REMOTE SENSING IMAGE SEGMENTATION USING META HEURISTIC ALGORITHMS AND CHANGE DETECTION

A Project report submitted in partial fulfilment of the requirements for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

ELECTRONICS AND COMMUNICATION ENGINEERING

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Sangivalasa, Bheemili mandal, Visakhapatnam dist.(A.P)

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CERTIFICATE

This is to certify that the project report entitled **"Remote Sensing Image Segmentation using Meta-Heuristic Algorithms and Change Detection"** submitted by **J Sri Ram Prateek (319126512086), K Bharath Kumar (319126512088), B Bindu (319126512074), M Rohini (320126512L14)** in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology in Electronics & Communication Engineering** of Anil Neerukonda Institute of technology and Sciences(A), Visakhapatnam is a record of bonafide work carried out under my guidance and supervision.

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ABSTRACT

Multilevel thresholding is a fast and convenient image segmentation method, but the choice of thresholds is critical for success. Traditional techniques can suffer from accuracy and high processing cost issues. To overcome these problems, Nature-inspired metaheuristic algorithms are used, which are faster, easy to implement, and gradient-free. Another challenge is the selection of a suitable objective function, which is addressed in this paper by proposing a new probabilistic non-extensive entropy based on Gaussian information. Two recently developed optimization algorithms, Henry Gas Solubility Optimization (HGSO) and Honey Badger Optimization (HBA), are used to optimize the objective function and generate optimal threshold values. The proposed thresholding method's performance is evaluated by creating segmented images from a set of natural and satellite images, using quality indicators such as PSNR and SSIM. The experimental results show that the proposed strategy performs well in segmenting both natural and satellite images.

CONTENTS

LIST OF SYMBOLS

'P'	Partial pressure of the gas in the atmosphere above the liquid.
'C'	Concentration of the dissolved gas.
$'k_H'$	Henry's law constant of the gas.
$'\nabla_{sol}E'$	Dissolution enthalpy
'R'	Gas constant and R = $8.314\ JK^{-1}mol^{-1}$.
$'Y_{(i)}'$	Position of ith gas in population size (N)
'r'	*R*andom number where r $\in (0,1)$
$'Y_{min}, Y_{max}'$	bounds of the problem
't'	iteration time
't'	Temperature
$'T^{\theta}'$	Constant which is the reference temperature and is equal to $298.15K$
$'iter'$	Number of iterations
$'k_{H_j}'$	Henry's law constant for cluster j.
$'Y_{(i,j)}'$	Position of gas i in cluster *j*
$'Y_{best}'$	The best gas in the swarm
$'Y'_{(i,best)}'$	The best gas in the cluster
$'\alpha'$	influence of other gases on gas i in cluster *j* and is equal to 1
$'\beta'$	constant
$'F_{best}'$	Fitness of the best gas in the entire system
$'F_{(i,j)}'$	Fitness of gas i in cluster *j*
$'F'$	The orientation of the search agent can be changed and diversity $= \pm$ can be provided by the flag
$'N'$	Population size
$'G'_{(i,j)}$	Location of gas i in cluster *j*
$'G_{max}\ and\ G_{min}'$	The upper and lower bounds of the problem
$'r_1'$	Random number between 0 and 1
$'y_i'$	i^{th} honey badger position referring to a candidate solution

$'ll_i$ and ul_i'	Lower and upper limits of the search domain
$'I_i'$	Smell intensity of the prey
$'S'$	Source strength
$'d_i'$	Distance between the prey i^{th} honey badger
$'t_{max}'$	Maximum number of iterations
$'H_{Sum} = \{H_1, H_2\}'$	Gaussian entropy of the diagonals of 2X2 Image
$'G = \{G_1, G_2\}'$	Diagonals of 2X2 Image
$'H = \{H_1, H_2, H_3\}'$	Gaussian entropy of the diagonals of 3X3 Image
$'G = \{G_1, G_2, G_3\}'$	Diagonals of 3X3 Image
$'H = \{H_1, H_2, \ldots H_n\}'$	Gaussian entropy of the diagonals of NXN Image
$'G = \{G_1, G_2, \ldots G_n\}'$	Diagonals of NXN Image
$H_{Sum} = H_1 + H_2 + \cdots + H_n$	H_n represents the entropy function calculated based on 2D-Histogram.
$'C'$	Constant ≥ 1(default = 2)
$'y_{prey}'$	Position of the prey (global best position)
‘β ≥ 1’ (default = 6)	ability of the honey badger to get food
$'r_3, r_4$ and r_5'	Three different random numbers between 0 and 1
‘F’	Flag that changes the search direction
$'r_7'$	Random number between 0 and 1
$'y_{new}'$	New position of honey badger
$'y_{prey}'$	Prey location
$'x$, b’	Base of the logarithmic function
$'H(x)'$	Entropy of the image
$'p_j'$	Probability of the pixel with gray level j
$'T'$	Threshold value
$'x, y'$	Coordinates of the threshold value point $p(x, y), f(x, y)$
$'Y_{ij}{}^k(t_1)$ and $Y_{ij}{}^k(t_2)'$	DN value of the pixel Y which is located at row i and column j and k at time t_1 and t_2.

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVATIONS

HGSOA	Henry Gas Solubility Optimization Algorithm
HBOA	Honey Badger Optimization Algorithm
PSO	Particle Swarm Optimization
GA	Genetic Algorithm
ABC	Artificial Bee Colony
GWO	Grey Wolf Algorithm
PSNR	Peak Signal to Noise Ratio
SSIM	Structural Similarity Index Measurement
FSIM	Feature Similarity Index Measurement

CHAPTER 1

INTRODUCTION

CHAPTER 1 - INTRODUCTION

Images are widely used in image processing and computer vision to convey useful information. A few applications such as: Medical diagnosis [1], Remote sensing [2], and Pattern recognition [3], where the raw images are used to extract desired region for further processing. Segmentation can be done in many ways mainly 2 ways Discontinuity based, and Similarity based. Again, Discontinuity based are sub-categorized into Isolated Point Detection, Line detection, Edge Detection and similarity based are sub categorized into Thresholding, Region Growing, Region Splitting and Merging. Out of all these Thresholding is the simplest way of segmenting an image. We perform Image segmentation using multilevel thresholding technique which separates the test images into multiple segments and used for certain applications. Thresholding is again classified into parametric and non- parametric approach-based techniques. In parametric approach we estimate the values based on probability density function to model each class. This way is more time-consuming and might not be accurate all the times and also requires more computation power. In a Non-parametric based approach, we employ several criteria such as between-class variance, entropy and error rate to verify how good is the threshold value and update to get the maximum.

Selection of appropriate threshold values in multilevel thresholding algorithm is the challenging task which decides the effectiveness of the methods. Non-parametric method: Tsallis Entropy [4], Kapur's Entropy [5], Otsu [6] between class variance, Masi Entropy [7], Renyi's Entropy [8], Gaussian Entropy [9] and Fuzzy Entropy [10]are used for obtaining optimal threshold values. Metaheuristic algorithms are widely used in non-parametric methods for threshold selection by maximizing the above objective functions in a short period of time.. Particle Swarm Optimization (PSO) [11], Genetic Algorithm (GA) [12], Artificial Bee Colony (ABC) [13], Grey Wolf Algorithm (GWO) [14] are some well-known Nature Inspired Optimization Algorithms which are successfully developed in the field of thresholding. In this project a new multilevel thresholding algorithm using Henry gas solubility optimization [15] and Honey badger optimization [16] are proposed.

Remote sensing is a field of science that involves acquiring and interpreting information about objects or phenomena without direct physical contact. Remote sensing can be done using a variety of techniques, such as aerial photography, LiDAR, and satellite imagery. Remote sensing has numerous applications, including environmental monitoring, land use management, and disaster management. Remote sensing data is typically very large and complex, making it difficult to analyse using traditional methods. In recent years, meta-heuristic algorithms have emerged as a powerful approach for analysing remote sensing data. This paper will provide a comprehensive review of remote sensing image segmentation and change detection using meta-heuristic algorithms.

Image segmentation is an essential task in image analysis, as it involves dividing an image into meaningful segments or regions based on their similarity in terms of spectral, spatial, and textural characteristics. Remote sensing image segmentation is particularly challenging due to the large size and high complexity of remote sensing data. Traditional segmentation techniques, such as thresholding and region growing, have limited accuracy and require manual parameter tuning. Meta-heuristic algorithms have been shown to be effective in optimizing the segmentation process and improving segmentation accuracy.

Meta-heuristic algorithms are a class of optimization algorithms that are inspired by natural processes such as evolution, swarm behaviour, and annealing. These algorithms are designed to solve complex optimization problems by exploring a large search space and finding optimal or near-optimal solutions. Examples of meta-heuristic algorithms include genetic algorithms, particle swarm optimization, ant colony optimization, and simulated annealing. Genetic algorithms are one of the most widely used meta-heuristic algorithms for remote sensing image segmentation. Genetic algorithms work by simulating the process of natural selection, where the fittest individuals in a population are selected to reproduce and pass on their traits to the next generation. In the context of remote sensing image segmentation, genetic algorithms can be used to optimize segmentation parameters such as threshold values, filter sizes, and kernel shapes. Genetic algorithms have been shown to be effective in optimizing segmentation accuracy while reducing the need for manual intervention.

Particle swarm optimization is another meta-heuristic algorithm that has been used for remote sensing image segmentation. Particle swarm optimization simulates the behaviour of a swarm of particles that move through a search space to find optimal solutions. In the context of remote sensing image segmentation, particle swarm optimization can be used to optimize segmentation parameters such as the number of clusters, the distance metric, and the convergence criterion. Particle swarm optimization has been shown to be effective in improving segmentation accuracy and reducing the computational cost of the segmentation process. Ant colony optimization is another meta-heuristic algorithm that has been used for remote sensing image segmentation. Ant colony optimization simulates the behaviour of ants that lay pheromone trails to find the shortest path between a food source and the nest. In the context of remote sensing image segmentation, ant colony optimization can be used to optimize segmentation parameters such as the threshold value, the neighbourhood size, and the connectivity criterion. Ant colony optimization has been shown to be effective in improving segmentation accuracy while reducing the computational cost of the segmentation process.

Simulated annealing is a meta-heuristic algorithm that is inspired by the process of annealing in metallurgy. Simulated annealing works by simulating the process of heating and cooling a material to reduce its defects and improve its structure. In the context of remote sensing image segmentation, simulated annealing can be used to optimize segmentation parameters such as the threshold value, the filter size, and the connectivity criterion. Simulated annealing has been shown to be effective in improving segmentation accuracy while reducing the need for manual intervention. Change detection is another important task in remote sensing image analysis. Change detection involves comparing two or more images of the same area acquired at different times to identify and quantify changes that have occurred. Change detection can be done using a variety of techniques, such as thresholding, principal component analysis.

CHAPTER 2

OPTIMIZATION TECHNIQUES

CHAPTER 2 - OPTIMIZATION TECHNIQUES

Image processing involves a wide range of tasks, such as image enhancement, image restoration, image segmentation, and object recognition. These tasks are often complex and computationally intensive, requiring the use of optimization techniques to find optimal solutions. Optimization techniques are mathematical methods that are used to find the best solution to a problem from a set of possible solutions. Optimization techniques have been widely used in image processing to improve the accuracy and efficiency of algorithms. Deterministic optimization techniques are based on mathematical models and are used to find the optimal solution to a problem. These techniques are widely used in image processing and include techniques such as gradient-based optimization, convex optimization, and dynamic programming. Gradient-based optimization techniques are used to optimize a function by finding the gradient of the function and moving in the direction of the steepest descent.

This technique is widely used in image processing for tasks such as image restoration, image registration, and image segmentation. Convex optimization techniques are used to optimize a function that is convex. Convex optimization techniques are widely used in image processing for tasks such as image denoising, image restoration, and image segmentation. Dynamic programming is a technique used to solve optimization problems by breaking them down into smaller sub-problems. These techniques are widely used in image processing and include techniques such as simulated annealing, genetic algorithms, and particle swarm optimization .Simulated annealing is a stochastic optimization technique that is used to find the global optimum solution by simulating the process of annealing in metals. This technique is widely used in image processing for tasks such as image segmentation and object recognition. Genetic algorithms are a stochastic optimization technique that is used to find the global optimum solution by simulating the process of natural selection. This technique is widely used in image processing for tasks such as image enhancement, image restoration, and image segmentation. Particle swarm optimization is a stochastic optimization technique that is used to find the global optimum solution by simulating the behaviour of a swarm of particles.

