Segregating Satellite Imagery Based on Soil Moisture Level Using Advanced Differential Evolutionary Multilevel Segmentation

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Abstract— **Soil Moisture aid analysts in study of soil science, agriculture and hydrology. Satellite imagery for soil moisture estimation is recorded through earth satellites. By segmenting these satellite imageries based on soil moisture content, we can effortlessly identify regions of wetter condition and regions of dry condition. Differential evolution (DE) is a popular evolutionary approach that is used to optimize problems like image segmentation. In this work, an Advanced Differential Evolution (aDE) technique is introduced which has enhanced performance in comparison to traditional DE approach. This approach is combined with Renyi's entropy for performing multilevel segmentation on the imagery. The resultant segmented images obtained on using the proposed technique is of enhanced quality.**

Keywords— Renyi's entropy, soil moisture content, PSNR, segmentation

I. Introduction

Water content has a significant part in agricultural science and soil science. The soil moisture level effectually assesses the limit of irrigation demand, and thus perform as a major indicator of irrigation water management. Adequate levels of soil moisture are a vital criterion for accurate plant development and high crop production. Plants have variant requirements for moisture subject to the weather settings and growth periods. By interpreting the regions on the basis of soil moisture content, numerous vital public requirements like water management, reservoir management, drought and flood warning, irrigation scheduling and agricultural monitoring can be done easily.

NASA's satellite Soil Moisture Active Passive (SMAP) provides remote sensing satellite imagery with soil moisture content with spatial coverage and chronological permanency. By segmenting the satellite imagery based on the bandwidth of soil moisture content, predicting changes and giving early alerts can be easily done by climatologists, soil scientists and hydrologists. Multilevel segmentation of color images is an area attracting a lot of research as the technique of determining optimal threshold in multilevel thresholding is time- consuming. Image segmentation is an unsupervised learning problem which can be solved using evolutionary approaches. Differential Evolution (DE) [1] is a popular evolutionary approach that is used to solve optimisation problems. Numerous variants of DE is developed to enhance the performance of classical DE approach.

This work proposes a variant of DE approach labelled as aDE which differs in the mutation strategy in comparison to conventional DE. aDE uses three control parameters in its mutation strategy. The outcomes show heightened results. This approach is combined with Renyi's entropy to attain optimal threshold. The quality of the resultant image after segmentation using the new technique is compared and verified.

II. Literature Review

Cuevas et al. [2] developed an automatic image multi-threshold method using differential evolution algorithm. Fan and Yang [3] proposed a chaos differential evolution (CDE) on the basis of Logistic map. This technique was used to find the optimum threshold using maximum entropy principle. Hu et al. [4] developed the first adaptive strategy selection-based approach for images. Gautam and Lakhwani [5] proposed a technique for colour image segmentation by preserving colors in divergent segments of input color image.

Khan et al. [6] developed an altered adaptive differential evolution for color image segmentation. Choudhury et al. [7] proposed quantum inspired evolutionary algorithm (QIEA) for getting optimum level of multilevel thresholding. Khehra et al. [8] developed an approach using two dimensional Renyi's entropy for image segmentation. Parihar [9] proposed a technique for segmenting satellite image using Differential Evolution by considering the features of image like correlation between spectral bands, Hughes principle etc. Parihar et al. [10] developed an approach using differential evolution technique for image contrast enhancement. Oliva e tal.[11] recommended using EMO to get optimum threshold value by reducing the cross entropy by using evolutionary approaches for image segmentation. Liu et al. [12] developed meta heuristic approach on the basis of breeding technique of Chinese hybrid rice to get optimum threshold rice for image segmentation using Renyi's entropy. Ramadas and Abraham [13] developed transformed Differential evolution combined with Kapur's entropy for detecting tumours by segregating MRI images. Peng and Zang [14] used Renyi's entropy with Levy's firefly algorithm to find the optimum threshold for multilevel image segmentation. Ramadas and Abraham [15] proposed composite differential evolution with Otsu technique for segmenting images to detect regions of sandstorm.

