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Research Article

Identify Earthquake Prone Regions by Segmenting Satellite Imagery Using Vade with Multilevel Thresholding

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ARTICLE INFO	ABSTRACT

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Introduction: Remote satellite imagery is a complex image that needs to be closely studied in detail to give appropriate alerts and to take actions. An earthquake is a serious geological hazard that can cause risk to human life and property. Due to the vast volume of satellite data, manual analysis is difficult, leading to growing interest in using intelligent computational methods to segment satellite images and identify features linked to earthquake-prone regions.

Objectives: By segmenting the satellite imagery, we can segregate the various regions based on its intensity. An optimisation problem like image segmentation is solved using evolutionary algorithms.

Methods: Differential Evolution (DE) is one such algorithm that is broadly used in optimisation, and various alternatives of this approach are developed to enhance its performance. In this work, a hybrid of the Differential Evolution algorithm named VaDE (variant Differential Evolution) is introduced and is combined with multilevel thresholding to segment satellite imagery of earthquakes based on their intensity.

Results The output obtained showed superior results compared to traditional methods.

Conclusions: Mi tempus imperdiet nulla malesuada. Magna fermentum iaculis eu non diam phasellus vestibulum. Consectetur adipiscing elit duis tristique sollicitudin nibh sit amet commodo. Elit scelerisque mauris pellentesque pulvinar. Et malesuada fames ac turpis egestas maecenas pharetra convallis posuere. Elementum integer enim neque volutpat ac tincidunt vitae semper.

Keywords: lorem ipsum.

INTRODUCTION

Earthquakes and other natural disasters pose a severe threat to human life and infrastructure around the world. Early identification and accurate assessment of seismic hazards are critical to effective disaster preparedness and mitigation efforts in vulnerable areas. Tracking geological occurrences and identifying seismically active areas can be accomplished through the analysis of satellite images. Thanks to recent advancements in remote sensing technology, high-resolution satellite images are now accessible, offering previously unachievable insights into the characteristics of the Earth's surface. However, because of the enormous amount of data generated by these satellites, traditional manual interpretation methods are severely challenged. The demand for automated techniques that might assist in assessing the danger of a disaster by obtaining valuable information from satellite data is therefore growing.

In this context, the ability to recognize unique features associated with earthquake-prone regions has drawn significant interest to the segmentation of satellite data using computational intelligence approaches. The Differential Evolution (DE) algorithm is one of these methods that has shown promise in optimizing difficult picture segmentation tasks by simulating the processes of natural selection and evolution. In this work, we present a unique method that uses multilevel thresholding to improve a Differential Evolution algorithm version for the purpose of segmenting satellite data and identifying earthquake-prone areas. Our goal is to increase the resilience and accuracy of the segmentation process by including multilevel thresholding techniques into the DE algorithm. This will allow us to identify tiny geological indicators that could be signs of seismic-dangers.

The principal aim of this study is to devise a dependable and effective approach for the automated identification of seismically vulnerable areas using satellite photography. Our hypothesis is that the incorporation of multilevel thresholding approaches along with versions of the DE algorithm will improve the segmentation process's discriminatory strength, making it possible to extract significant spatial patterns linked to seismic activity. We undertake experiments utilizing real-world satellite imaging datasets received from seismic monitoring organizations to verify the efficacy of our suggested method. We assess our method's effectiveness by contrasting the segmentation outcomes with ground truth data and current cutting-edge methods. We also evaluate our method's scalability and computational efficiency to make sure it can be used in real-world scenarios for extensive seismic hazard mapping. This is how the remainder of the work is organised: In Section II, pertinent research on satellite image segmentation and earthquake detection methods is reviewed. In the remaining sections, the theoretical underpinnings of the multilevel thresholding techniques and the Differential Evolution algorithm are discussed. The characteristic of the final imagery following segmentation with the novel method is contrasted and confirmed.