2.1 Henry Gas Solubility Optimization Algorithm

2.1.1 Henry's Law:

Henry's law is a physics-based gas law. It was first formulated by the English physician and chemist William Henry in the year 1803. The law was named after him. This law holds good only for solutions that are dilute and gases with low pressure.

According to Henry's law, "at a constant temperature, the solubility of a given gas in a specific type and volume of liquid is directly proportional to the amount of partial pressure applied to it," and the proportionality constant is known as Henry's constant. (k_H).

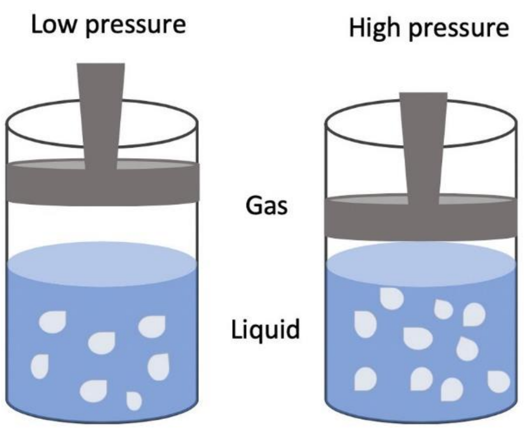


Fig. 1 Henry's Law

Henry's law can be mathematically expressed as:

$$P \alpha C \text{ or } P = k_H . C \tag{1}$$

Where $'P'$ denotes the partial pressure of the gas in the atmosphere above the liquid, $'C'$ represents the concentration of the dissolved gas and $'k_H'$ is Henry's law constant of the gas which is specific for the given gas-solvent combination at a given temperature. At constant pressure, the greater the value of Henry's constant, the lower the solubility of the gas in the liquid. Similarly, the more the partial pressure, the more the solubility of the gas in the liquid.

According to Charles Coulston Gillispie, John Dalton assumed that "In the vapour phase, the interatomic distance of the gas molecules in solution bears a maximal whole number related to the separation of the gas particles from one another. If this ratio is constant for each gas at a specific temperature, Henry's law will follow."

An example from daily life where Henry's law can be seen is one's experience during the intake of carbonated soft drinks, which contain dissolved carbon dioxide. When the bottle is closed, only pure carbon dioxide gas is present inside the container above the liquid, given the pressure inside the container is greater than that of atmospheric pressure. When the bottle is opened, the pressure inside the bottle becomes lower than that of the atmosphere. Due to this effect, the carbon dioxide that is dissolved in the solution escapes resulting in degassing.

Henry's law constant (k_H) varies with variations in temperature for a specific gas type. That can be mathematically expressed with the help of Van Hoff's equation as follows:

$$\frac{d\, ln\, k_H}{d\left(\frac{1}{T}\right)} = \frac{-\nabla_{sol}E}{R} \tag{2}$$

Where k_H is Henry's law constant, $\nabla_{sol}E$ is the dissolution enthalpy and R is the gas constant. The ideal value of R in S.I. is $8.314\, JK^{-1}mol^{-1}$.

k_H is a function of the parameters A and B, and we can obtain the following by integrating it with eq-(1)

$$k_H(T) = \exp\left(\frac{B}{T}\right) \times A \tag{3}$$

Where k_H is a function with parameters A and B that define the T functional dependence of k_H.The expression of k_H at a reference temperature T = $298.15K$, can be given by the expression:

$$k_H(T) = (k_H)^\theta \times \exp\left(\frac{-\nabla_{sol}E}{R}\left(\frac{1}{T} - \frac{1}{T^\theta}\right)\right) \tag{4}$$

This is valid only when the dissolution enthalpy ($\nabla_{sol}E$) is a constant. So, the equation can be rewritten as:

$$k_H(T) = \exp\left(-C \times \left(\frac{1}{T} - \frac{1}{T^\theta}\right)\right) \times {k_H}^\theta \tag{5}$$

2.1.2 HGSO Introduction

Henry gas solubility optimisation (HGSO) is a novel metaheuristic algorithm that is population-based and used to solve optimisation problems. It is a physics-based optimisation algorithm based on Henry's law. This is used to solve complex optimization problems by balancing the two phases, i.e., they are the exploration and the exploitation phases, and it is used to escape from the local optima as it maintains a pool of solutions. It checks in a large pool of solution matrices to identify the most suitable global solution. The efficacy of this algorithm is compared with the seven famous metaheuristic algorithms, which include algorithms like PSO, GSA, CS, GWO, WOA, EHO, and SA, and is assessed using forty-seven mathematical optimization problems and three actual design optimization issues which are regarded as most challenging test problems in the literature and the obtained results can be used further research.

2.1.3 HGSO'S Inspiration

William J Henry proposed Henry's law for the first time in 1800. At a given temperature and pressure, solubility is defined as the quantity of solute that can be dissolved in each quantity of solvent.. So, the HGSO imitates the behaviour of gases that obey Henry's law. For different temperatures and pressures, the solubility varies. So, the principal factors that influence solubility are temperature and pressure. As the partial pressure increases, the more is the solubility of gases in the liquid and vice-versa.

2.1.4 Mathematical Model OF HGSO

The mathematical model of the HGSO algorithm can be expressed in a series of mathematical steps. The steps can be reported as follows:

i. Initialisation:

The following equation is used to initialise all of the required initial parameters, including the number of gases and their positions:

$$Y_i(\mathrm{t}+1) = Y_{min} + \mathrm{r} \times (Y_{max} - Y_{min}) \tag{6}$$

Where $Y_{(i)}$ denotes the position of ith gas in population size (*N*), 'r' is a random number where r $\in (0,1)$, and Y_{min}, Y_{max} are the bounds of the problem, and t is the iteration time. With the help of the following equation, the number of gas i values of Henry's constant of type $j(k_{H_j}(t))$, partial pressure $P_{i,j}$ of gas i in cluster j, and $\frac{\nabla_{sol}E}{R}$ is a constant value of type $j(C_i)$ are initialised.

$$(k_H)_j = l_1 \times rand(0,1) , C_j = l_3 \times rand(0,1) \tag{7}$$

Where $l_1 = 5\text{E} - 02, l_2 = 100 \; and \; l_3 = 1E - 02$ are defined constants.

ii. Clustering:

According to the number of different gas types, the population agents are separated into equal clusters. Each cluster is of a similar kind of gas and Henry's constant value (k_{H_j}) is different for different clusters and each cluster of similar kinds of gases has the same Henry's constant value (k_{H_j}).

iii. Evaluation:

Determine which gas attains the highest equilibrium state among the others of its type, each cluster j is examined. The optimal gas in the entire swarm is then chosen by ranking the gases.

iv. Update Henry's coefficient:

As per the following formula, Henry's coefficient is updated.

$$k_{H_j}(t+1) = k_{H_j}(t) \times \exp\left(-C_j \times \left(\frac{1}{T(t)} - \frac{1}{T^\theta}\right)\right) \tag{8}$$

where,

$$T(t) = \exp\left(-\frac{t}{iter}\right) \tag{9}$$

In the above equation, *t* is the temperature, T^θ is a constant which is the reference temperature and is equal to $298.15K$ and the number of iterations is given by $iter$ and k_{H_j} is Henry's law constant for cluster j.

v. Update solubility:

With the updated Henry's law constant, Solubility is also updated and can be given by the following equation:

$$S_{i,j}(t) = K \times k_{H_j}(t+1) \times P_{i,j}(t) \tag{10}$$

Where K is a constant, $S_{i,j}$ is the solubility of the gas i in cluster j.

vi. Update position:

The position of the gas is updated as per the following equation:

$$\begin{gathered} Y_{i,j}(t+1) = Y_{i,j}(t) \\ +F \times r \times \gamma \times \left(Y_{i,best}(t) - Y_{i,j}(t)\right) F \times r \times \alpha \times \left(S_{i,j}(t) \times Y_{best}(t) - Y_{i,j}(t)\right) \end{gathered} \tag{11}$$

$$\gamma = \beta \times exp\left(-\frac{F_{best}(t) + \varepsilon}{F_{i,j}(t) + \varepsilon}\right), \varepsilon = 0.05 \tag{12}$$

Where $Y_{(i,j)}$ stands for the position of gas i in cluster j, and r and t are, respectively, a random constant and the iteration time. The best gas in the swarm is Y_{best}, while the best gas in the cluster is $Y_{(i,best)}$. Additionally, α is the influence of other gases on gas i in cluster j and is equal to 1, β is a constant and γ is the ability of gas i in cluster j to interact with the gases in its cluster. F_{best} is the fitness of the best gas in the entire system, while $F_{(i,j)}$ is the fitness of gas i in cluster j. The orientation of the search agent can be changed and diversity $= \pm$ can be provided by the flag F. The exploration and exploitation phases are balanced by the two parameters $Y_{(i,best)}$ and Y_{best}, where Y_{best} is the best gas in the entire swarm and $Y_{(i,best)}$ is the best gas i in cluster j.

vii. Escaping from local optimum:

The step is used to escape from the local optima and the following equation helps in ranking and choosing the worst agents (N_w):

$$N_w = N \times (rand(c_2 - c_1) + c_1) \tag{13}$$

Where c_1=0.1 and c_2=0.2 and N is the population size.

viii. Update the position of the worst agents:

$$G_{(i,j)} = G_{min_{(i,j)}} + r \times \left(G_{max_{(i,j)}} - G_{min_{(i,j)}}\right) \tag{14}$$

Where $G_{(i,j)}$ denotes the location of gas i in cluster j, r is a random number, and G_{max} and G_{min} are the upper and lower bounds of the problem, respectively.

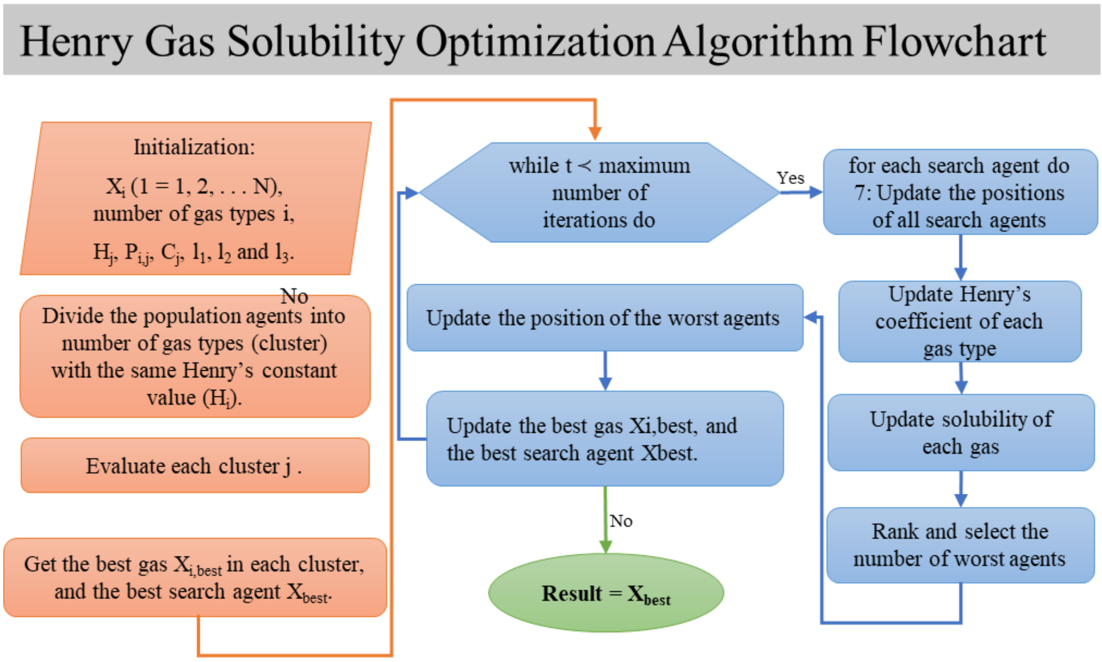


Fig. 2 Flowchart of HGSO

2.2 Honey Badger Optimization Algorithm

Fig. 3 Honey Badger & Honey Badger with honey Bird

The Honey Badger Algorithm (HBA) it is a swarm-based optimization technique which imitates the digging and following behaviour of honey badgers. It is a population -based optimization approach. The honey badger smells to locate the approximate location of the prey, then chooses an appropriate location for digging and catching the prey or follows the honey guide bird in search of food source. The entire process is divided into two phases, which are the "digging phase" and the "honey phase". The mathematical formulation of the suggested HBA algorithm is introduced in this section.