III. DE ALGORITHM

Storn and Price [1] proposed DE approach where a known number of vectors are arbitrarily recognized from a populace of n-dimensions of probable outcomes. Populace of NP candidate is considered as $X_{i,G}$ where index $i = 1,2...$ 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. Donor vector $V_{i,G}$ is given 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]. During binomial crossover, the trial vector $U_{i,G}$ is developed for target vector $X_{i,G}$. Components of donor vector enter trial vector with crossover probability $C_r \in [0,1]$.

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

Here $rand_{i,j} \approx \cup[0,1]$ and I_{rand} is subjective integer between 1 to N. During selection phase, the populace for next generation is chosen from vectors in current populace and its following trial vectors. The target vector $X_{i,G}$ is matched with the trial vector $V_{i,G}$ and the optimal value is selected into next cycle.

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

IV. ADVANCED DIFFERENTIAL EVOLUTION ALGORITHM

aDE arbitrarily selects three variables $X_{r1,G}, X_{r2,G}, X_{r3,G}$. This approach uses best solution vector $X_{best,G}$ so that the new approach will coincide.

The constraint F recognized as amplifying parameter takes a static value of 0.5. The new constraints F1 takes changeable value using the formula

$$F1 = 0.5 * (1 - rand(0,1)) \quad (4)$$

The other constraint N takes the product of F1 and F. Selection of constraint values greatly affect the result of the algorithm. The control parameters are fine tuned for controlling the evolution. The usage of three control parameters escalates the mutation probability which in turn decreases the CPU time. By considering three diverse constraints, the resultant donor vector shows improved outcomes and better exploration of search space in comparison to traditional DE approach thereby enhancing the efficiency of aDE approach. The mutation strategy for aDE is presented as:

$$X' = N * (X_{r,G}) + (F * (X_{best,G} - X_{r2,G}) - F1 * (X_{best,G} - X_{r3,G})) \quad (5)$$

By introducing the best solution vector $X_{best,G}$, this approach has faster convergence in comparison to the traditional DE strategies that considers random vectors only.

V. EXPERIMENTAL OUTCOMES

The proposed technique aDE was achieved via MATLABr2018b. The outcomes obtained with the 5 old-style mutation strategies of DE and aDE technique was tabulated and compared by considering crossover probability C_r as 0.8. Fifteen benchmark functions were computed by fixing the value to reach and number of iterations for various magnitudes and by considering the dimension as 25, 75 and 50. The outcomes for CPU time taken, number of function evaluation and the best value attained for the five diverse mutation strategies were compared with the respective outcome of aDE. The comparative results showed enhanced performance for aDE approach. A sample observation for the CPU time taken for 100 turns is shown in Table 1.

Observations were tabulated and compared for numerous dimensions. The study offered competent consequences on the basis of number of function evaluation (NFE), the best value and the CPU time of diverse function strategies by modifying the magnitudes and value-to-reach (VTR). The anticipated technique aDE gave optimum results for majority of standard functions.

TABLE 1. CPU TIME TAKEN WITH 100 TURNS FOR BENCHMARK FUNCTIONS

Function	DE/best/1	DE/best/2	DE/rand/1	DE/best-to-rand/1	DE/rand/2	aDE
Sphere	13.64	57.76	13.07	50.02	89.76	**11.16**
Beale	7.65	10.06	11.56	7.4	**5.8**	11.7
Booth	7.84	11.4	40.1	7.24	10.21	**7.1**
Schwefel	7.81	7.27	10.56	11.3	8.87	**7.02**
Michlewicz	17.21	**4.9**	10.3	8.9	6.21	10.3
Schaffer N.2	14.12	15.27	17.3	18.4	9.8	**9.14**
Schaffer N.4	131.2	135.6	143.1	133.2	166.2	**130.2**
HimmelBlau	11.2	7.77	8.33	**7.01**	15.32	11.3
Bird	8.24	4.25	5.66	6.57	7.41	**4.13**
Extended Cube	163.2	154.1	155.3	157.7	**146.38**	152.3
Ackeley	**12.5**	17.47	17.97	19.45	35.67	20.6
Gold	**97.19**	97.7	99.3	98.76	110.2	100.2
Griewank	141.3	82.7	38.4	110.3	101.5	**30.2**
Rastrigin	103.2	97.2	97.54	101.2	88.7	**52.3**
Rosenbrock	41.16	106.2	38.2	84.48	101.87	**30.3**

