A comparative study of RIFCM with other related algorithms from their suitability in analysis of satellite images using other supporting techniques

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Abstract

Purpose – The purpose of this paper is to provide a way to analyze satellite images using various clustering algorithms and refined bitplane methods with other supporting techniques to prove the superiority of RIFCM.

Design/methodology/approach – A comparative study has been carried out using RIFCM with other related algorithms from their suitability in analysis of satellite images with other supporting techniques which segments the images for further process for the benefit of societal problems. Four images were selected dealing with hills, freshwater, freshwatervalley and drought satellite images.

Findings – The superiority of the proposed algorithm, RIFCM with refined bitplane towards other clustering techniques with other supporting methods clustering, has been found and as such the comparison, has been made by applying four metrics (Otsu (Max-Min), PSNR and RMSE (40%-60%-Min-Max), histogram analysis (Max-Max), DB index and D index (Max-Min)) and proved that the RIFCM algorithm with refined bitplane yielded robust results with efficient performance, reduction in the metrics and time complexity of depth computation of satellite images for further process of an image.

Practical implications – For better clustering of satellite images like lands, hills, freshwater, freshwatervalley, drought, etc. of satellite images is an achievement.

Originality/value – The existing system extends the novel framework to provide a more explicit way to analyze an image by removing distortions with refined bitplane slicing using the proposed algorithm of rough intuitionistic fuzzy c-means to show the superiority of RIFCM.

Keywords Artificial intelligence, Cybernetics, Image processing, Metrics, Clustering methods-rough intuitionistic fuzzy c-means (RIFCM), Edge detection techniques, Refined bitplane filter, Depth computation, Satellite images

Paper type Research paper

1. Introduction

Cluster analysis is one of the most widely used methods in data mining (Mitra and Acharya, 2003). It has been applied to many fields such as web mining (Mecca et al., 2007), biology (Xu and Wunsch, 2010; Valafar, 2002), image processing (Jain and Dubes, 1988), and market segmentation (Bigus, 1996). The primary task of clustering technique is to divide an unlabeled dataset into several groups so that samples within

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the same group share more similarity than those selected from different groups. Therefore, clustering algorithms help to discover the intrinsic structural complexity of a dataset.

C-means algorithm has being regarded as a classical partitive clustering method. In c-means algorithm (Tou and Gonzalez, 1974) each object is assigned into one cluster. It exhibits the advantage of fast convergence rate, but it still has some difficulty in dealing with overlapping or skewed data distributions problems (Xiong et al., 2009). However, the real-world datasets are always characterized by uncertainty and overlapped boundaries. In this case, there are considerable demands for soft computing with the ability of flexible information processing that exactly meet the demand of practical applications.

As a widespread soft computing technique, fuzzy set (Dubois and Prade, 2012; Pedrycz et al., 2012; Vieira et al., 2012) is widely used in real applications (Vieira et al., 2012; Bermudez et al., 2012; Niros and Tsekouras, 2012), and was added into the framework of c-means algorithm for developing into a fuzzy c-means (FCM) algorithm (Bezdek, 1981). FCM relaxes the subordination requirement in c-means algorithm. Thus, an object can be assigned to many clusters with different membership values. FCM can obtain a desirable result in dealing with overlapping circumstances.

Recently, rough set-based clustering algorithms (Lingras and West, 2004; Mitra, 2004; Maji, 2011) have been proposed as another type of soft clustering technology. Based on rough set theory (Tiwari and Srivastava, 2013; Chen et al., 2012), a cluster is strictly defined by means of two approximations. For this reason, rough set-based clustering algorithms can better deal with uncertainty and vagueness of the dataset with the help of two approximations. Both fuzzy set and rough set have their respective advantages and drawbacks.

In the beginning it was thought that these two theories are rivals of each other. But, it was established by Dubois and Prade (1990) that far from being competitive these two theories are complementary to each other. In fact they developed the hybrid models of rough fuzzy sets and fuzzy rough sets. Later, an integrated technology called rough-fuzzy c-means (RFCM) algorithm was proposed (Maji and Pal, 2007a). Although rough set-based clustering algorithms have been considered as effective soft computing methods, a prevalent problem that appears is the parameter selection. Since no prior knowledge is given, an appropriate parameter may not be easily chosen. No matter what the actual distribution of each cluster is, a constant weighted parameter is always set manually.

The notion of intuitionistic fuzzy sets (IFSs) introduced by Atanassov (1986) generalizes the notion of fuzzy sets. Using this notion the intuitionistic fuzzy c-means (IFCM) algorithm was introduced by Chaira and Sneh (2011). Very recently, Tripathy et al. have introduced the rough intuitionistic fuzzy c-means (RIFCM) algorithm (Bhargav et al., 2013) and studied their properties through some experimental analysis by taking synthetic data as well as images as input. It was established that RIFCM outperforms all the existing algorithms in this direction by taking some measuring indexes like the Dunn index and DB index.