The population of candidate solution in HBA is represented as

$$\begin{bmatrix} y_{11} & y_{12}\cdots & y_{1D} \\ y_{21} & \ddots & \vdots \\ \vdots & \ddots & \vdots \\ y_{D1} & \cdots & y_{DD} \end{bmatrix} \tag{15}$$

2.2.1 Mathematical Modelling of HBO

1. 1.Initialization Phase
2. Defining Intensity
3. Updating density Factor
4. Updating Agents Position
   4.1 Digging Phase
   4.2 Honey Phase

2.2.1.1 Initialization phase:

Initialize the population size (N) and positions of the honey badgers based on the above equation.

$$y_i = ll_i + r_1 \times (ul_i - ll_i) \tag{16}$$

Where, r_1 is a random number between 0 and 1.

where y_i is i^{th} honey badger position referring to a candidate solution in a population of N,while ll_i and ul_i are respectively lower and upper limits of the search domain.

2.2.1.2 Defining intensity (I):

I_i is the smell intensity of the prey. It helps it to know the distance to the prey. The movement of the honey badger is directly proportional to the intensity, which is given by Inverse Square Law.

$$I_i = r_2 \times \frac{S}{4\pi d_i^2} \tag{17}$$

be random number between 0 and 1

$$S = (y_i - y_{i+1})^2 \tag{18}$$

$$d_i = y_{prey} - y_i \tag{19}$$

I_i is smell intensity of the prey.

S is source strength

d_i denotes the distance between the prey.

i^{th}honey badger.

2.2.1.3 Update density factor

Provide a seamless transition from exploration to exploitation, the density factor (α) governs time-varying randomness. Using an update decreasing factor that decreases with iterations to reduce randomness over time.

$$\alpha = C \ \times exp\left(\frac{-t}{t_{max}}\right) \tag{20}$$

t_{max} = maximum number of iterations, C is a constant ≥ 1(default = 2)

Escaping from local optimum: This step is used to escape from local optima regions and here it is achieved by using a flag F, which changes the search direction to help the agents to scan the search-space rigorously.

2.2.1.4 Updating the agents' positions

2.2.1.4.1 Digging phase

In this phase the honey badger performs action like Cardioid shape.

$$\begin{aligned} y_{new} = {} & y_{prey} + F \times \beta \times I \times y_{prey} \\ & + F \times r_3 \times \alpha \times d_i \times |\cos(2\pi r_4) \times [1 - \cos(2\pi r_5)]| \end{aligned} \tag{21}$$

Where y_{prey} is position of the prey (global best position), β ≥ 1 (default = 6) is ability of the honey badger to get food. d_i is the distance between prey and the i^{th} honey badger, r_3, r_4 and $r_5$are three different random numbers between 0 and 1, F works as flag that changes the search direction.

$$F = \begin{cases} 1, & if\ r_6 \leq 0.5 \\ -1, & else\ \ r_6\ is\ a\ random\ number\ between\ 0\ and\ 1 \end{cases} \tag{22}$$

In this phase, a honey badger heavily relies on smell intensity I of prey x prey, distance between the badger and prey di, and time-varying search influence factor α.

Moreover, during digging activity, a badger may receive any disturbance F which allows it to find even better prey location.

2.2.1.4.2 Honey phase

Honey phase is the case when a honey badger follows honey guide to reach beehive which can be simulated as

$$y_{new} = y_{prey} + F \times r_7 \times \alpha \times d_i \qquad (23)$$

r_7 is a random number between 0 and 1.

Where y_{new} is the new position of honey badger, y_{prey} is prey location. F and α are determined.

Honey Badger Optimization Algorithm Flowchart

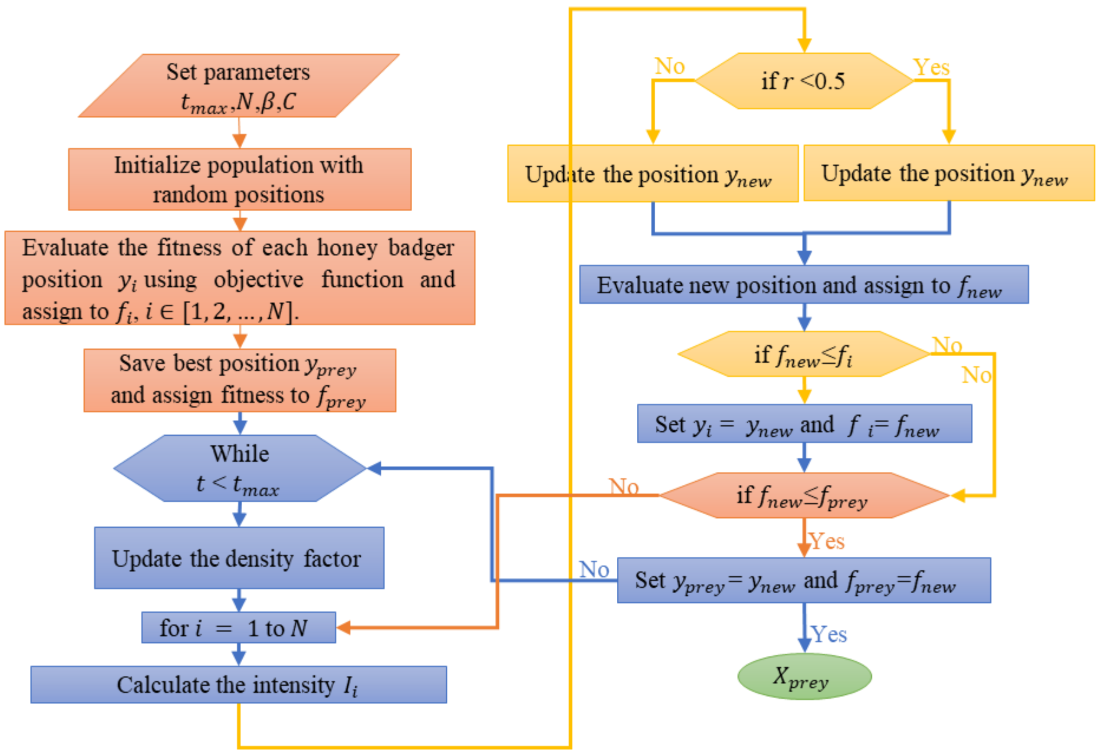


Fig. 4 Flowchart of HBO

CHAPTER 3

ENTROPY

CHAPTER 3 – ENTROPY

3.1 What Is Entropy?

In image analysis, entropy plays a significant role. Entropy means the measure of information or measurement of order. It is used to calculate the amount of information contained within an image. It is a statistical measure of randomness which is used to describe the quality of the input picture. Entropy is seen in relation to the degree of uncertainty surrounding an occurrence that corresponds to a specific probability distribution. Entropy can be used to quantify disorder. With the increase in disorder, which increases entropy and therefore events become less predictable.

Entropy is also used to know the homogeneity which shows how much similar certain pixels of an image are. They employ the smoothness criteria in conjunction with the entropy criterion to categorize the components. Entropy may also think of as a measurement of information content. An image with a low level of entropy also has a low level of information content. A vector with an important level of entropy also has a comparatively prominent level of information content.

When any operations are performed on images, it is important to make sure that maximum amount of information is extracted from the image. When it is the case of image segmentation, we need to carefully segment the image in such a way that no features or properties of images are lost or extract maximum amount of information which can be used for further research. If we segment the image without considering the entropy, then after performing the operations needed, we will not obtain correct results. So, to get better results and obtain good efficacy it is important to calculate entropy.

The entropy of an image $H(x)$ can be calculated from the following equation:

$$H(x) = -\sum p_j log_b p_j \tag{24}$$

Where $H(x)$ is the entropy of the image x, b is the base of the logarithmic function, p_j is obtained from the normalized histogram of the image x where it p_j is the probability of the pixel with gray level j. The more is the entropy the more will be the efficacy which means the more robust is the algorithm considered.

3.2 Properties of Entropy

1. Entropy (H) is zero if the event is sure.

$$H = 0 \text{ if } p_j = 1\ (or) p_j = 0$$

2. When p_j the probability of the occurrence of the pixel with gray level j is same for all m gray levels i.e. $\frac{1}{m}$, then they are equally likely with base b of the logarithmic is 2

$$H = log_2 m \tag{25}$$

3. The upper bound of an entropy is given as

$$H_{max} = log_2 m \tag{26}$$

3.3 Entropy Based Objective Function

3.3.1 Kapur's entropy

Kapur's entropy is an unsupervised automated thresholding methodology, which chooses the best thresholds based on the entropy of segmented classes. It is a non-parametric thresholding, in which the image is segmented into several classes by comparing the entropy of the histogram. The higher the value of entropy the more homogenous the classes are.

The Kapur's entropy based objective function can be given by:

$$p_i = \frac{h_i}{\sum_{i=0}^{L-1} h(i)} \tag{217}$$

where 'i' denotes the grey level, hi denotes the number of pixels, N denotes the total number of pixels, and L denotes the number of levels.

Kapur's entropy can be defined as:

$$f(t_1, t_2, \cdots, t_n) = H_0 + H_1 + H_2 + \cdots + H_n \tag{28}$$

where

$$H_0 = -\sum_{i=0}^{t_1-1} \frac{p_i}{\omega_0} \ln \frac{p_i}{\omega_0}\ , \omega_0 = \sum_{i=0}^{t_1-1} p_i \tag{29}$$

$$H_1 = -\sum_{i=t_1}^{t_2-1} \frac{p_i}{\omega_1} \ln \frac{p_i}{\omega_1}, \omega_1 = \sum_{i=t_1}^{t_2-1} p_i \tag{3022}$$

$$H_n = -\sum_{i=t_n}^{L-1} \frac{p_i}{\omega_n} \ln \frac{p_i}{\omega_n}, \omega_n = \sum_{i=t_n}^{L-1} p_i \tag{31}$$

H_1, H_2,. . . , H_n denote Kapur's entropies of various classes, and ω_0, ω_1, . . . , ω_n denote the probabilities of various classes.

3.3.1.1 The benefits of using Kapur's entropy:

1. Few computations needed.
2. High stability
3. Quick processing speed
4. Simpler implementation

3.3.2 Gaussian Entropy

The exponential function is commonly used as a non-linear information gain function to identify textures with strong spatial correlation and non-additive information content. In classical probability theory, the entropy or uncertainty surrounding an experiment approach zero as the probability of some occurrences approaches one and the probabilities of remaining events approaches zero. As a monotonically decreasing function that approaches zero with increasing likelihood of an event, it is possible to use a one-sided zero mean Gaussian function with a standard deviation of 1/√2 to simulate information gain. Similarly, a one-sided zero mean Gaussian function with a standard deviation of 1/2 can also be used to simulate information gain, which monotonically decreases as the probability of an event increases. As the Gaussian information gain is non-linear, only the data falling within the "bell" of the curve will be considered when computing entropy, with the remaining data ignored. The Gaussian entropy based objective function is defined by:

Consider a random variable $X = \{x_1, x_2 \dots x_n\}$ with the probabilities $P = \{p_1, p_2 \dots p_n\}$. where, n is the number of probabilistic experiments and H is the Gaussian Entropy Function.

$$H = \sum_{i=1}^{n} p_i e^{-p_i^2} \tag{32}$$

3.3.2.1 Properties of Gaussian Entropy:

1. The Gaussian entropy function is a continuous function.
2. Entropy is a concave function.
3. When the occurrence of events is equally likely, then it is an increasing function.
4. Entropy will be the minimum when all the probabilities of the pixels except one probability are zeroes and the remaining one probability is one.

$$H_{min} = e^{-1} \tag{33}$$

5. The entropy is maximum when all the p_j's are equal, for all $j = 1,2, \dots \dots . n$

$$H_{max} = e^{-1/n^2} \tag{34}$$

3.3.2.2 The desirable properties of Gaussian entropy which makes it suitable for segmentation applications are:

i. $e^{-(p_j)^2}$ can be defined for all possible points in search space.

ii. $\lim_{p_{j \to 0}} e^{-(p_j)^2} = h_1 > 0$ and finite.

iii. $h_1 > h_2$

iv. $e^{-(p_j)^2}$ decreases monotonically with an increase in the probability, in other words, with decrease in the uncertainty the gain in information decreases normally.

v. H_G is continuous over the range of $0 \le p_j \le 1$.

vi. Maximum value of H_G will be obtained when each event has equal probability.

CHAPTER 4

2D HISTOGRAM BASED ENTROPY CALCULATION

CHAPTER 4 - 2D HISTOGRAM BASED ENTROPY CALCULATION

2D-Histogram [17] represents the relationship between two images. Involving 2D-Histogram in the calculation of entropy is more efficient because considering more information regarding the image helps in differentiation of objects and boundaries in the image very easy and error free. The 2D-Histogram of an image requires two components which may be the image and mean or median or any other component for more detailed histogram calculation than 1D-Histogram. Thus, giving better results compared to that of 1D-Histogrm. Example of 2D-Histogram is as shown in Fig. 5.