VI. STATISTICAL TESTS

Statistical analysis for Table 1 using Friedman's Rank Test is tabularized in Table 2. Table 2 depicts that there is an overall statistically substantial dissimilarity between the mean ranks of the five diverse mutation strategies and aDE technique. Table 3 represents the performance ranking of the various traditional DE techniques used in the study and aDE with respect to CPU time achieved. The tables reveal that aDE has finest outcomes in comparison to the traditional variants of DE. Figure 1 represents a graphical illustration of the consequences obtained.

TABLE 2. TEST STATISTICS USING FRIEDMAN'S TEST

N	100
Chi sq	22.67
Df	5
Asymptotic Significance	0.0001

TABLE 3. RANKS OF THE DIFFERENT STRATEGIES

Strategies	Mean Rank on CPU time
De/rand/1	3.2
De/best/2	3.8
DE/best-to-rand/1	2.7
DE/best/1	3.0
DE/rand/2	4.9
aDE	2.5

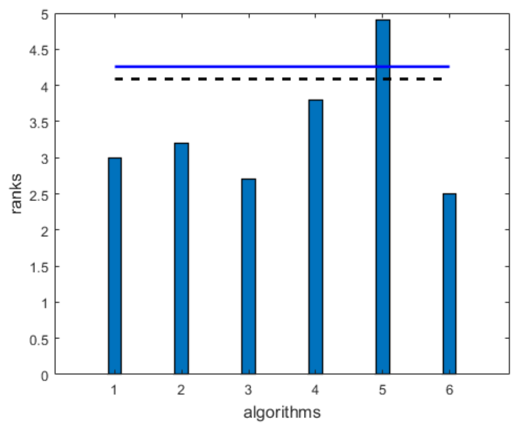

FIGURE 1. BONFERRONI DUNN CHART FOR RANKS BASED ON CPU TIME

VII. MULTILEVEL SEGMENTATION USING RENYI"S ENTROPY

In multilevel thresholding of image segmentation, the histogram of the image is segmented into various groups of pixels $k_1, k_2, \ldots k_n$ defined by grayscale intensity values each having a static threshold. The resultant probability of occurrence of pixel of intensity i is given as:

$$p_i = \frac{n_i}{total\ number\ of\ pixel} \tag{6}$$

where n_i is the number of pixels at intensity i. Let $P = (p_0, p_1, p_2, \ldots p_n)$ be the finite set of probability distribution for the complete image and the different classes of pixel denoted as:

$$c_1 = (p_0, p_1, \ldots p_{k_1}) \quad , \qquad c_2 = (p_{k+1}, p_{k+2}, \ldots p_{k_2}) \quad \ldots.$$
$$c_{n+1} = (p_{k_n+1}, p_{k_n+2}, \ldots p_n) \tag{7}$$

Total class probability is denoted as:

$$P(c_1) = \sum_{i=0}^{k_1} p_i \quad ,$$
$$P(c_2) = \sum_{i=k_1+1}^{k_2} p_i , \ldots \quad P(c_{n+1}) = \sum_{i=k_n+1}^{p_n} p_i \tag{8}$$