Edges are intensity discontinuities in an image. These are formed from pixels with derivative values that exceed a preset threshold. The idea of an edge is a “local” concept that is based on a measure of gray level discontinuity at a point. Edge detection is by far the most common approach for detecting meaningful discontinuities in gray level.
One of the segmentation or edge detection techniques in image processing is essential as it is the forefront of satellite image processing for object detection. The edge detection significantly reduces the amount of data and filters out useless information when storing the significant structural properties in an image. A comparative analysis of various image edge detection techniques can be found in Maini and Aggarwal (2002).

There are many edge detection methods, which are used to visualize different layers existing in a satellite image. As a result of abrupt change in brightness levels in satellite images we cannot obtain smooth edges. This is why satellite images have been segmented using fuzzy techniques which deal with clustering of images into several images. Yet another approach to deal with impreciseness existing in satellite images is to use rough set techniques.

Depth computation is essential for better visualization of images for satellite applications. The disorder portion of satellite images may lead to many natural disasters of rocket launching due to inaccurate clustering of satellite images.

In this paper, we use our new hybrid algorithm RIFCM for analysis of satellite images of four different types; namely hills, fresh water, fresh water valley and drought. We use the refined bit plane slicing algorithm in order to remove distortions. For the purpose of analysis we use four metrics; namely the Otsu (Max-Min), peak signal noise ratio (PSNR) and root mean square error (RMSE) (40%-60%-Min-Max), histogram analysis (Max-Max), and the DB index and the D index. The analysis establishes the superiority of the RIFCM algorithm over the other existing algorithms in this direction; that is the traditional methods, FCM, rough c-means (RCM), RFCM and IFCM. Also, we use the depth computation technique for further processing of images.

The subsequent organisation of the paper is as follows. In the next section we discuss the definitions and notations to be used in this paper. This includes the concepts of fuzzy set, rough set, IFS, the indices like the DB and D used to measure the efficiency of the clustering algorithms In Section 3, we state the existing algorithms like the FCM, RCM, RFCM, IFCM and the RIFCM. Also, we present the refined bitplane algorithm. Section 4 deals with the experimental observations. In Section 5, analysis of the experimental results is carried out. We summarize the contribution of the paper in the form of conclusion in Section 6. Finally we end up by listing the source materials used during the compilation of this work.

2. Definition of concepts
In this section we introduce some definitions to be used throughout this paper. A cluster is a collection of data elements that are similar to each other but dissimilar to elements in other clusters. Clustering techniques are applied in the analysis of statistical data used in fields such as machine learning, pattern recognition, image analysis, information retrieval, bioinformatics and satellite image analysis and is a major task in exploratory data mining. A wide number of clustering algorithms have been proposed to suit the requirements in each field of its application. The notion of fuzzy set was introduced by Zadeh (1965), as an extension of the notion of crisp sets in order to model uncertain data. It uses the concept of graded membership of elements in a set instead of crisp binary membership.

**Fuzzy set**
A fuzzy set (Zadeh, 1965) is defined as over a universal set $U$ is a pair $(A, m_A)$ where $m_A : U \rightarrow [0, 1]$. For each $x \in U$ the value $m_A(x)$ is called the grade...
of membership of x in U. For a finite set U = {x₁, x₂, ..., xₙ} the fuzzy set (A, mA) is often denoted by {mA(x₁)/x₁, ..., mA(xₙ)/xₙ}.

Let x ∈ U. Then x is said to be not in the fuzzy set A if mA(x) = 0, x is called fully included if mA(x) = 1, and x is called a fuzzy member if 0 < mA(x) < 1. The set \{x ∈ U | mA(x) > 0\} is called the support of (U, mA) and the set \{x ∈ U | mA(x) = 1\} is called its kernel. The function mA is called the membership function of the fuzzy set (U, mA).

Sometimes, more general variants of the notion of fuzzy set are used, with membership functions taking values in a (fixed or variable) algebra or structure L of a given kind; usually it is required that L be at least a poset or lattice. These are usually called L-fuzzy sets, to distinguish them from those valued over the unit interval. The usual membership functions with values in [0, 1] are then called [0, 1]-valued membership functions.