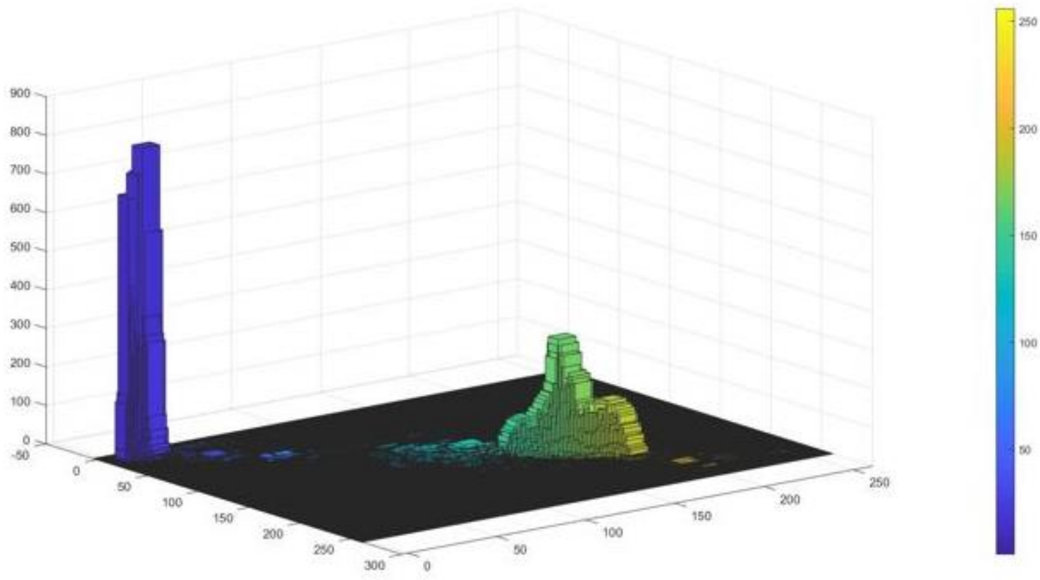


Fig. 5 2D - Histogram Bar Plot

4.1 A 2-level image's 2D-Histogram Calculation

For 2×2 image. Let the diagonals be $G = \{G_1, G_2\}$. And the gaussian entropy of the diagonals are $H = \{H_1, H_2\}$. Then the $H_{Sum} = H_1 + H_2$. Here if H_{Sum} value should be more which implies more information is retained from the original image.

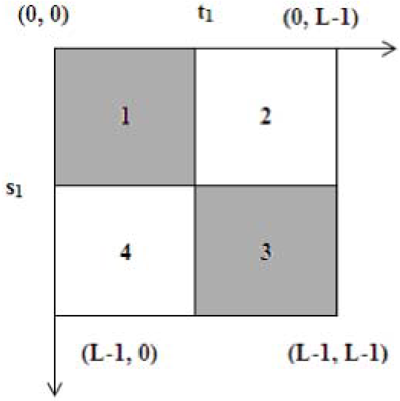


Fig. 6 2-level image's 2D- Histogram

4.2 A 3-level image's 2D-Histogram Calculation

Similarly, For 3×3 image. Let the diagonals be $G = \{G_1, G_2, G_3\}$. And the gaussian entropy of the diagonals are $H = \{H_1, H_2, H_3\}$. Then the $H_{Sum} = H_1 + H_2 + H_3$. Here if H_{Sum} value should be more which implies more information is retained from the original image.

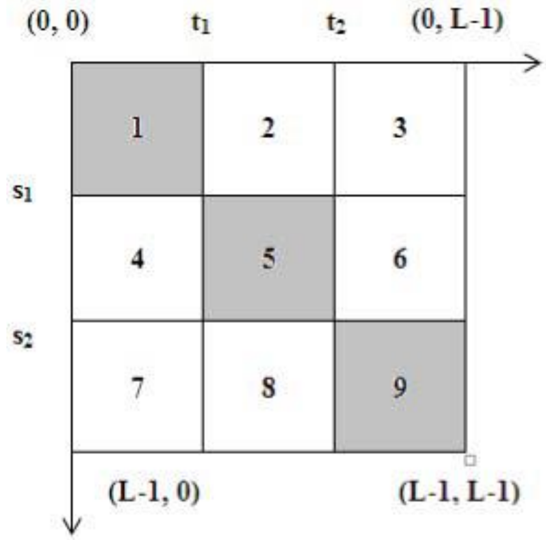


Fig. 7 3-level image's 2D- Histogram

Similarly, For $n \times n$ image. Let $H = \{H_1, H_2, ... H_n\}$ be the gaussian entropies of diagonals $G = \{G_1, G_2, ... G_n\}$. Then the $H_{Sum} = H_1 + H_2 + \cdots + H_n$. Where H_n represents the entropy function calculated based on 2D- Histogram.

CHAPTER 5

MULTILEVEL THRESHOLDING AND CHANGE DETECTION

CHAPTER 5 - MULTILEVEL THRESHOLDING AND CHANGE DETECTION

5.1 Multilevel Thresholding

5.1.1 Segmentation

Segmentation refers to the process of dividing images into subregions that share similar properties, such as grey level, color, texture, brightness, and contrast. The extent of the subdivision is determined by the problem being addressed, and segmentation should be stopped once the regions of interest or objects for the application have been identified. The accuracy of segmentation is critical in determining the success or failure of automated analysis methods. Image segmentation is widely used to detect objects and boundaries, including lines and curves, in images. While manual segmentation is feasible, it is a time-consuming process and is subject to operator variability. Furthermore, reproducing a manual segmentation result is challenging.

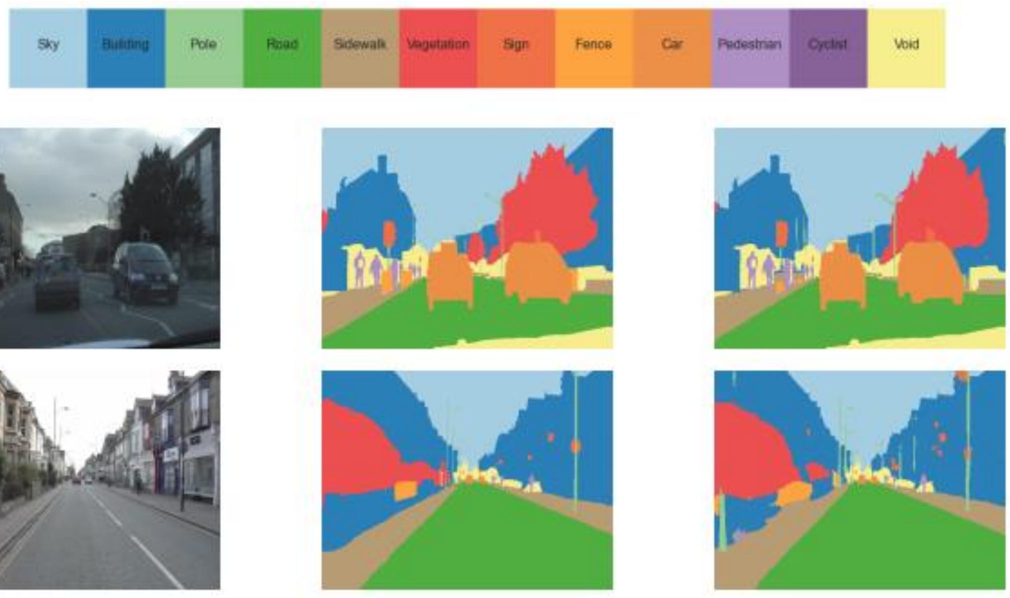


Fig. 8 Segmentation

5.1.1.1 Remote Sensing - Applications of segmentation

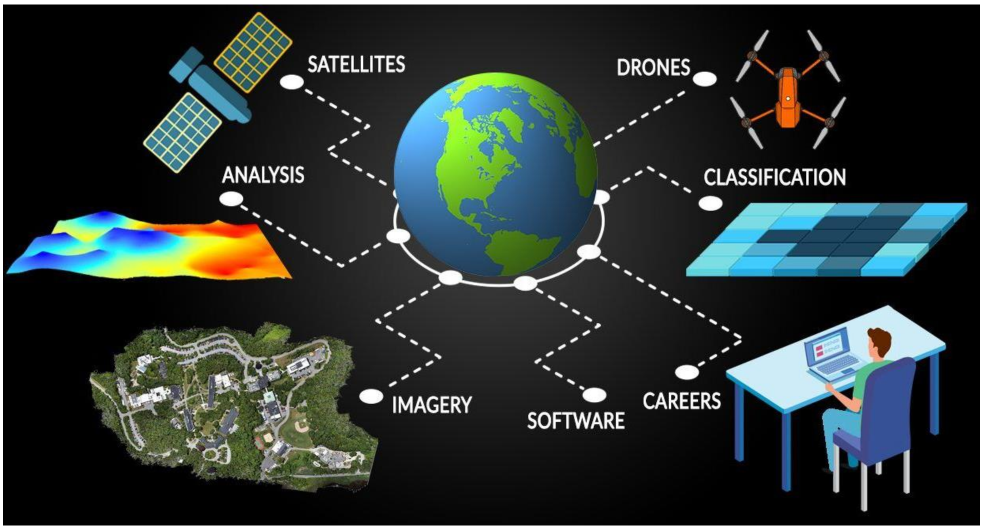


Fig. 9 Remote Sensing

- Analysing the condition of rural roads.
- Controlling forest fires.
- Detecting land use and land covered.
- Analysing the snow and dense forest areas.
- Locating construction and building alteration.

Over the past few decades, a multitude of segmentation methods have been proposed. However, due to the shared properties of different approaches, it is difficult to categorize them definitively. Nonetheless, the following categories can be used:

Threshold-based Segmentation: This method segments an image by utilizing histogram thresholding techniques, which may be directly applied to an image or combined with pre- and post-processing techniques.

Edge-based Segmentation: In this technique, edges detected in an image are considered to represent object boundaries and are used to identify those objects.

Clustering Techniques: While clustering is sometimes used interchangeably with (agglomerative) segmentation techniques, it is commonly used in data analysis of high-dimensional measurement patterns. Clustering methods group together patterns that are similar in some sense, which is similar to what we aim to achieve when segmenting an image. Some clustering techniques can be applied for image segmentation.

Matching: When we already know the appearance of the object we want to identify in an image, we can use this knowledge to locate the object in the image. This approach to segmentation is referred to as matching.

5.1.2 Thresholding

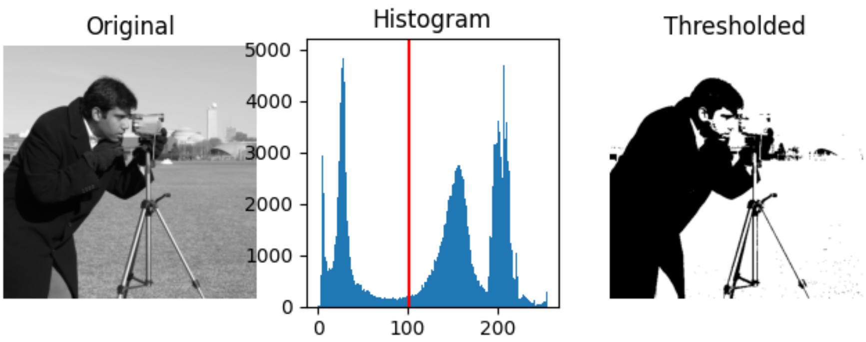


Fig. 10 Thresholding

Segmentation is the process of separating an image into regions corresponding to objects by identifying common properties or differences between regions. Intensity is the simplest property that pixels in a region can share, making thresholding a natural way to segment such regions. Thresholding is a widely used method for image segmentation, particularly for discriminating foreground from background. By selecting an appropriate threshold value T, a grey level image can be converted to a binary image that contains all essential information about the position and shape of the objects of interest (foreground). This binary image simplifies the process of recognition and classification by reducing data complexity.

The most common way to convert a grey-level image to a binary image is to select a single threshold value T, where all grey level values below T are classified as black (0), and those above T are white (1). However, selecting the proper value for T can be challenging, particularly when the histogram of the image presents many peaks and lacks a clear valley. One method for selecting T is by analyzing the histogram of the image, and the ideal case is when the histogram presents only two dominant modes and a clear valley (bimodal). In real applications, the histogram is often more complex, making it difficult to select the value of T. Therefore, metaheuristic algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Artificial Bee Colony (ABC), and Grey Wolf Algorithm (GWO) are used to find optimized threshold values successfully.