Renyi's entropy for individual class is shown as:

$$H_\alpha \alpha[c_1] = \frac{1}{1-\alpha}\left[\ln \sum_{i=0}^{k_1}\left(\frac{p_i}{p(c_1)}\right)^\alpha\right]$$
$$H_\alpha \alpha[c_2] = \frac{1}{1-\alpha}\left[\ln \sum_{i=k_1+1}^{k_2}\left(\frac{p_i}{p(c_2)}\right)^\alpha\right]$$
$$H_\alpha \alpha[c_{n+1}] = \frac{1}{1-\alpha}\left[\ln \sum_{i=k_n+1}^{n}\left(\frac{p_i}{p(c_{n+1})}\right)^\alpha\right] \tag{9}$$

Total Renyi's entropy of the imagery is denoted as:

$$H_\alpha[I] = H_\alpha[c_1] + H_\alpha[c_2] + \cdots H_\alpha[c_{n+1}] \tag{10}$$

Optimum threshold value for which entropy is maximized is denoted as:

$$K_\alpha^* = \arg \max_{K^* \epsilon L^n} \{H_\alpha[I]\} \tag{11}$$

VIII. SEGMENTING SATELLITE IMAGE USING ADE WITH RENYI'S ENTROPY

Numerous research work is constantly done to improve the performance of image segmentation [16,17,18,19]. The proposed technique aDE is applied for image segmentation using Renyi's entropy. This technique is then used to segment the satellite imagery. aDE approach is used to maximize eq.11.The flowchart for the proposed technique is shown below in Figure 2.

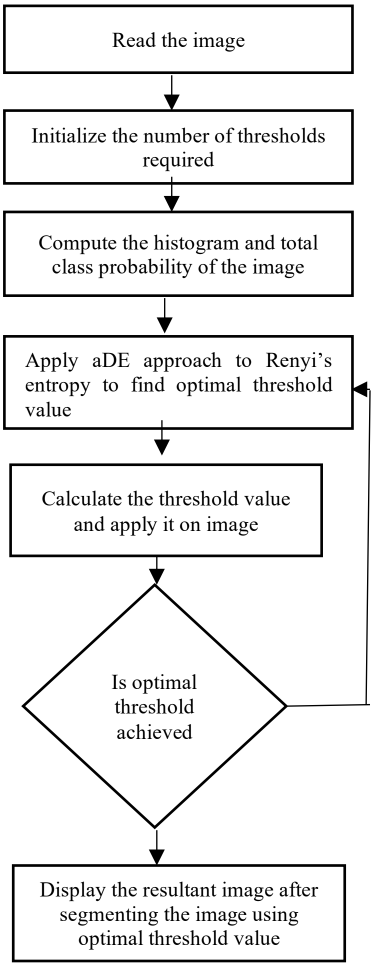

FIGURE. 2. FLOWCHART FOR THE PROPOSED TECHNIQUE

The proposed technique aDE is combined with Renyi's entropy approach to achieve multilevel image thresholding. This method was applied on satellite radar images attained from Soil Moisture Active Passive (SMAP) satellite to observe moisture in soil. The execution of the algorithms employed is certified using the peak to signal ratio (PSNR) and CPU time. PSNR is the extent of quality between the original imagery and the segmented imagery based on mean square error (MSE). It is defined as:

$$PSNR(\sigma, s) = 20log_{10}\left[\frac{255}{\sqrt{MSE(\sigma,s)}}\right] \tag{12}$$

where, σ is the original imagery and s is the segmented imagery. If the dimension of imagery is $m \times n$, then the mean square error (MSE) is defined as:

$$MSE = \frac{1}{m*n}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[\sigma(m,n) - s(m,n)] \tag{13}$$

The values for PSNR and CPU time for the algorithms under consideration is tabulated in Table 4. Samples of satellite image attained from www.smap.jpl.nasa.gov was taken and the image segmentation was performed using aDE technique. The original imagery and the segmented imagery for two sample images are shown in Figure 3.