Intuitionistic fuzzy set
As per Atanassov (1986), IFS theory emerges from simultaneous consideration of membership values mA and non-membership values nA of elements of a set. An IFS A in X is given as \{x, mA(x), nA(x) | x ∈ X\}, where mA(x) → [0, 1] and nA(x) → [0, 1] for 0 ≤ mA(x) + nA(x) ≤ 1. mA(x) and nA(x) are membership and non-membership values of an element x to set A in X. When nA(x) = 1 − mA(x) for every x in set A, then set A becomes a fuzzy set. For all IFSs, Atanassov also indicated an intuitionistic degree, πA(x), which arises due to lack of knowledge in defining membership degree, for each element x in A and is given as:

\[ πA(x) = 1 − mA(x) − nA(x), \quad 0 ≤ πA(x) ≤ 1 \]

Due to hesitation degree, membership values mA(x) lie in an interval range:

\[ [mA(x) − πA(x), \ mA(x) + πA(x)] \]

Construction of IFS intuitionistic fuzzy image is constructed from intuitionistic fuzzy generator (IFG). In this study, Sugeno’s IFG is used. Sugeno’s intuitionistic fuzzy complement is written as:

\[ N(mA(x)) = (1 − mA(x))/(1 + λ mA(x)) \lambda > 0, \quad N(1) = 0, \quad N(0) = 1 \]

Non-membership values are calculated using Sugeno type intuitionistic fuzzy complement N(mA(x)). Thus, using Sugeno type intuitionistic fuzzy complement, IFS becomes:

\[ A_{IFS} = \{x, mA(x), (1 − mA(x))/(1 + λ mA(x)) | x ∈ X\} \]

with hesitation degree as:

\[ πA(x) = 1 − mA(x) − (1 − mA(x))/(1 + λ mA(x)). \]

Rough set
The notion of rough sets was introduced by Pawlak (1982), as an extension of the crisp sets. We provide below the definition of a rough set.

Let U (≠ Ø) be a finite set of objects, called the universe and R be an equivalence relation over U. By U/R we denote the family of all equivalence classes of R
(or classification of U) referred to as categories or concepts of R and [x]R denotes a category in R containing an element x ∈ U. By a knowledge base, we understand a relation system k = (U, R), where U is as above and R is a family of equivalence relations over U.

For any subset P (≠ ∅) ⊆ R, the intersection of all equivalence relations in P is denoted by IND(P) and is called the indiscernibility relation over P. The equivalence classes of IND(P) are called P-basic knowledge about U in K. For any Q ∈ R, Q is called a Q-elementary knowledge about U in K and equivalence classes of Q are called Q-elementary concepts of knowledge R. The family of P-basic categories for all P ⊆ R will be called the family of basic categories in knowledge base K. By IND(K), we denote the family of all equivalence relations defined in k. Symbolically, IND(K) = {IND(P): P ⊆ R}.

For any X ⊆ U and an equivalence relation R ∈ IND(K), we associate two subsets, RX = ∪{Y ∈ U/R: Y ⊆ X} and RX = ∪{Y ∈ U/R: Y ∩ X ≠ ∅}, called the R-lower and R-upper approximations of X, respectively. The R-boundary of X is denoted by BN_R(X) and is given by BN_R(X) = RX − RX. The elements of RX are those elements of U which can be certainly classified as elements of X employing knowledge of R. The borderline region is the undecidable area of the universe. We say X is rough with respect to R if and only if RX ≠ RX, equivalently BN_R(X) ≠ ∅. X is said to be R-definable if and only if RX = RX, or BN_R(X) = ∅. So, a set is rough with respect to R if and only if it is not R-definable.

Rough fuzzy set
In the beginning when rough sets were introduced by Pawlak in the early 1980s, it was supposed to be a rival to the theory of fuzzy sets. But it was established by Dubois and Prade (1990) that instead of being rival theories, they complement each other. In fact they combined these two models to develop the hybrid models of fuzzy rough sets and rough fuzzy sets. The notion of rough fuzzy sets was introduced by Dubois and Prade (1990) as follows. Let (U, R) be an approximation space and U/R = {1, 2, ..., n}. Then for any X ∈ F(U), RX and RX, the lower and upper approximations of X with respect to R are fuzzy sets in U/R. That is, RX RX U RX j [0, 1], such that (2.3.1) y (RX)(X) = inf X(y). j ∈ Xj and (2.3.2) y (RX)(X) = sup X(y), for all j = 1, 2, ..., n. j j ∈ X. The pair (RX, RX) is called a rough fuzzy set associated with X.

Conventional edge detection techniques
The problem of false edge detection gives thin or thick lines which was troubled due to noise, etc. was used by reducing the total of data and filters out useless information, by preserving the significant structural properties in an image. These type of images are helpful for applications in depth computation, key stages of image processing, etc. The “Sobel operator” edge detection method is simple enough to detect the edges and their orientation negatives which are sensitive to noise.

The zero-cross edge detection method aims in detection of edges and their orientations having fixed characteristics in all directions that can respond to some of the existing edges, sensitivity to noise. Canny edge detection method can use probability for finding error rate, localization and response which improves signal to noise ratio with better detection especially in noise conditions. But it involves complex computations, false zero crossing and also it is time consuming.
The Robert-cross edge detection method deals with the properties of the produced edges which should be well-defined, the background should contribute as little noise as possible and the intensity of edges should match as close as likely to what a human would recognized in Frías-Velázquez and Philips (2010). The Canny edge detection technique is used for the detection of high range of edges in images that may lead to detection and localization as good. Filters as horizontal, vertical and diagonal edges can be detected using Canny edge detection algorithm to determine the intensity gradient of the image by way of as given in equations (1.a) and (1.b).