5.1.2.1 Threshold Selection

Metaheuristic is a problem-solving approach that is not restricted to a specific type of problem. It can be categorized into two types: single solution-based (local search) and population-based (random search) metaheuristics. In combinatorial optimization, metaheuristics can efficiently find good solutions by searching through a large set of feasible solutions, requiring less computational effort than optimization algorithms, iterative methods, or simple heuristics. They are suitable for optimization problems and most metaheuristic algorithms are derivation-free, making them appropriate for solving complex problems with unknown derivative information in the search space. To select the best threshold, we can use two types of metaheuristic algorithms: swarm-based and physics-based algorithms.

5.1.2.2 Threshold Techniques

Threshold technique is one of the important techniques in image segmentation. This technique can be expressed as:

$$T = T[x, y, p(x, y), f(x, y)] \tag{35}$$

Where T is the threshold value.

x, y are the coordinates of the threshold value point. $p(x, y), f(x, y)$

Are points the grey level image pixels. Threshold image $g(x, y)$ can be defined:

$$g(x, y) = \begin{cases} 1\ if\ (x, y) \leq T \\ 0\ if\ g(x, y) > T \end{cases} \tag{36}$$

5.1.3 Multilevel Thresholding

For image segmentation, the convenient and effective method is Multilevel thresholding which splits the image into several regions with the help of one or more threshold values which are obtained by optimizing a suitable objective function.

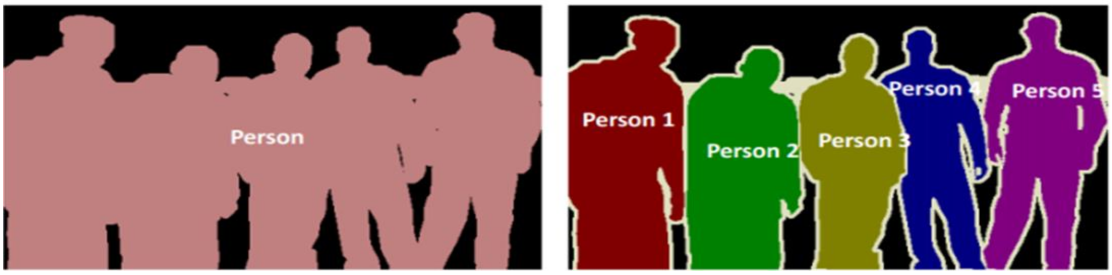


Fig. 11 Multi-Level Thresholding

5.1.4 Mathematical formulation of multilevel thresholding

Let us consider an image of size $X \times Y$ having L grey levels {0,1,2…. …. L-1} divided into m + 1 distinct regions depending upon their intensity level. *k thresholds* values are required for generating m + 1 distinct regions which can be shown by following simple rule of thresholding. Where g denotes the intensity of pixels, U_i represents the i^{th} segmented region. $\{TH_1, TH_2 \ldots. \ldots.TH_m\}$ are the threshold values used for segmentation.

$$\begin{cases} U_1 \leftarrow n, & if\ 0 \leq g < TH_1 \\ U_2 \leftarrow n, & if\ TH_1 \leq g < TH_2 \\ U_3 \leftarrow n, & if\ TH_2 \leq g < TH_3 \\ & \vdots \\ & \vdots \\ & . \\ U_{m+1} \leftarrow n, & if\ TH_m \leq g < 255 \end{cases} \tag{37}$$

Choose optimized threshold values using meta-heuristic algorithms. In this chapter a detailed note of algorithms which we used, honey badger optimization technique (HBO) and henry gas law of solubility optimization technique (HGSO).

5.2 Change Detection

5.2.1 Introduction to Change Detection

Change detection in remote sensing involves identifying changes in land features by comparing them over time. This can be done either manually or with the help of remote sensing software. To manually interpret changes, an observer or analyst selects regions of interest and compares images taken at different intervals. This can be done on paper or on a computer screen, using a GIS software. In aerial photo analysis, a stereoscope can be used to view two overlapping shots in three dimensions. Manual image interpretation is particularly effective when evaluating changes between discrete classes, such as forest openings, land use, and land cover maps, or when changes are significant, such as construction site impacts. It is also a useful alternative when attempting to identify change using pictures or photos from multiple sources.

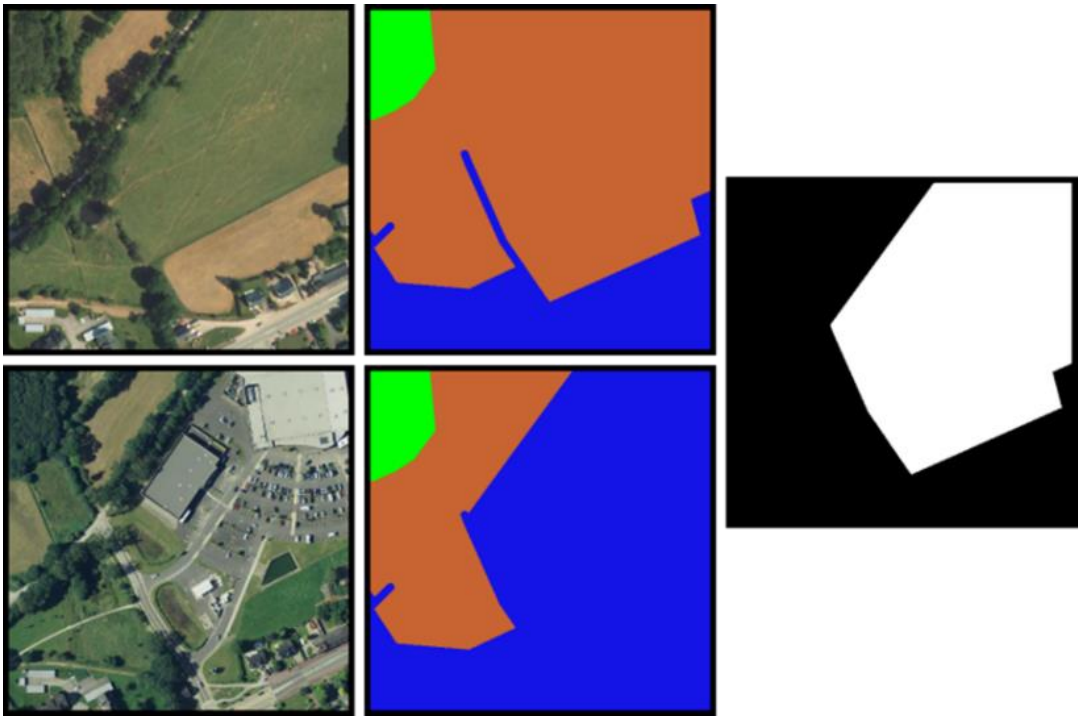


Fig. 12 Change Detection

5.2.2 What Is Change Detection?

In Geographic Information Systems, change detection is a method that measures how different properties of a particular area have changed by comparing the multi-temporal images of that area. Comparing aerial photos or satellite images of the area obtained at various periods is a traditional procedure of change detection. The impact of natural catastrophes like earthquakes and tsunamis, changing agriculture, deforestation, and urban growth have been all examined using change detection. It is a technique which can be used to obtain the differences between regions over different time stamps. Regular detection of surface feature changes on Earth establishes the foundation for a profound understanding of the interactions and links between natural occurrences and human activity to better manage and utilize resources. Change detection typically entails the use of multi-temporal datasets to statistically analyse the temporal consequences of the phenomenon.

When examining multi-temporal satellite pictures, change detection can identify spatial changes brought on by artificial or natural causes. It is crucial for distant sensing, tracking environmental changes, and spotting changes in land use and cover. Satellite images with different resolutions are collected by remote sensing satellites and used for change detection. Numerous techniques have been developed over time for processing remote sensing data and are constantly being developed. The basis for assessing the interactions and links between natural and human events for improved resource management is the timely and precise change detection of Earth's surface features. To statistically evaluate the temporal consequences of the phenomenon, change detection often employs multi-temporal datasets. It is crucial to track changes to the Earth's surface by using change detection techniques based on current image processing algorithms and remote sensing data. Both the armed services (using, for instance, visual intelligence) and the civilian sector use change detection. Examples of civilian uses include urban planning, environmental monitoring, precision agriculture, tracking of land changes, and object movement analysis.

5.2.3 Remote Sensing

Remote sensing is the science of acquiring information about the Earth's surface and atmosphere using sensors onboard satellites, aircraft, and other platforms. The sensors detect and measure the electromagnetic radiation reflected or emitted from the Earth's surface and atmosphere. Remote sensing is a valuable tool for monitoring and understanding natural and human-induced changes on the Earth's surface.

It has many applications in various fields, including agriculture, forestry, geology, meteorology, oceanography, urban planning, and environmental monitoring. With the development of new sensor technologies and platforms, remote sensing has become an essential tool for scientific research and decision-making in many areas. Remote sensing data can be used to derive a wide range of information about the Earth's surface and atmosphere. This includes information about land cover and land use, vegetation health, soil moisture, atmospheric temperature, and composition. Remote sensing data can be used to monitor natural disasters like hurricanes, floods, and wildfires, and to track the effects of climate change on the Earth's surface.

Remote sensing data is processed and analyzed using various techniques, including image processing, data fusion, and machine learning. Image processing techniques are used to enhance and analyze the images acquired by remote sensing sensors. Data fusion techniques are used to combine data from multiple sensors and platforms to improve the accuracy and completeness of the information obtained. Machine learning techniques are used to automate the analysis of large volumes of remote sensing data.

In conclusion, remote sensing is an essential tool for understanding and monitoring the Earth's surface and atmosphere. It provides valuable information for scientific research, decision-making, and policy development in various fields. Remote sensing technology is continuously evolving, and new applications are being developed as the demand for remote sensing data continues to grow.

5.2.4 Change Detection Methods

Various approaches are used to identify and examine changes to the earth's surface. It is important to understand the process of change detection before learning about various change detection approaches. According to Jensen, there are six crucial actions that must be taken to identify changes to the earth's surface. They are as follows:

1. The types of issues with change detection
2. Data from remote sensing images is chosen
3. Image preparation
4. Clustering or image processing
5. Deciding on the methodology for change detection

5.2.5 Remote Sensing Change Detection (RSCD)

Remote sensing can be effective at detecting change, i.e., change that happens between a single image in different timestamps. Remote sensing change detection (RSCD) is the process of identifying changes between remotely sensed images of the same location acquired at separate times. This is an active research area with a broad range of applications.

Remote sensing enables us to manage ecosystems and manage socioeconomic management. Remote sensing data gathering enables synoptic assessments of Earth System function patterning and change detection at local, regional, and global scales throughout time.

There are two types of change detection techniques: the pre-classification method and the post-classification method. Pre-Classification methods examine changes without identifying the image value. "Vegetation Index Differencing (NDVI)" is among the most popular and commonly employed pre-classification approach. After the NDVI, many more indices emerged, including NDWI, MNDWI, Change Vector Analysis (CVA), etc.

The most popular change detection technique today, however, is the post Classification approach. Based on a meticulously characterized classification of land cover, post-classification classification assesses the change in land cover. Some of the popular change detection techniques include post-classification classification comparison, aerial difference analysis, image differencing, image rationing, image modelling, etc.

5.2.6 Procedure of Change Detection:

The procedure of change detection is as follows:

1.Image selection

2.Image Registration

3.Radiometric and atmospheric corrections

4.Mutli-temporal analysis

5.Finally, perform change detection

5.2.7 Image Differencing

This technique is used to perform change detection of multi-temporal images. This approach involves subtracting, group by group and pixel by pixel DN values of two spatially registered imageries that were obtained at various time stamps. The following formula is used to determine the difference between the DN value.

$$DY_{ij}{}^{k} = Y_{ij}{}^{k}(t_2) - Y_{ij}{}^{k}(t_1) \tag{38}$$

Where $Y_{ij}{}^{k}(t_1)$ and $Y_{ij}{}^{k}(t_2)$ represents the DN value of the pixel Y which is located at row i and column j and k at time t_1 and t_2.

If there is no change, then the difference between the DN value is 0. If there is a change present, then the difference of the DN values will be either positive or negative. If we find the absolute difference of the DN values, then the result will be a positive value which represents that there is a change present in both the images.