LITERATURE STUDY

Image segmentation is a critical process in diverse domains such as medical imaging, remote sensing, and computer vision. Differential Evolution (DE) algorithms have demonstrated potential in optimizing image segmentation. Several studies have investigated the use of DE and its variations to enhance image segmentation accuracy and efficiency. For instance, proposed an enhanced DE variant for sensor node deployment and localization, illustrating the adaptability and effectiveness of DE in optimization tasks (Roy et al., 2011). introduced an Adaptive Bi-Mutation-Based DE Algorithm for Multi-Threshold Image Segmentation to address challenges like large calculations and low accuracy in segmentation tasks (Sun & Yang, 2022). presented an Otsu Multi-Threshold Image Segmentation method based on Adaptive Double-Mutation DE, highlighting the efficacy of DE in improving segmentation outcomes (Guo, 2023). Furthermore, researchers have explored integrating DE with other optimization techniques to further improve image segmentation processes. combined the Grey Wolf Optimization (GWO) algorithm with DE for SAR image segmentation, demonstrating enhanced precision compared to traditional methods (Li et al., 2018). introduced the Differential Immune Clone Clustering Algorithm (DICCA), merging immune clone selection and DE for image segmentation, showcasing the potential of hybrid algorithms in this field (Ma et al., 2013). Furthermore, a hybrid strategy demonstrating the benefits of combining several optimisation techniques was developed, combining DE with a Genetic Algorithm for colour image segmentation (Krishna & Kumar, 2016). Additionally, one of the main areas of research has been the development of DE algorithms to address difficulties in picture segmentation. created a DE method for image registration using a population knowledge fusion approach, highlighting the significance of incorporating domain knowledge into optimisation procedures (Sun et al., 2021). Studies such as the one on utilising a divergent DE algorithm to segment remote sensing data for atmospheric air pollution further demonstrate how versatile DE is in handling different segmentation challenges (Ramadas & Abraham, 2022). The combined findings of these studies highlight DE's potential and variability in improving picture segmentation approaches across various domains.

Guo (2023) introduced an Adaptive Double-Mutation Differential Evolution variant for Otsu Multi-Threshold Image Segmentation, emphasizing the optimization of interclass variance for improved segmentation outcomes. Fan & Yan (2016) highlighted the significance of mutation strategies and control parameters in the performance of DE algorithms, underscoring the need for adaptive approaches in optimizing image segmentation processes. Additionally, Krishna & Kumar (2016) proposed a hybrid methodology combining DE with a Genetic Algorithm for Color Image Segmentation, showcasing the benefits of integrating different optimization techniques for enhanced segmentation results. Ma et al. (2013) presented the Differential Immune Clone Clustering Algorithm, which merges immune clone selection with DE for image segmentation, demonstrating the effectiveness of hybrid algorithms in this domain. These studies collectively contribute to the advancement of DE variants in optimizing image segmentation tasks.

In conclusion, the research landscape concerning DE algorithms in image segmentation is diverse and robust, with studies demonstrating the effectiveness of DE variants in enhancing segmentation accuracy, efficiency, and

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adaptability. By combining DE with other optimization techniques, leveraging domain-specific knowledge, and tailoring DE algorithms to specific segmentation challenges, researchers have made significant progress in improving image segmentation processes. The continuous evolution and exploration of DE algorithms in image segmentation hold promise for further advancements in this critical research area.

Evolutionary algorithms have been extensively studied and implemented to improve image segmentation techniques, offering efficient solutions to optimization challenges in this process. Several studies have illustrated the effectiveness of evolutionary algorithms in enhancing segmentation accuracy and robustness. Felzenszwalb & Huttenlocher (2004) introduced an algorithm based on graph construction for image segmentation, demonstrating its results on both real and synthetic images. Zhang et al. (2020) proposed an unsupervised fuzzy clustering approach using evolutionary algorithms for image segmentation. Liu et al. (2020) addressed the challenges of multi-level thresholding for image segmentation and the limitations of exhaustive search, suggesting the use of evolutionary algorithms to overcome these obstacles. Cuevas et al. (2015) successfully applied evolutionary principles to image segmentation, highlighting the promising performance of such algorithms. Moreover, Jiao et al. (2020) developed a two-stage evolutionary fuzzy clustering framework for noisy image segmentation. Shou et al. (2018) presented an enhanced segmentation algorithm based on genetic algorithms and mathematical morphology for microscopic image processing. Additionally, Ali (2008) devised a robust evolutionary algorithm for edge-based segmentation in medical images. These studies collectively showcase the versatility and effectiveness of evolutionary algorithms in improving image segmentation processes.

DE ALGORITHM

Differential Evolution (DE) algorithm is a population-based optimization algorithm .It tackles complex problems by simulating natural selection. It begins by randomly creating a population of potential solutions. Then, it generates new solutions by combining existing ones and mutating them. These mutations are based on the differences between randomly selected individuals within the population. A trial solution is formed by blending the mutated solution with an original one. If the trial solution proves better, it replaces the original in the next generation. This process iterates until a stopping criterion, like a set number of iterations, is met. DE's flexibility and efficiency make it a popular choice for solving various optimization challenges. The steps are discussed in detail :