Otsu thresholding
Thresholding is computationally inexpensive and fast. It is one of the oldest segmentation methods and is still widely used in simple applications. Using range values or threshold values, pixels are classified using either of the thresholding techniques like global and local thresholding. Global thresholding method selects only one threshold value for the entire image. Local thresholding selects different threshold values for different regions. Structuring elements are applied to the pixels of the image. That is, using the structuring elements the pixels in the image can be classified into different classes and then by performing the set difference operation the features of the affected area can be extracted from the image for which the horizontal structuring element must be varied. A particular intensity value is considered and all the pixels whose intensity values lie below that value are obtained.

Using this technique the defects can be obtained by finding a particular intensity value that exists below the previous value (Swarnalatha and Tripathy, 2012).

Statistical methods
The different mathematical statistical methods can be applied on the bit-plane to get the enhanced image as per (Swarnalatha and Tripathy, 2012; Swarnalatha et al., 2009).

In this paper, RMSE and PSNR has to be computed for better interpretation of all steps.

RMSE and PSNR value
Peak signal-to-noise ratio can be characterized as PSNR, which is the relation with the majority likely power of a signal and the power of corrupting distortions that influence the fidelity of its demonstration.

The PSNR value can be computed through mean squared error (MSE). For an example distortion-free m × n monochrome image “I” with its noisy approximation “K”, MSE can be represented as equation (4.a). The RMSE of a model prediction is defined as the square root of the MSE: hence, the PSNR is defined as equation (4.b), where MAX_I is the most possible 0’s and 1’s values of an image. And it will be replaced with 255, as and when the 0’s and 1’s are given using eight bits per model. And MSE will become “0”; when the distortion is null indicating that the two input images are same.

Here, MAX_I is the maximum possible pixel value of the image. When the pixels are represented using eight bits per sample, this is 255. In the absence of noise, the two images I and K are identical, and thus the MSE is 0. In this case the PSNR is undefined.

Histogram analysis
Histograms can be applied to review graphically of images resulting in terms of allocation and deviation. Let the variable “u” represent the gray levels of the
image to be enhanced. We assume that “u” has been normalized to the interval [0, 1], with u = 0 representing black and u = 1 representing white.

Later, we consider a discrete formulation and allow pixel values to be in the interval [0, G-1] where G is the highest gray level value.

For any “u” satisfying the aforementioned conditions, we focus attention on transformations of the form that produces a level s for every pixel value r in the original image. We assume that the transformation function T(u) satisfies the following conditions: s = T(u) 0 ≤ u ≤ 1:

(a) T(u) is single-valued and monotonically increasing in the interval 0 ≤ u ≤ 1; and
(b) 0 ≤ T(u) ≤ 1 for 0 ≤ u ≤ 1.

Let pu(u) and pv(v) denote the probability density functions of random variables u and v, respectively, where the subscripts on p are used to denote that pu and pv are different functions.

For discrete values we deal with probabilities and summations instead of probability density functions and integrals. The probability of occurrence of gray level uk in an image is approximated by equation (6).

Where n is the total number of pixels in the image, nk is the number of pixels that have gray level uk, and G is the total number of possible gray levels in the image. The discrete version of the transformation function given in equation (6) is equation (7).

Thus, a processed (output) image is obtained by mapping each pixel with level uk in the input image into a corresponding pixel with level v_k in the output image via equation (7).

As a result, we can get a blurred image from the given input image by removing the noise present on raw unprocessed data.

**DB index and D index**

The Davis-Bouldin (DB) and Dunn (D) indexes are one of the most basic performance analysis indexes. They help in evaluating the efficiency of clustering. The results are dependent of the number of clusters one requires.

The DB index is defined as the ratio of sum of within-cluster distance to between-cluster distance. It is formulated as given (Dunn, 1974; Bezdek and Pal, 1998) in equation (8).

The within-cluster distance S(v_j) have been formulated independently of each RCM and RFCM. The aim of this index is to minimize the within cluster distance and maximize the between cluster separation. Therefore, a good clustering procedure should give value of DB index as low as possible, Tripathy et al. (2013), respectively.

Similar to the DB index the D index is used for the identification of clusters that are compact and separated. It is computed by using equation (9).

It aims at maximizing the between-cluster distance and minimizing the within-cluster distance. Hence a greater value for the D index proves to be more efficient.