Image differencing technique is best suited for:

1. Monitoring Land cover
2. Land-use / Land-cover change detection.
3. Forest change detection
4. Disaster management

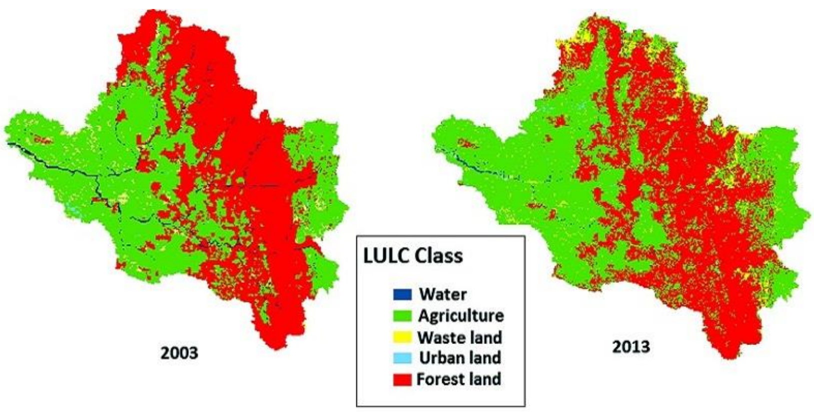


Fig. 13 Forest Change Detection

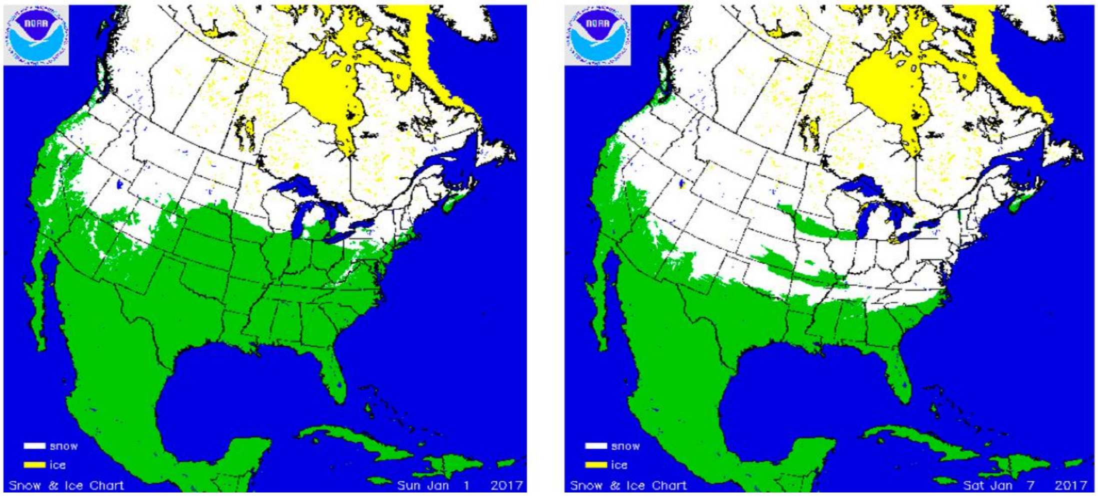


Fig. 14 Snow Cover Mapping

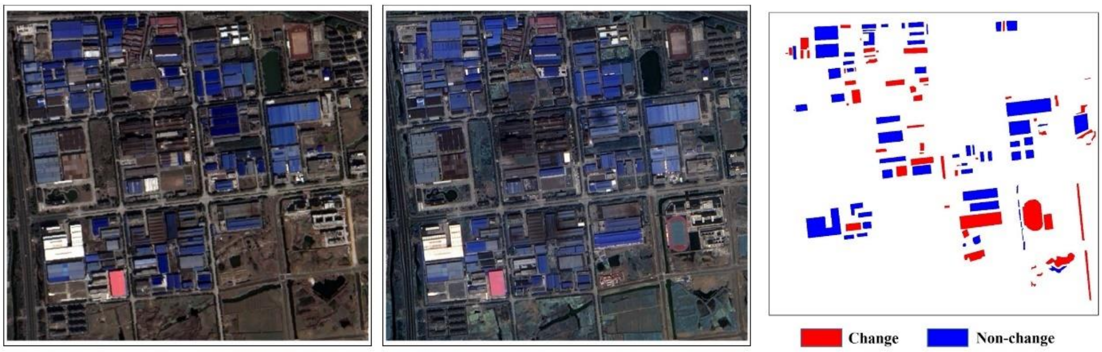


Fig. 15 Urban Planning

5.2.8 Methodology

The primary objective of change detection methods is to analyse the condition of a specific location to identify variations from the images captured at different periods. With the help of satellite-based remote sensing, high spatial and spectral resolution-oriented images are captured that are used to analyse the scale of change.

The following are the steps to perform change detection on multilevel thresholder images:

1. Obtain the multi-level thresholded images of the multi-temporal images.
2. Performing the Image differencing i.e., finding the absolute difference of both the images.
3. Finally, the differences between the multi-temporal images are obtained.

5.2.8 Applications

In the context of Remote sensing, change detection has a plethora of uses. The method is employed to track transformations of the forest area (deforestation), crop state, urban expansion, snow cover mapping, and glacier cracking. The discovery of man-made climate change in the world's oceans assists in identifying the problem's extent and formulating a successful solution.

Mapping historical changes in land use and land cover is possible with the use of the change detection technique in remote sensing. Human activity and natural disasters are responsible for these changes on the planet. The variation in the DN values in the multi-temporal images may be caused by changes in the surface of the planet, variations in lighting, weather patterns, sensor alignment, or faulty multi-temporal image registration.

There are various applications of change detection, a few of which are as follows:

- Deforestation
- Crop surveillance
- Soil moisture
- Urban planning
- Quality of the water, etc.

CHAPTER 6

RESULTS

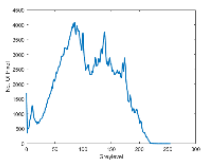
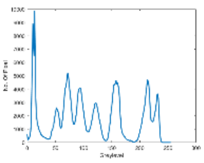
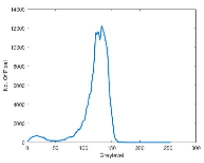
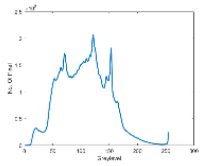
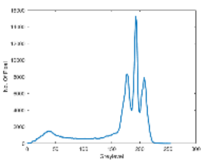
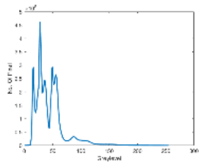
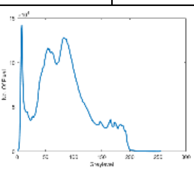
CHAPTER 6 - RESULTS

6.1 Result Evaluation

The Images 1, 2, 3, 4 [18] from Table-1 and Images 5, 6, 7 [19] from Table-1 are taken as sample images for multi-level thresholding, respective histograms are shown. Tables 2, 3, 4, 5 shows the segmented images in Table 1. The thresholding is done with 3, 4, 5 thresholds with gaussian and kapur entropies using HBA and HGSO algorithms. Tables 6 & 7 show performance of the change detection algorithm. PSNR, SSIM are the performance metrics for assessing the quality of the algorithm. Here the bold ones indicate better performance compared to other. The Gaussian entropy shown better results compared to that of Kapur's. In some cases, it is comparable to the Kapur's. Multi-temporal images [20] are considered for the change detection algorithm. The change detection results for threshold 3, 4, 5 for HBA and HGSO are as shown in Fig. 16 & 17

6.2 Raw Images Table for multi-level thresholding

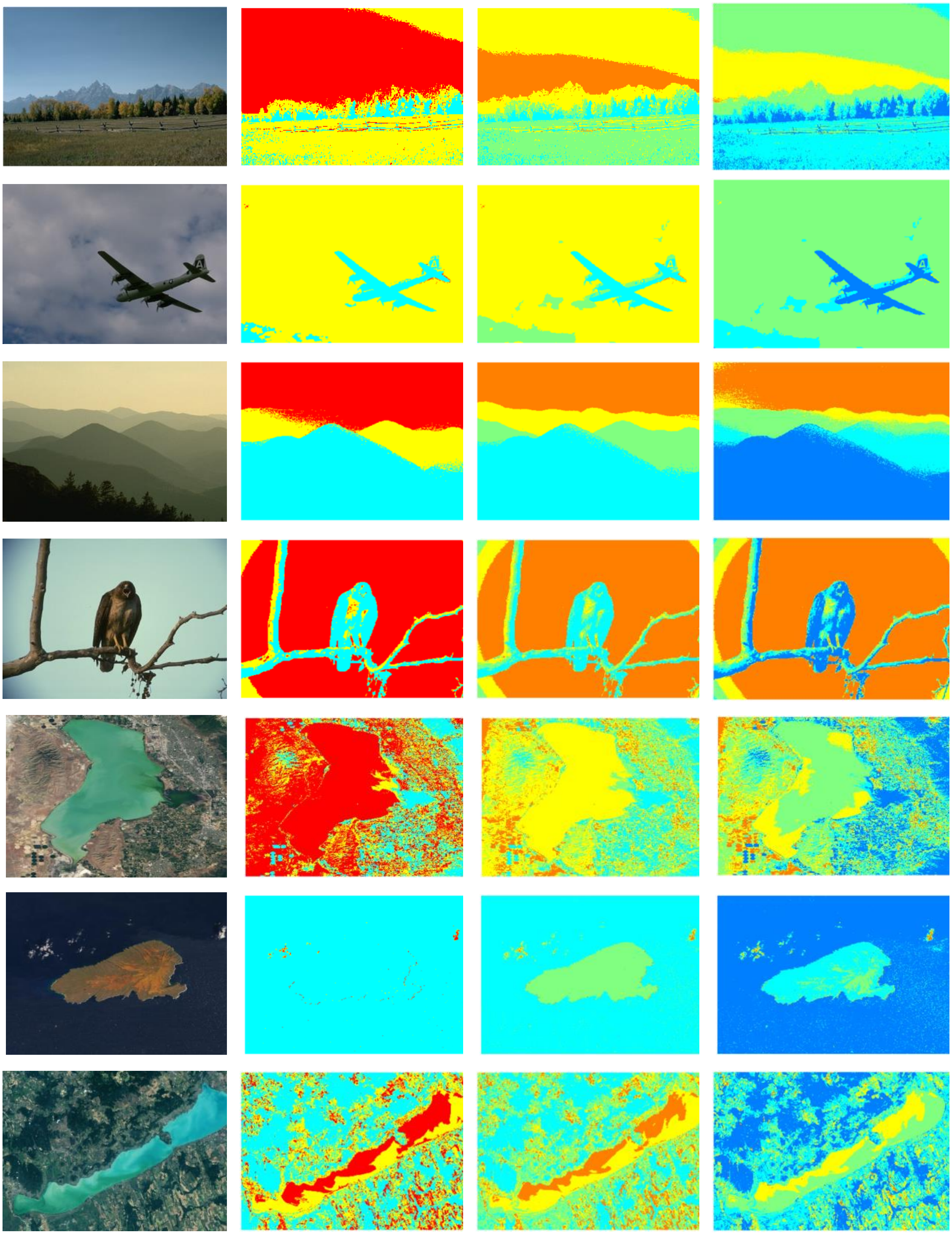
Table-I Raw Images Table for multi-level thresholding

Image	Histogram	Image	Histogram
			
			
			
			