DE starts by initializing a population of candidate solutions , denoted as vectors in the search space randomly within the search space. Each solution relates to a set of threshold values for image segmentation. Populace of NP candidate taken as $X_{i,G}$ where index $i = 1,2\ldots$NP and generation of populace is denoted as G. Three vectors $X_{r1,G}, X_{r2,G}$ and $X_{r3,G}$ are indiscriminately selected for a particular constraint $X_{i,G}$, for varied r_1, r_2, r_3. Perform mutation operations on the candidate solutions to explore the search space and generate new potential solutions. . It involves the generation of trial solutions based on the difference between randomly selected solutions from the population. The mutation operation gives the donor vector $V_{i,G}$ as:

$$V_{i,G} = X_{r1,G} + F \times (X_{r2,G} - X_{r3,G}) \quad (1)$$

F is the mutation factor that takes a static value between [0,1].

Crossover operations combines information from different candidate solutions and generate offspring solutions. The crossover operation determines the composition of threshold values for the offspring based on the crossover rate parameter. Elements of donor vector enter trial vector with crossover probability $C_r \in [0,1]$.

$$U_{j,i,G+1} = \begin{cases} V_{j,i,G+1} & \text{if } rand_{i,j}[0,1] \le C_r \text{ or if } j = I_{rand} \\ X_{j,i,G+1} & \text{if } rand_{i,j}[0,1] > C_r \text{ or if } j \ne I_{rand} \end{cases} \quad (2)$$

Here $rand_{i,j} \approx \cup[0,1]$ and I_{rand} any value from 1 to N. During selection phase, the best-performing solutions (parents and offspring) based on their fitness values are chosen to form the next generation population. The target vector $X_{i,G}$ is compared with the trial vector $V_{i,G}$ and the optimal value is selected into next cycle.

$$X_{i,G+1} = \begin{cases} U_{i,G+1} & if\ f(U_{i,G+1}) \leq f(X_{i,G})\ where\ i = 1,2,..N \\ X_{i,G} & otherwise \end{cases} \tag{3}$$

VADE ALGORITHM

In order for the new technique to coincide more quickly, this approach makes use of the best solution vector $X_{best,G}$. $X_{r1,G}, X_{r2,G}, X_{r3,G}$ are chosen randomly . The amplifying parameter, identified as constraint F and F1 takes a changeable value using the below eq..

$$F1 = 0.5 * (1 - rand(0,1)) \tag{4}$$

$$F = (1 - rand(0,1)) \tag{5}$$

The product of F1 and F is what the other constraint N uses. The algorithm's outcome is significantly impacted by the choice of constraint values. The evolution is regulated by fine-tuning the control settings. The CPU time is reduced when three control parameters are used, as this increases the likelihood of mutation. The resulting donor vector, which takes into account three different limitations, outperforms the classic DE strategy in terms of results and search space exploration, increasing the effectiveness of the VaDE approach. The VaDE mutation approach is described as follows:

$$X' = N * (X_{best,G} - X_{r1,G}) + \begin{pmatrix} F * (X_{best,G} - X_{r2,G}) - \\ F1 * (X_{best,G} - X_{r3,G}) \end{pmatrix} \tag{6}$$

Compared to typical DE techniques that solely take into account random vectors, this approach offers faster convergence by introducing the best solution vector, Xbest,G.

EXPERIMENTAL OUTCOMES

Suggested method VaDE was computed using MATLABr2018b. Using a crossover probability of 0.8, the results of the five traditional mutation techniques of the DE and VaDE technique were tallied and compared. Fifteen benchmark functions were calculated with the dimension set at 25, 75, and 50, with the vtr and amount of iterations fixed for different scales. Results of VaDE were compared to the CPU time spent, number of runs estimated, and best value obtained for each of the five different mutation techniques. The comparative findings demonstrated that VaDE approach's improved performance. Table 1 displays an example outcomes attained for the CPU time required for 100 rotations.

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Function	DE_Best_2	DE_rand_1	DE_rand_2	DE_best_1	DE_best-to-rand_1	VaDE
F1	56.6	13.12	88.6	13.16	51.10	**11.01**
F2	10.12	12.15	**5.12**	7.26	7.8	10.7
F3	12.14	38.1	10.31	7.34	7.43	**7.01**
F4	7.12	10.45	8.34	8.1	10.89	**6.98**
F5	**4.5**	11.2	5.67	17.34	8.78	9.3
F6	15.89	16.8	9.12	14.35	17.89	**8.9**
F7	134.2	142.9	165.8	130.9	132.7	**128.2**
F8	7.87	8.23	15.12	11.3	**7.1**	12.3
F9	4.51	6.76	7.34	8.32	5.57	**4.03**
F10	153.5	154.5	146.21	162.5	156.7	**140.8**
F11	17.34	17.25	34.77	**12.15**	18.54	21.2
F12	98.1	98.7	108.1	**96.7**	99.1	99.3
F13	81.8	37.8	100.4	141.5	110.5	**29.6**
F14	96.8	97.1	89.8	103.1	101.5	**51.2**
F15	105.8	38.1	100.89	42.1	83.38	**28.2**