**Depth computation**

The third dimension calculation is vital for depth computation which can be processed with length, width and depth of an image as (Swarnalatha et al., 2009; Swarnalatha and Tripathy, 2012) a proposal to apply rough fuzzy set theory is made to compute the lower and upper approximations of the affected area of an image in order to reduce the
effort and the labour of a person in finding the depth in underground pipes with SIFT invariant features (Biswas and Veloso, 2012) for better scaling of satellite images.

The fast sampling plane filtering (FSPF) algorithm, which classifies locally grouped sets of points as belonging to planes in 3D is used in Biswas and Veloso (2012) to deal with the challenging task is to process in real time with respective to indoor mobile robot localization.

The above issues have been solved individually but in this paper we deal with a method to detect edges that clusters, thresholds, and then detects edges of distortions using conventional methods and techniques. Clustering can be used to segment an image into several clusters with Otsu thresholding (OT) and statistical techniques; we are able to remove unwanted clusters. Finally, image is edge detected, where a clear boundary is obtained. But the proposed algorithm, RIFCM with RBP performs better clustering to existing edge detection methods and FCM, RCM, IFCM, RFCM. The implementation results better clustering of satellite images with refined bitplane of RIFCM which takes minimum time complexity for depth computation using the existing tool and SIFT invariant features for further reconstruction.

To have proper analysis of the above applications, using statistical moments, depth assessment was implemented using centroid model gives less accurate results (Swarnalatha and Tripathy, 2012), the paper proved the superiority of RIFCM, Tripathy et al. (2013) with other clustering and other supporting methods for better clustering of the satellite images with reduction in time complexity of depth computation which can be used for further reconstruction of clustered satellite images for the benefit of society.

3. Methodology and algorithms

Our approach is based on rough intuitionistic fuzzy c-means with refined bitplane filter method (RBPRIFCM). The paper deals with four c-means conventional methods (Canny, Sobel, Robert-cross, zero-based) and clustering methods (RBPPFCM, RBPRCM, RBPIFCM, RBPRFCM) using with refined bitplane and without refined bitplane for comparative study at four levels of methodology as given below:

1. Refined bitplane filter algorithm where the images are divided into slices.
2. OT, statistical methods, PSNR and RMSE and histogram analysis with conventional edge detection techniques and comparison between without refined bitplane and with refined bitplane.
3. OT, statistical methods, PSNR and RMSE and histogram analysis with FCM, RCM, IFCM, RFCM and comparing between without refined bitplane and with refined bitplane (FCM, RCM, IFCM, RFCM).
4. OT, statistical methods, PSNR and RMSE, histogram analysis, DB index and D with proposed RIFCM and comparing between without refined bitplane and with refined bitplane, for better clustering for depth computation and future process of reconstruction.

As the first step, OT is applied for an original image that can be used for the refined bitplane filter, which divides the images into slices to have better visuality and methodology as follows: an image is divided into a set of bits corresponding to a given bit position in each of the 0’s and 1’s which represents an image. And that image can be used to divide
them into slices to determine the trivial information with updated OT of the refined bitplane (WRBPOT) and compared with applying without refined bitplane (WORBPOT).

And as the second step, for the refined bitplane sliced image can be used for conventional edge detection techniques (Sobel, Canny, zero-based, Robert-cross, etc.) with conventional OT (WRBPCOT) and statistical methods and compared with applying without refined bitplane (WORBPCOT).

In the third step, for the refined bitplane image, we have to apply FCM with fuzzy OT (WRBPFOT), RCM (WRBPROT), IFCM (WRBPIFOT), and RFCM (WRBPRFOT) and compared with applying without refined bitplane (WORBPFOT, WORBPROT, WORBPIFOT, WORBPRFOT).

In the fourth step, for the refined bitplane image, we have to apply RIFCM using refined bitplane (WRBPRIFOT) and compared with applying without refined bitplane (WORBPRIFOT by extracting the features of Otsu, PSRN and RMSE, histogram analysis, DB and D index.

And comparison of four conventional and clustering techniques (Sobel, Canny, zero-based, Robert-cross, FCM, RCM, IFCM, RFCM) have been applied to an image to cluster images in terms of lands, hills, freshwater, freshwatervally for depth computation which is necessary for further reconstruction of an image.

Figure 1 deals with four levels as (1) with gray scale image as an input with original OT (OOT) for two categories of without using refined bitplane OT (WORBPOT)/refined bitplane and using with OT/refined bitplane (WRBPOT). In comparison, WRBPOT gives an efficient performance to WORBPOT. In level (2) the three methods of conventional (3), clustering methods (4) should be applied for without

![Block diagram of a novel approach conventional, clustering and proposed RIFCM clustering methods of a satellite image using without and with refined bitplane with depth computation](image-url)
and with using refined bitplane, thereby getting conventional Otsu thresholds
(WORBPCOT and WRBPCOT), cluster OT (WORBPFOT, WORBPROT,
WORBPIFOT, WORBPRFOT, WORBPRT and WRBPFOT, WRBPRFOT, WRBPIFOT, WRBPRIFOT, WRBPRIFOT).