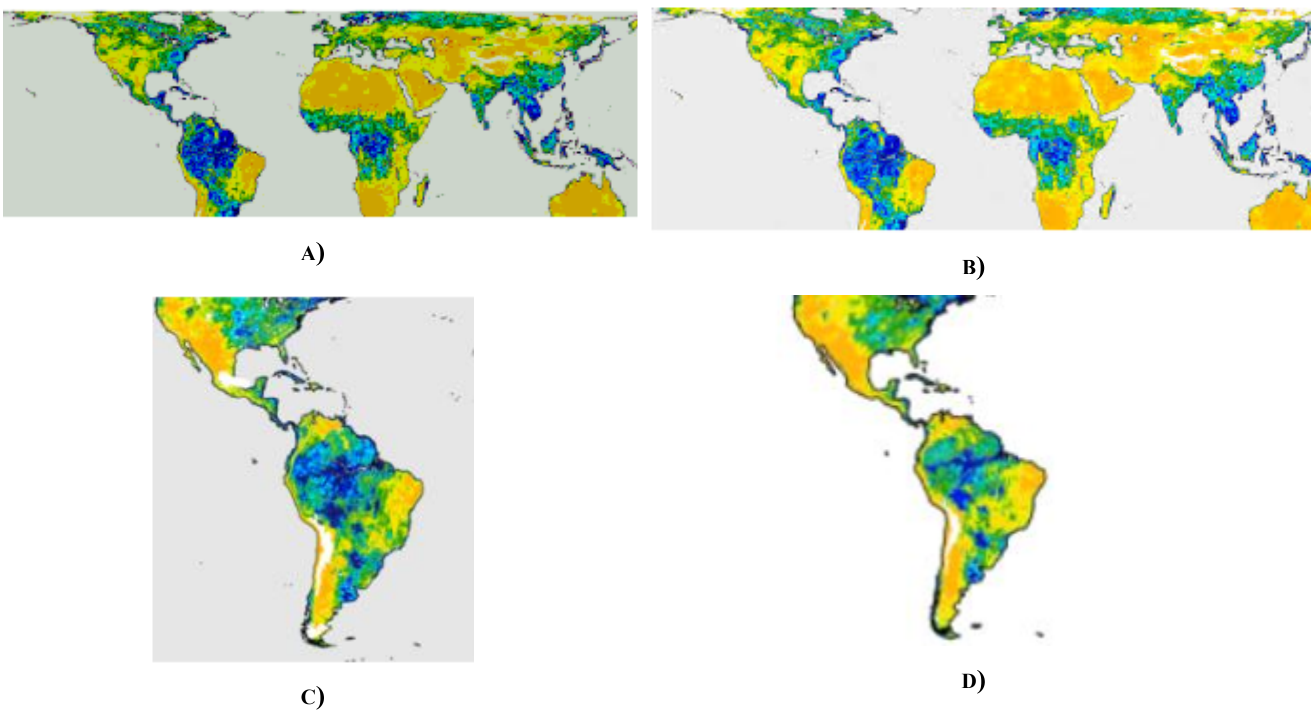

FIGURE 3. A). ORIGINAL IMAGERY OF IMAGE 1 B). SEGMENTED IMAGE USING ADE TECHNIQUE OF IMAGE 1 C). ORIGINAL IMAGERY OF IMAGE 2 D). SEGMENTED IMAGE USING ADE TECHNIQUE OF IMAGE 2

TABLE 4. COMPARISON OF PSNR VALUE AND CPU TIME

Image	PSNR				CPU Time			
	Otsu method	Renyi's entropy	DE with Renyi's entropy	aDE with Renyi's entropy	Otsu method	Renyi's entropy	DE with Renyi's entropy	aDE with Renyi's entropy
Image 1	11.2	10.2	10.8	12.4	2.21	2.23	2.1	2.01
Image 2	10.1	9.4	10.2	11.3	2.2	2.1	2.12	2.08