6.3 Results Table of HBO Gauss for images in 5.1

Table-II Results Table of HBO Gauss for images in Table-I

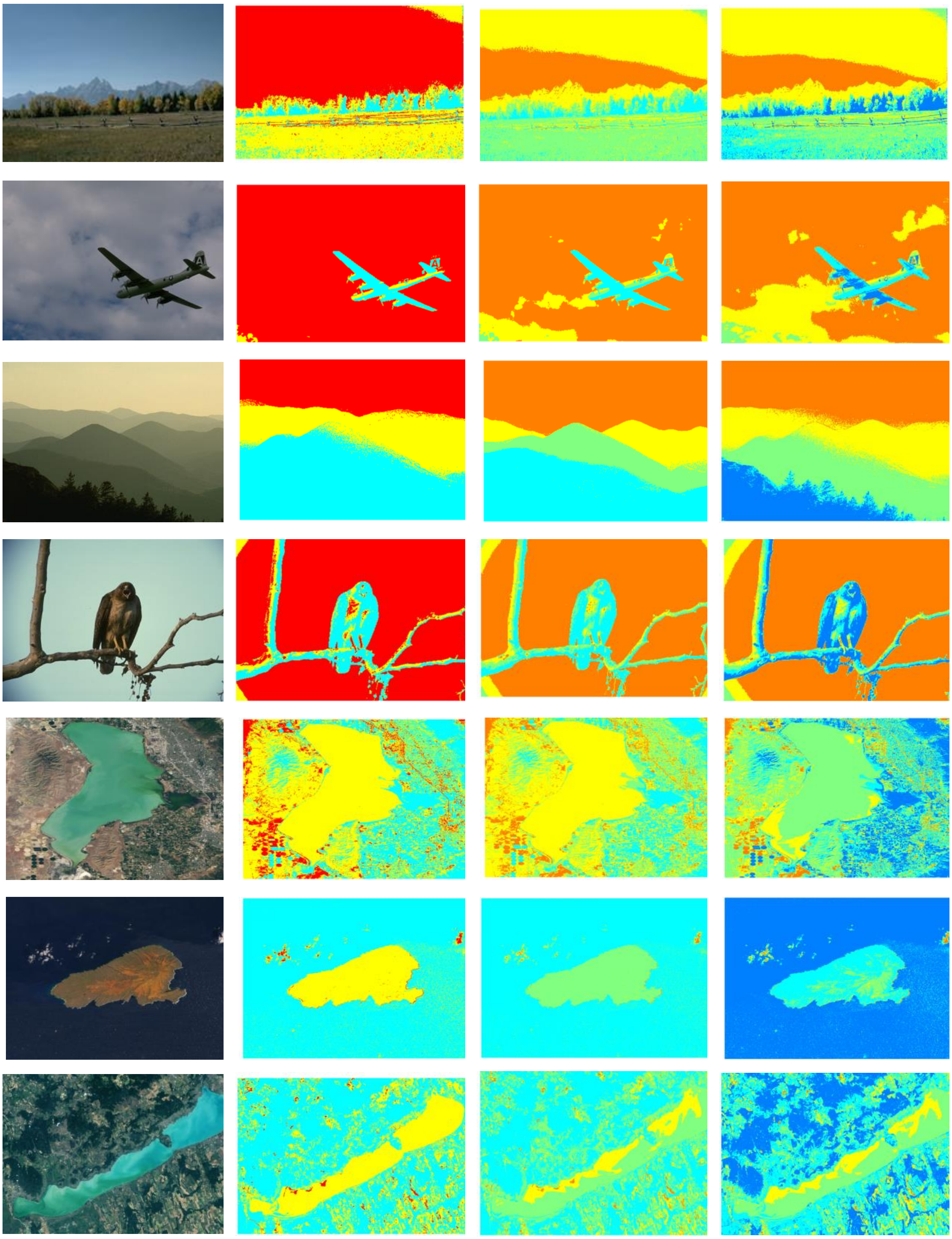
Original Image Th=3 Th=4 Th=5



6.4 Results Table of HBO Kapur's for images in 5.1

Table-III Results Table of HBO Kapur's for images in Table-I

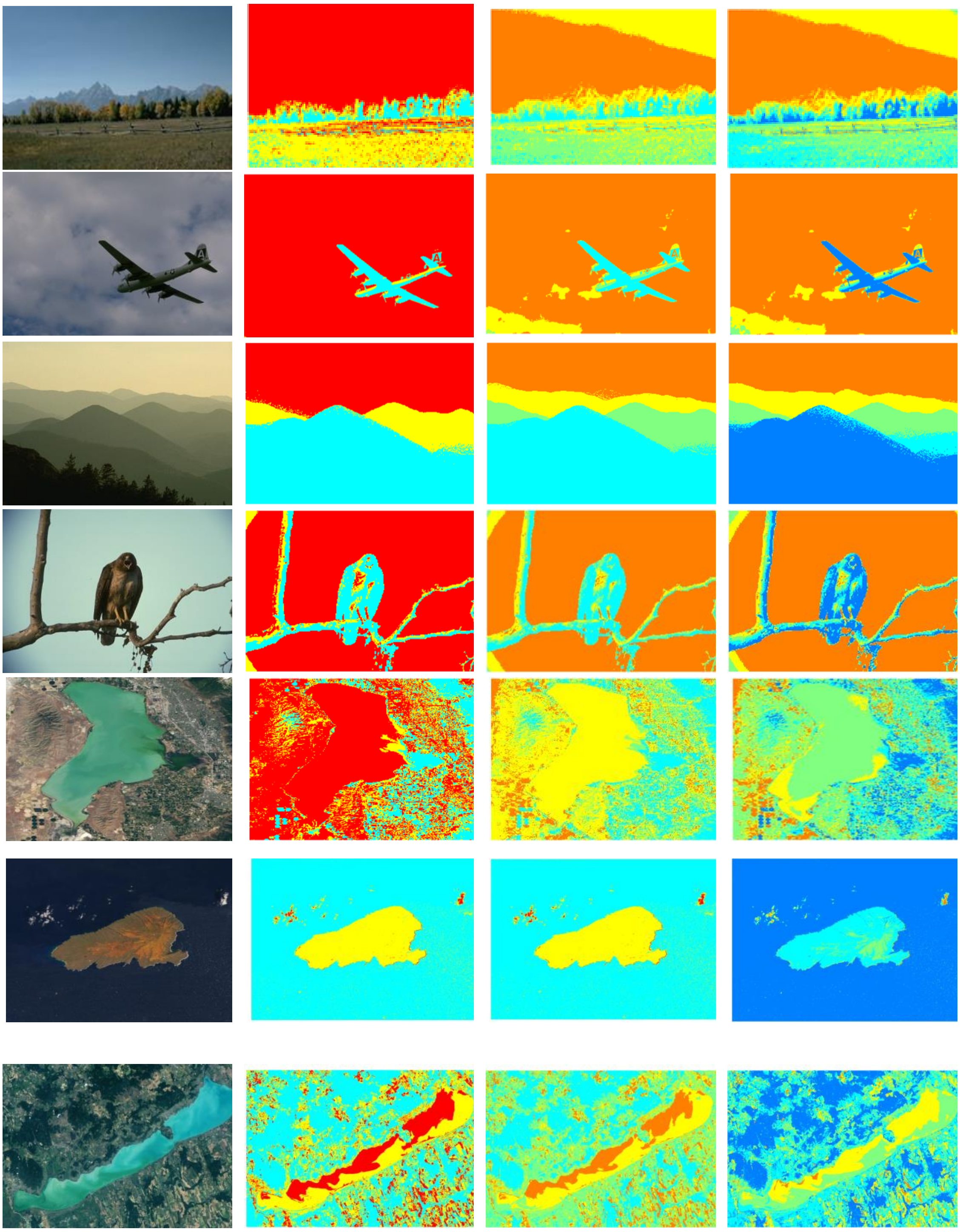
Original Image Th=3 Th=4 Th=5



6.5 Results Table of HGSO Gauss for images in 5.1

Table-IV Results Table of HGSO Gauss for images in Table-I

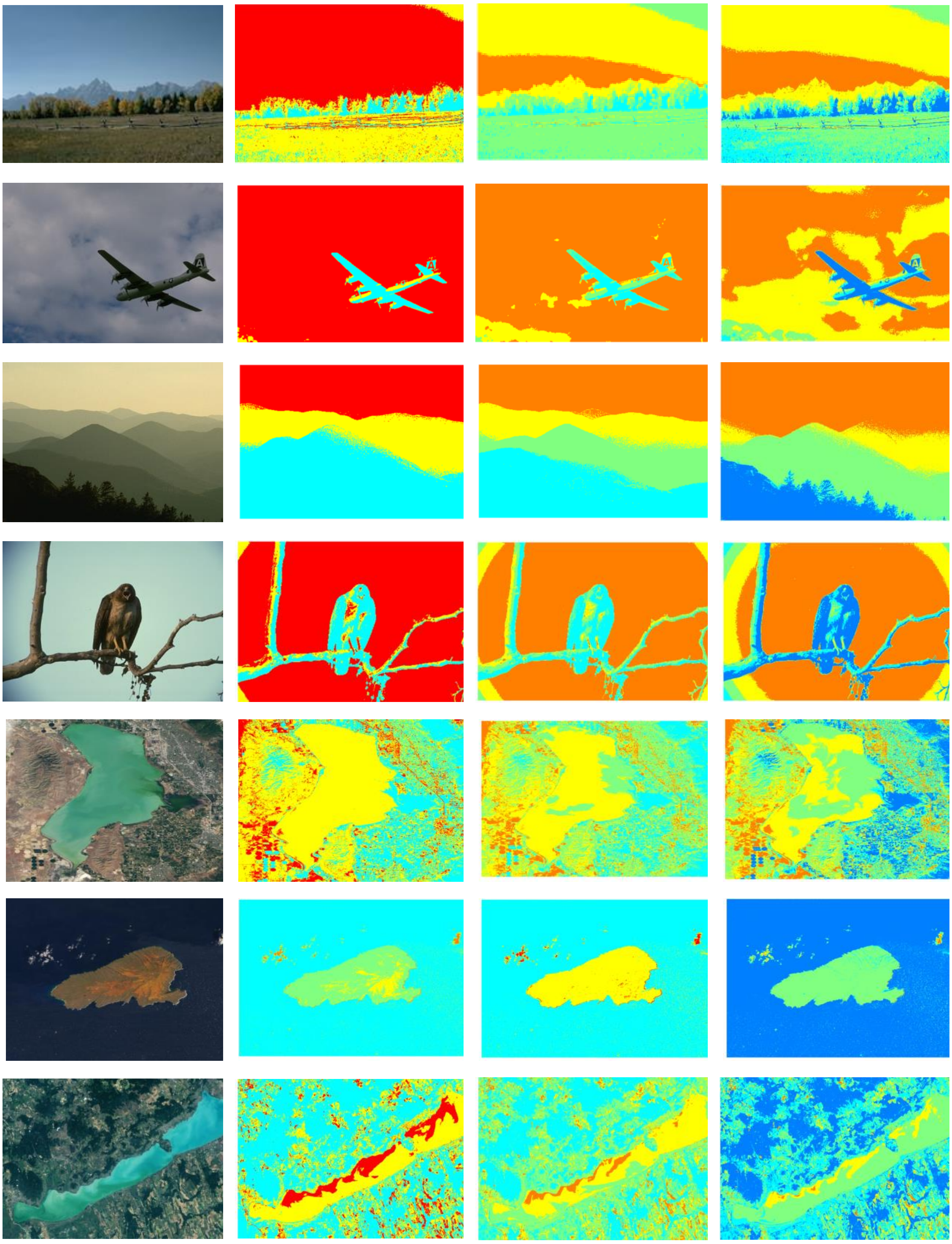
Original Image Th=3 Th=4 Th=5



6.6 Results Table of HGSO Kapur’s for images in 5.1

Table-V Results Table of HGSO Kapur’s for images in Table-I

Original Image	Th=3	Th=4	Th=5



6.7 Performance HGSO Gauss & Kapur for images in 5.1

TABLE VI: PERFORMANCE OF HGSO BASED THRESHOLDING USING GAUSSIAN AND KAPURS ENTROPY

Method		HGSO-Gauss			HGSO-Kapur		
Image	k	Thresholds	PSNR	SSIM	Thresholds	PSNR	SSIM
Image-1	3	51, 96, 143	**26.2776**	0.8241	45, 93, 144	26.1136	0.8166
	4	43, 87, 122, 148	**27.7750**	0.8412	45, 105, 149, 194	26.9167	0.7923
	5	36, 76, 104, 132, 154	27.7750	0.8412	38, 69, 102, 143, 196	**28.0793**	0.8722
Image-2	3	37, 78, 114	26.8590	0.9335	34, 73, 101	**27.1847**	0.9297
	4	36, 66, 101, 121	**31.0363**	0.9899	27, 68, 96, 159	30.6633	0.9339
	5	32, 48, 70, 94, 114	**33.4462**	0.9035	37, 69, 89, 123, 158	32.2936	0.9021
Image-3	3	98, 131, 191	**21.1248**	0.7859	96, 166, 193	20.7375	0.7551
	4	88, 129, 165, 196	22.1107	0.7881	76, 118, 170, 196	**23.3187**	0.7694
	5	82, 100, 128, 16. 186	28.8363	0.7989	28, 58, 97, 124, 187	**28.9680**	0.8781
Image-4	3	66, 109, 158	27.4775	0.9321	67, 116, 172	**27.9566**	0.9180
	4	53, 91, 126, 164	29.2530	0.9295	61, 108, 151, 184	**29.9397**	0.9229
	5	47, 77, 104, 138, 167	**30.2865**	0.9329	65, 111, 145, 185, 213	29.9738	0.9222
Image-5	3	74, 111, 168	**25.5581**	0.7949	96, 157, 206	24.2153	0.7537
	4	75, 112, 164, 194	**26.5388**	0.8163	69, 119, 158, 208	26.3643	0.8049
	5	72, 110, 137, 173, 200	27.793	0.8366	62, 92, 126, 155, 207	**28.5761**	0.8488
Image-6	3	56, 133, 182	29.5221	0.8440	49, 128, 194	**29.5886**	0.8444
	4	73, 129, 176, 217	**30.6477**	0.8652	46, 104, 135, 198	29.8702	0.8368
	5	51, 84, 138, 172, 197	**31.6782**	0.8747	48, 74, 136, 186, 217	31.6605	0.8902
Image-7	3	82, 131, 204	24.5903	0.7465	48, 129, 186	**26.4426**	0.7826
	4	62, 105, 139, 208	**27.9062**	0.8240	69, 114, 156, 202	26.4426	0.7826
	5	59, 95, 138, 182, 211	**28.6568**	0.8375	64, 97, 148, 171, 210	27.3093	0.8147