Existing algorithms
The author proves the superiority of RIFCM in comparison with other clustering
techniques and other supporting methods. The existing algorithms have been stated below.

Fuzzy c-means
FCM is an algorithm proposed by Bezdek (1981). In fuzzy clustering (also referred to as
soft clustering), data elements can belong to more than one cluster, and associated with
each element is a set of membership levels. These indicate the strength of the
association between that data element and a particular cluster. Fuzzy clustering is a
process of assigning these membership levels, and then using them to assign data
elements to one or more clusters:

(1) Assign initial cluster centers or means for c clusters.
(2) The cluster centroids are calculated using the formula (10).
(3) Calculate the distance $d_{ik}$ between data objects $x_k$ and centroids $v_i$ using
Euclidean formula (11).
(4) Generate the fuzzy partition matrix or membership matrix $U$:

$$\mu_{ik} = \frac{1}{\sum_{j=1}^{c} (d_{ik}/d_{jk})^{2/(m-1)}}$$

if $d_{ij} > 0$ then
else $\mu_{ik} = 1.$

(5) Calculate new partition matrix $U^{(r+1)}$.

Rough c-means
RCM algorithm was introduced by Lingras (2002) which describes a cluster by its centroid
and its lower and upper approximation. In RCM an object can belong completely in one
cluster or in between two clusters. The lower and upper approximations are weighted
differently. Since the objects in the lower approximation completely belong to the cluster,
therefore they are assigned a greater weight denoted by $w_{low}$. The objects in the upper
approximation are assigned a relatively lower weight denoted by $w_{up}$. The algorithm is
given as follows:

(1) Assign initial means $V_i$ for c clusters.
(2) Let $d_{ik}$ be the minimum and $d_{jk}$ be the next to minimum distance of $x_k$ from
clusters $U_i$ and $U_j$. Assign each data object to the lower or upper approximation
by computing $d_{ik} - d_{jk}$.
(3) If $d_{ik} - d_{jk}$ is less than threshold ($e$) then
$\ x_k \in \tilde{B}U_i$ and $x_k \in \tilde{B}U_j$ and is not the member of any lower approximation.
Else $x_k \in \tilde{B}U_i$.
(4) Calculate new centroids for each cluster using.
(5) Repeat from step 2 until there are no more assignment.
Intuitionistic fuzzy c-means

The IFCM proposed by Chaira and Sneh (2011), brings into account a new parameter that helps in increasing the accuracy of clustering. This parameter is known as the hesitation value and denoted by $\pi$:

1. Assign initial cluster centers or means for $c$ clusters.
2. Calculate the distance $d_{ik}$ between data objects $x_k$ and centroids $v_i$ using Euclidean formula (11).
3. Generate the fuzzy partition matrix or membership matrix $U$:

$$\mu_{ik} = \frac{1}{\sum_{j=1}^{c}(d_{ik}/d_{jk})^{2/(m-1)}}$$

if $d_{ij} > 0$ then

else $\mu_{ik} = 1$.

4. Compute the hesitation matrix $\pi$ using:

$$\pi_A(x) = 1 - \mu_A(x) - \frac{1 - \mu_A(x)}{1 + \lambda \mu_A(x)} \quad x \in X$$

5. Compute the modified membership matrix $U'$ using:

$$\mu'_{ik} = \mu_{ik} + \pi_{ik}$$

6. The cluster centroids are calculated using the formula (10).
7. Calculate new partition matrix by using step 2-5.
8. If $\|U^{(r)} - U^{(r+1)}\|$ then stop else repeat from step 4.

Rough-fuzzy c-means

RFCM is an algorithm proposed by Mitra et al. (2006) and Maji and Pal (2007a); it combines the concepts of rough set theory and fuzzy set theory. The concepts of lower and upper approximations in rough set deals with uncertainty, vagueness and incompleteness whereas the concept of membership function in fuzzy set helps in enhancing and evaluating overlapping clusters:

1. Assign initial means $v_i$ for $c$ clusters.
2. Compute $\mu_{ik}$ using:

$$\mu_{ik} = \frac{1}{\sum_{j=1}^{c}(d_{ik}/d_{jk})^{2/(m-1)}}$$

3. Let $\mu_{ik}$ and $\mu_{jk}$ be the maximum and next to maximum membership values of object $x_k$ to cluster centroids $v_i$ and $v_j$.

If $\mu_{ik} - \mu_{jk} < \varepsilon$ then

$x_k \in \overline{B}u_i$ and $x_k \in \overline{B}u_j$ and $x_k$ cannot be a member of any lower approximation.