TABLE 1. CPU TIME FOR BENCHMARK FUNCTIONS WITH 100 TURNS

Data were tallied and compared across multiple dimensions. By altering the magnitudes and value-to-reach (VTR), the study provided competent results based on the number of function evaluation (NFE), the best value, and the CPU time of various function techniques. The expected method, VaDE, produced the best outcomes for most typical functions.

Statisitical tests were computed and tabulated results of Friedman's Rank Test statistical analysis for Table 1 are shown in Table 2. Table 2 shows that the mean ranks of the five different mutation techniques and the VaDE methodology differ generally in a statistically significant way. The performance rating of the different traditional DE

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approaches utilized in the study and VaDE in terms of CPU time achieved is shown in Table 3. The tables show that VaDE produces the best results when compared to the conventional forms of DE.

TABLE 2. TEST STATISTICS USING FRIEDMAN'S TEST

N	100
Df	5
Chi sq	21.54
Asymptotic Significance	0.0001
Chi sq	21.54

TABLE 3. RANKS OF THE DIFFERENT STRATEGIES

Strategies	**Mean Rank on CPU time**
De_best _2	3.7
De_rand_1	3.5
DE _rand_2	4.9
DE _best_1	3.02
DE_ best-to-rand_1	2.8
VaDE	2.85

MULTILEVEL SEGMENTATION USING RENYI"S ENTROPY

Multilevel segmentation involves a hierarchical or iterative process of dividing the image into smaller and more refined segments . The core idea behind multilevel segmentation is to begin with a coarse, high-level segmentation and then progressively refine the segmentation by introducing additional levels of detail. This approach can be advantageous in scenarios where the image content exhibits a range of scales or where the objects of interest have varying levels of complexity.

Here, the histogram of the image is segmented into various groups of pixels $k_1, k_2, \dots k_n$ defined by grayscale intensity values each with a static threshold. The resultant probability of occurrence of pixel of intensity i is given as:

$$p_i = \frac{n_i}{total\ number\ of\ pixel} \tag{7}$$

where n_i is the number of pixels at intensity i. The different classes of pixel represented as:

$$c_1 = (p_0, p_1, .. p_{k_1}), \quad c_2 = (p_{k+1}, p_{k+2}, .. p_{k_2}) \ \dots. \quad c_{n+1} = (p_{k_n+1}, p_{k_n+2}, .. p_n) \tag{8}$$

where $P = (p_0, p_1, p_2, \dots p_n)$ is the finite set of probability distribution for the complete image . Total class probability is represented as:

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$$P(c_1) = \sum_{i=0}^{k_1} p_i \quad , \qquad P(c_2) = \sum_{i=k_1+1}^{k_2} p_i \, , \dots \quad P(c_{n+1}) = \sum_{i=k_n+1}^{p_n} p_i \tag{9}$$

Renyi's entropy for individual class is displayed as:

$$H_\alpha \alpha[c_1] = \frac{1}{1-\alpha} \left[\ln \sum_{i=0}^{k_1} \left(\frac{p_i}{p(c_1)} \right)^\alpha \right]$$

$$H_\alpha \alpha[c_2] = \frac{1}{1-\alpha} \left[\ln \sum_{i=k_1+1}^{k_2} \left(\frac{p_i}{p(c_2)} \right)^\alpha \right]$$

$$H_\alpha \alpha[c_{n+1}] = \frac{1}{1-\alpha} \left[\ln \sum_{i=k_n+1}^{n} \left(\frac{p_i}{p(c_{n+1})} \right)^\alpha \right] \tag{10}$$

Total Renyi's entropy of the images is symbolized as:

$$H_\alpha[I] = H_\alpha[c_1] + H_\alpha[c_2] + \cdots H_\alpha[c_{n+1}] \tag{11}$$

Optimal threshold value for which entropy is maximized is symbolized as:

$$K_\alpha^* = \arg \max_{K^* \epsilon L^n} \{H_\alpha[I]\} \tag{12}$$

SEGMENTING SATELLITE IMAGE USING VADE WITH RENYI'S ENTROPY

Numerous research work is constantly done to improve the performance of image segmentation. The proposed technique VaDE is applied for image segmentation using Renyi's entropy. This technique is then used to segment the satellite imagery.VaDE approach is used to maximize eq.12.

