V. Conclusion

This research work has endeavored to design a method for segmentation of satellite images to aid in the process of disaster management. The researcher has exploited the potential of both Enhanced Genetic Algorithm (EGA) and Enhanced Bacterial Foraging Optimization Algorithm (E-BFOA) in performing the segmentation of the satellite images. Visual interpretation of the segmented results and the performance evaluation parameters prove that the proposed method has a better performance factor in comparison with the other methods discussed in this research work. The Damage Assessment Index can be able ally in quantifying the damage and serve to aid the decision making process better.

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