Else

$x_k \in \overline{B}u_i$
(4) Calculate new cluster means by using equation (12).

(5) Repeat from step 2 until termination condition is met or until there are no more assignment of objects.

The paper presents the proposed algorithms of RIFCM (Tripathy et al., 2013), refined bitplane algorithm (Swarnalatha and Tripathy, 2012), and depth computation (Swarnalatha et al., 2009).

Rough intuitionistic fuzzy c-means
The RIFCM, Tripathy et al. (2013) uses the concept of rough sets, fuzzy sets and as well as IFSs, thereby making it a perfect combination of IFCM and RCM. It can also be considered to be RFCM with IFS, hence adding the concept of lower and upper approximation of rough set, fuzzy membership of fuzzy set, non-membership and hesitation value of IFS. It provides a holistic approach to clustering of data as it deals with uncertainty, vagueness, incompleteness which, enables the efficient handling of overlapping partitions and improves accuracy.

In RIFCM, each cluster can be identified by three properties, a centroid, a crisp lower approximation and an intuitionistic fuzzy boundary. If an object belongs in the lower approximation of a cluster then its corresponding membership value is 1 and hesitation value is 0. The objects in the lower region have same influence on the corresponding cluster. If an object belongs in the boundary of one cluster then it possibly belongs to that cluster and potentially belongs to another cluster. Hence the objects in the boundary region have different influence on the cluster. Thus, we can say that in RIFCM the membership value of objects in lower region is unity ($\mu'_{ij} = 1$) and for those in boundary region behave like IFCM.

The objective of this algorithm is to reduce the cost function given in Maji and Pal (2007b). The parameters $w_{low}$ and $w_{up}$ have the standard meanings. Also $\mu_j$ has the same definition as in IFCM.

The steps that are to be followed in this algorithm are as given below:

1. Assign initial means $v_i$ for $c$ clusters by choosing any random $c$ objects as cluster.

2. Calculate $d_{ik}$ using Euclidean distance formula (11).

3. Compute $U$ matrix
   
   if $d_{ik} = 0$ or $x_j \in BU_i$ then $\mu_{ik} = 1$
   
   else compute $\mu_{ik} = \frac{1}{\sum_{j=1}^{C}(d_{ik}/d_{jk})^{2/(m-1)}}$

4. Compute $\pi_{ik}$:

   $\pi_A(x) = 1 - \mu_A(x) - \frac{1 - \mu_A(x)}{1 + \lambda}$ $x \in X$

5. Compute $\mu'_{ik}$ and normalize $\mu'_{ik} = \mu_{ik} + \pi_{ik}$.

6. Let $\mu'_{ik}$ and $\mu'_{jk}$ be the maximum and next to maximum membership values of object $x_k$ to cluster centroids $v_i$ and $v_j$. 
If $\mu_{ik}^l = \mu_{jk}^l + \epsilon$ then
$x_k \in BU_i$ and $x_k \in BU_j$ and $x_k$ cannot be a member of any lower approximation.

Else
$x_k \in BU_i$

(7) Calculate new cluster means by using equation (12).

(8) Repeat from step 2 until termination condition is met or until there are no more assignment of objects:

$$\Theta = \arctan\left(\frac{G_y}{G_x}\right)$$  \hspace{1cm} (1.a)

$$G = \sqrt{G_x^2 + G_y^2}$$  \hspace{1cm} (1.b)

$$\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x$$  \hspace{1cm} (2)

$$S^2 = \frac{1}{n-1} \sum_{i=1}^{n} (x - \bar{x})^2$$  \hspace{1cm} (3.a)

$$S = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (x - \bar{x})^2}$$  \hspace{1cm} (3.b)

$$\text{MSE} = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2$$  \hspace{1cm} (4.a)

$$\text{PSNR} = 20 \cdot \log_{10}(MAX_I) - 10 \cdot \log_{10}(\text{MSE})$$  \hspace{1cm} (4.b)

$$P_u(u_k) = n_k/n \quad k = 0, 1, 2, \ldots, G - 1$$  \hspace{1cm} (6)

$$v_k = T(uk) = \sum_{j=1}^{n} p_u(uj) = \sum_{j=1}^{n} n_j/n \quad k = 0, 1, 2, \ldots, G$$  \hspace{1cm} (7)

$$B = \frac{1}{c} \sum_{i=1}^{c} \max_{k \neq i} \left\{ \frac{s(v_i) + s(v_k)}{d(v_i, v_k)} \right\} \quad \text{for} \quad 1 < i, k < c$$  \hspace{1cm} (8)

$$D = \min_i \left\{ \min_{k \neq i} \left\{ \frac{d(v_i, v_k)}{\max_i s(v_i)} \right\} \right\} \quad \text{for} \quad 1 < k, i, l < c$$  \hspace{1cm} (9)

$$V_i = \frac{\sum_{j=1}^{N} (\mu_{ij})^m x_j}{\sum_{j=1}^{N} (\mu_{ij})^m}$$  \hspace{1cm} (10)

$$d(x,y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \cdots + (x_n - y_n)^2}$$  \hspace{1cm} (11)
Refined bitplane slice method