The proposed approach begins by applying Otsu's multilevel thresholding to the input image, which provides an initial set of threshold values based on the number of desired segments. These initial thresholds are then used as the starting population for VaDE algorithm, which iteratively refines the thresholds to minimize Renyi's entropy. The VaDE algorithm's ability to explore the search space efficiently and its robust convergence properties make it a suitable choice for this optimization problem. Once the optimization process converges, the final set of threshold values obtained through the DE algorithm represents an optimal segmentation of the satellite imagery. The segmented image can then be analyzed to identify regions indicative of seismic hazards, such as fault lines, geological structures, or land cover changes associated with tectonic activity.

This scheme was implemented on satellite images obtained from NASA website. The values for threshold, entropy and CPU time was computed. Samples of satellite image was taken from www.appliedsciences.nasa.gov and the segmented image using aDE technique is shown in Figure 3.

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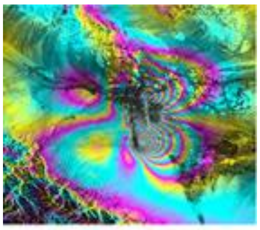
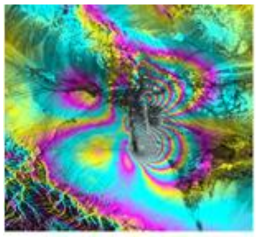


A)



B)

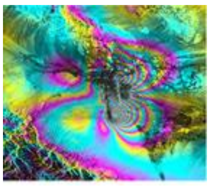
FIGURE 1. A) ORIGINAL IMAGERY OF IMAGE 1 B) SEGMENTED IMAGE USING VADE TECHNIQUE OF IMAGE 1

Using CPU time and PSNR value, the suggested technique's performance and image quality are confirmed. Using the DE technique, simple Renyi's entropy, and VaDE with Renyi's entropy, the findings of image segmentation are linked to the consequences. Table 4 presents the corresponding results.

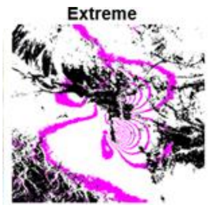
TABLE 4. PSNR VALUE AND CPU TIME COMPARISON

Image	**PSNR**			**CPU Time**		
	Renyi's entropy	**DE with Renyi's entropy**	**VaDE with Renyi's entropy**	**Renyi's entropy**	**DE with Renyi's entropy**	**VaDE with Renyi's entropy**
Image 1	10.8	11.2	12.5	2.3	2.21	2.12

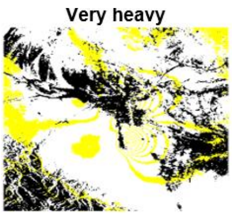
In contrast to the conventional DE approach, the findings obtained indicate that the projected VaDE approach with Renyi's entropy exhibits improved results for picture segmentation. The new method exhibits improved CPU time and better entropy. The image can be segmented so that areas based on soil moisture content can be extracted and studied. This prevents damage and maintains water resources while helping to control the depth and frequency of irrigation water supply for crop water requirements. The following is an example of segmented satellite imagery.



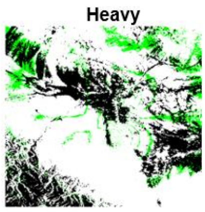
A)



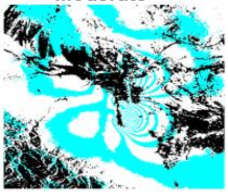
B)



C)



D)



E)

FIGURE 2. A) SEGMENTED IMAGE B) SEGMENTED IMAGE EXTREME CONDITION C) SEGMENTED IMAGE FOR VERY HEAVY CONDITION D) SEGMENTED IMAGE FOR HEAVY CONDITION E) SEGMENTED IMAGE FOR MODERATE CONDITION

It is simpler to detect portions of a given wavelength when the image has been clustered based on specific color bands. Segmenting the picture makes it easy to identify areas impacted by major catastrophes and allows for the appropriate announcement of notifications. This might lessen the loss sustained in times of such disasters.

CONCLUSIONS

A novel DE variation called VaDE was created, and many statistical analyses were used to confirm the effectiveness of this algorithm. Renyi's entropy multilevel thresholding is an effective method for segmenting images. The effectiveness of picture segmentation is greatly increased by combining VaDE with the Renyi's entropy approach. This study uses this approach to segment satellite imagery. This technique may be further extended for picture analysis, texture enhancement, and image enhancement, among other purposes.

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