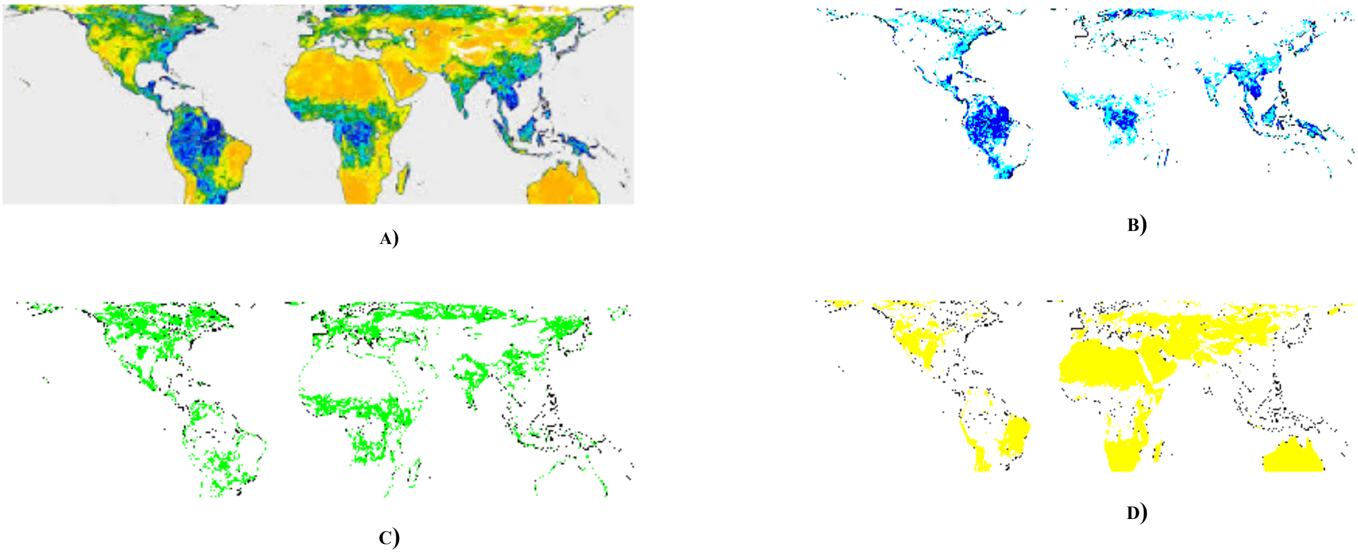

FIGURE 4. A). SEGMENTED IMAGE B). SEGMENTED IMAGE FOR HIGHER SOIL MOISTURE CONTENT C). SEGMENTED IMAGE FOR MODERATE SOIL MOISTURE CONTENT D). SEGMENTED IMAGE FOR LOWEST SOIL MOISTURE CONTENT

The quality of the image and the performance of the algorithm is measured using PSNR value and CPU time. The outcomes are compared with the results of image segmentation using Otsu method , simple Renyi's entropy and DE with Renyi's entropy. The comparative results are displayed in Table 4. SMAP satellite provides a global image of surface soil moisture images. The different color bars represent the different levels of soil moisture content. Yellow color designates drier soil planes while blue color denotes damper settings. The outcomes gained reveals that the projected aDE approach with Renyi's entropy shows heightened results for image segmentation in comparison to traditional DE approach. The new approach shows better entropy and improved CPU time. By segmenting the image, we can extract and study regions of the imagery on the basis of soil moisture content. This aids in regulating the frequency and deepness of irrigation water supply for crop water requirements, while avoiding damages and sustaining water resources. A sample of segmented satellite images on the basis of soil moisture content is shown in Figure 4.

IX. CONCLUSIONS

Here, a new variant of DE algorithm termed as aDE is introduced. This technique was compared with classical DE approaches and statistical analysis verifies the efficiency of the new approach. aDE with combined with Renyi's entropy approach to get optimal threshold value for image segmentation of satellite imagery on the basis of soil moisture content. The quality of the resultant segmented image was compared and the results showed enhanced results. This work can be extended for enhancing the image. The new approach can be applied on other areas of application like medical image segmentation, weather forecasting etc.

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