6.8 Performance HBO Gauss & Kapur for images in 5.1

TABLE VII: PERFORMANCE OF HBA BASED THRESHOLDING USING GAUSSIAN AND KAPURS ENTROPY

Method		HBA-Gauss			HBA-Kapur		
Image	k	Thresholds	PSNR	SSIM	Thresholds	PSNR	SSIM
Image-1	3	50, 110, 187	**26.5720**	0.7857	49, 98, 144	26.4143	0.8143
	4	49, 96, 142, 188	**26.4390**	0.8169	45, 92, 140, 195	26.2787	0.8188
	5	48, 96, 142, 187, 222	**27.1231**	0.8155	42, 68, 93, 145, 189	26.4297	0.8732
Image-2	3	83, 158, 207	26.8828	0.7467	35, 72, 100	**27.1231**	0.9309
	4	55, 98, 158, 207	25.2609	0.9205	36, 73, 101, 160	**27.1231**	0.9300
	5	55, 98, 158, 191, 224	28.3746	0.9188	20, 49, 83, 113, 158	**29.1834**	0.9233
Image-3	3	100, 150, 221	**21.8828**	0.7567	95, 130, 196	21.5205	0.7535
	4	98, 137, 184, 221	**23.2609**	0.7815	78, 101, 138, 187	21.8249	0.8086
	5	97, 129, 167, 195, 222	23.3745	0.7684	22, 58, 93, 155, 194	**27.0189**	0.8540
Image-4	3	91, 156, 206	**27.7211**	0.5661	67, 116, 166	24.7872	0.9203
	4	69, 106, 156, 206	**27.9569**	0.6981	59, 104, 143, 181	27.9163	0.9254
	5	69, 105, 150, 188, 222	30.6599	0.7075	50, 83, 115, 154, 179	**30.7069**	0.9341
Image-5	3	72, 111, 167	**25.7380**	0.8013	99, 160, 212	24.0123	0.7482
	4	72, 110, 158, 197	**26.7888**	0.8190	72, 108, 161, 211	26.4789	0.8127
	5	67, 99, 133, 166, 200	**28.8173**	0.8549	69, 102, 157, 191, 208	26.5837	0.8161
Image-6	3	134, 171, 207	21.2879	0.7820	45, 133, 198	**22.2351**	0.8091
	4	53, 134, 171, 207	**30.2079**	0.8597	46, 132, 171, 209	28.7038	0.8216
	5	47, 102, 138, 173, 207	**30.3580**	0.8472	44, 99, 126, 170, 196	29.4070	0.8198
Image-7	3	79, 126, 206	**24.7996**	0.7488	98, 169, 204	22.3482	0.6989
	4	65, 99, 135, 206	**27.8984**	0.8244	83, 139, 171, 207	25.2612	0.7340
	5	64, 98, 133, 174, 211	**28.3982**	0.8311	59, 98, 143, 179, 209	27.7851	0.8190

6.9 Results of Change detection Mechanism for image samples shown

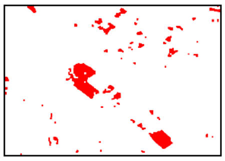
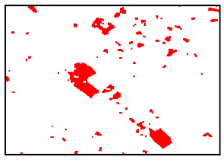
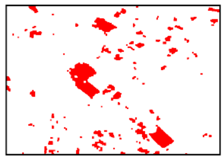
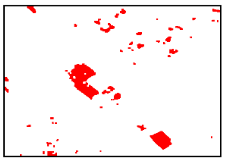
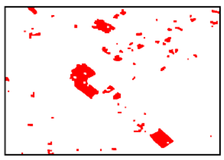
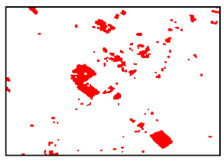
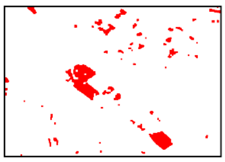
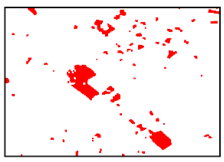
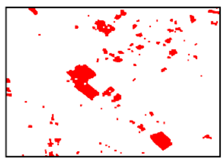
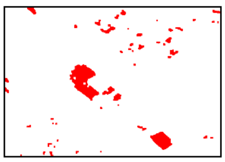
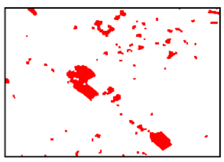
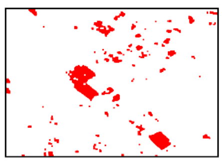
<table>
<tr><td colspan="2">Image Sample (Before)</td><td colspan="2">Image Sample (After)</td></tr>
<tr><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td></td><td>Th=3</td><td>Th=4</td><td>Th=5</td></tr>
<tr><td>HGSO Gauss</td><td></td><td></td><td></td></tr>
<tr><td>HGSO Kapur</td><td></td><td></td><td></td></tr>
<tr><td>HBO Gauss</td><td></td><td></td><td></td></tr>
<tr><td>HBO Kapur</td><td></td><td></td><td></td></tr>
</table>

Fig. 16 Results of Change detection 1

6.10 Results of Change detection Mechanism for image samples shown

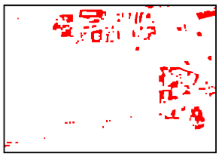
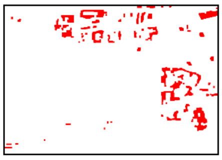
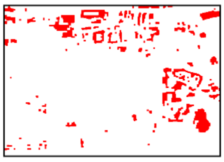
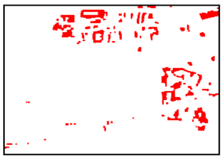
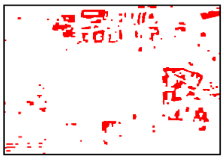
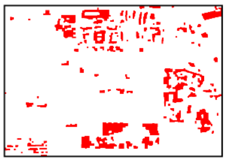
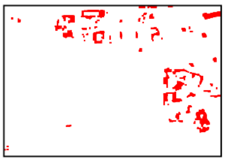
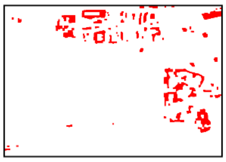
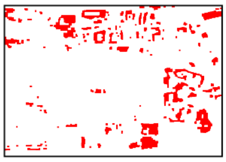
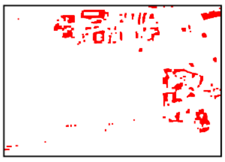
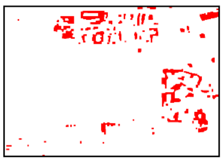
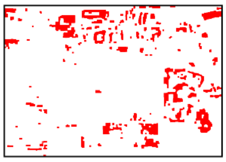
Image Sample (Before)		Image Sample (After)	
			
	Th=3	Th=4	Th=5
HGSO Gauss			
HGSO Kapur			
HBO Gauss			
HBO Kapur			

Fig. 17 Results of Change detection 2

CONCLUSION
&
FUTURE SCOPE

CONCLUSION & FUTURE SCOPE

Conclusion

Remote Sensing Image Segmentation and Change Detection are crucial components of remote sensing applications, which involve the identification of specific objects and the detection of changes that occur over time. These processes are essential in numerous applications such as land use mapping, forest management, urban planning, and environmental monitoring. The use of meta-heuristic algorithms has become increasingly popular in recent years as they provide a more efficient and accurate solution to these problems.

In image segmentation, the primary goal is to partition an image into homogeneous regions that are perceptually similar based on specific criteria. Several meta-heuristic algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) have been employed in remote sensing image segmentation. These algorithms have shown to provide excellent results in terms of computational efficiency, accuracy, and robustness. For instance, the use of GA in image segmentation enables the creation of optimal partitions by finding the best combination of segmentation parameters such as the number of regions and the similarity measure used.

Change detection involves comparing two or more images acquired at different times to identify and quantify changes that have occurred in the study area. Change detection is a challenging task due to various factors such as radiometric and geometric differences between images, atmospheric conditions, and sensor characteristics. Meta-heuristic algorithms have been used in change detection to improve the accuracy of the results. For instance, PSO has been applied to optimize the threshold values used in change detection. PSO can quickly find the optimal threshold values that minimize the difference between the two images, making it a popular algorithm for change detection applications.

Meta-heuristic algorithms have several advantages in remote sensing applications. They can be applied to a wide range of problems, and their results are often superior to traditional methods in terms of accuracy and robustness. Meta-heuristic algorithms are also computationally efficient, which is crucial in applications such as real-time monitoring, where speed is essential.

In conclusion, remote sensing image segmentation and change detection are essential components of remote sensing applications. The use of meta-heuristic algorithms has become increasingly popular in recent years as they provide a more efficient and accurate solution to these problems. Several meta-heuristic algorithms such as GA, PSO, and ACO have been employed in remote sensing image segmentation and change detection and have shown to provide excellent results in terms of computational efficiency, accuracy, and robustness. The use of these algorithms has significantly improved the accuracy of remote sensing applications, making them an indispensable tool for a wide range of applications.

Future Scope

Remote sensing image segmentation and change detection are critical areas of research in the field of image processing and computer vision. These techniques are used to analyze and interpret images acquired from remote sensing systems like satellites, UAVs, and airborne platforms. The primary objective of image segmentation is to partition an image into meaningful regions based on their similarity, while change detection aims to identify the differences between two images captured at different times. In recent years, meta-heuristic algorithms have emerged as a popular approach for solving image segmentation and change detection problems due to their ability to search the solution space effectively and efficiently.

Meta-heuristic algorithms are optimization techniques that use iterative search procedures to explore the solution space and find the optimal or near-optimal solutions. These algorithms are inspired by natural phenomena like evolution, swarm behavior, and the behavior of living organisms. Some of the commonly used meta-heuristic algorithms for image segmentation and change detection are Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), and Grey Wolf Optimizer (GWO).

The future scope for remote sensing image segmentation and change detection using meta-heuristic algorithms is promising, and here are some of the reasons:

1. Scalability: Meta-heuristic algorithms are scalable and can be used to solve problems of different sizes and complexities. With the increasing availability of high-resolution remote sensing data, meta-heuristic algorithms can be used to process and analyze these data more efficiently.

2. Flexibility: Meta-heuristic algorithms are flexible and can be easily adapted to solve different image segmentation and change detection problems. This makes them suitable for a wide range of applications in different fields like agriculture, forestry, urban planning, and environmental monitoring.

3. Accuracy: Meta-heuristic algorithms have been shown to provide accurate results in image segmentation and change detection problems. These algorithms can handle noise, occlusions, and other challenges that are often encountered in remote sensing data.

4. Integration: Meta-heuristic algorithms can be easily integrated with other techniques like machine learning and deep learning to improve the accuracy and efficiency of remote sensing image segmentation and change detection.

5. Automation: Meta-heuristic algorithms can be automated, which means that they can run without human intervention. This is particularly useful in situations where a large volume of data needs to be processed.

In conclusion, the use of meta-heuristic algorithms in remote sensing image segmentation and change detection is a promising area of research. These algorithms can provide accurate and efficient solutions to complex image processing problems. As remote sensing data continue to grow in volume and complexity, the use of meta-heuristic algorithms will become even more critical for processing and analyzing these data.

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Track Name: Sensing and Signal Processing

Paper ID: 112

Paper Title: Nature-Inspired Optimization Algorithm Based Multilevel Thresholding Technique using 2D-Histogram based Gaussian Entropy and Change Detection

Abstract:
Multilevel thresholding is the easiest way for image segmentation. Most important factor in determining whether a threshold-based segmentation of a picture is successful is the choice
of thresholds. Accuracy issues and high processing costs plague traditional multilevel thresholding techniques. This problem is resolved by use of Nature-inspired metaheuristic algorithm which are easy to implement, gradient free and faster. Another challenging task is the selection of suitable objective function. This
paper suggests a new objective function which is based on Gaussian Entropy. To generate optimized threshold values, two different and recently developed optimization algorithms, Henry gas solubility optimization (HGSO) and Honey badger optimization (HBA) are used to optimize the objective functions. By considering values like peak signal-to-noise ratio (PSNR), and

structure similarity index (SSIM), the performance of the suggested thresholding method is assessed by creating segmented images from a set of natural and satellite images. The results of the
experiments show that the suggested strategy performs admirably in segmenting both natural and satellite images.

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Thanks,
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