Input image: ordinary image

START

Step 1: read the satellite image in jpeg format
Step 2: convert the RGB image to gray scale image
Step 3: apply contrast enhancement using histogram equalisation for better quality image
  Step 3.1: perform contrast enhancement by way of checking validity of array
  Step 3.2: histogram normalization using \( h_{norm} = \frac{h_{norm} \times \text{variable (z)}}{\text{sum (hnorm)}} \); Step 4: refined bit planes extraction on histogram equalization with mean, standard deviation, variance and epsilon values (statistical moments)
  Step 4.1: use loop to iterate 1:8 planes assign bitplanes of image to \( x \)
Step 5: if (refined bit plane reconstruction after extraction of the 8 refined bit planes)
  Step 5.1: assign the best refined bit plane based on probability as \( B = \text{zeros (size (im))} \)
Output image:
  Step 5.2: display the refined best refined bit plane (enhanced image)
else
Step 6: find the maximum area region (ROI) //this step is applicable for extraction of particular portion as: \( v[M,indx] = \text{max(ar)} \)
Step 7: crop the region of interest when applied to particular area
Step 8: output the cropped portion of refined bit plane (particular region)
Output image:
  Step 9: cropped refined bitplane image

STOP
The input image is converted from RBG to gray scale image for equalizing the histogram by applying contrast enhancement. It performs preprocessing by checking the validity of an array and normalizing the pixel for the enhancement of intensity. The histogram equalization with statistical moments has been applied for extracting refined bitplanes by iterating eight slices. The best slice with minimum threshold and its corresponding statistical values has been assigned to display the required low threshold refined bitplane for the entire satellite image. If the user purpose is for ROI, a particular portion of an image can be clustered using refined bit plane for clustering a satellite image.

Hence, a reduction can take place in an image slice by slice until the last slice value becomes $2^{(m-n)}$ with which is a better approximation having trivial information as per, Ashok Kumar et al. (2012).

**Depth computation**
As per Swarnalatha et al. (2009, 2012), the computation of depth can be carried out based on the degree of X-rays and the image dimensions of width, height and length have been considered as an input from the end-user. The damaged portion of an image is shown below with the formula for finding the depth of an image. And SIFT invariant features for better scaling of satellite images to compute depth of clustered satellite images.

The solution for computing height is:

$$Height = \left(\frac{l/2 + x}{\tan \alpha + \delta}\right) - \frac{W}{\sin \alpha}$$

1. measurement lengthwise of the damaged portion.
2. $x$; assuming that affected portion is accurately in the midpoint.
3. $\alpha$; scale of the X-rays.
4. $W$; distance across the affected region.
5. $\delta$; width of an image.

4. Experimental observations
The experimental observations of the paper deals with satellite images (hills – H, freshwater – FW, freshwatervally – FWV, drought – D) concerning the following tables and figures which consist of refined bitplane, conventional methods, clustering methods and depth computation with that of their four metrics which proved the superiority of RIFCM with RBP to other techniques.

Figure 2 shows the refined bitplanes that have been justified based on the statistical values of mean, standard deviation, variance with their thresholds of hills (H), freshwater (FW), freshwatervally (FWV) and drought (D) (dry lands) images. Figure 2 shows that an image which has been sliced into eight planes (i.e. 0-7 and 8 as original image for comparison) for better visualization has been used as the refined filter algorithm. Thereby, the mathematical values like mean, standard deviation, variance showing improved result compared to the original image. The epsilon value is reduced for hills from 161 to 128, freshwater from 125 to 92, freshwatervally from 174 to 131...
and for drought from 132 to 97 as for a refined bitplane proving that the refined bitplane value (WRBPOT) < threshold > (WORBPOT).

The images with conventional methods, clustering methods and a proposed method using without refined bitplane and with refined bitplane for better visualization is shown in Figure 3-5.

Figures 6 and 7 give the performance of threshold/epsilon values for conventional and clustering methods of H, FW, FWV and D images. The clustered techniques have been applied in two ways using without refined bitplane and with refined bitplane procedures. Figures 3-5 consider the use of four conventional methods (Canny, Sobel, zero-based, Robert-based) and clustering methods (FCM, RCM, IFCM, RFCM). The epsilon values of traditional methods give segmented image with different performances. And we cannot proceed with all images of an application taking traditional method values which will be varying for four conventional methods and clustering methods to images with that of a proposed clustering method (RIFCM). As a whole, RIFCM using refined bitplane algorithm gives better clustered image compared to other clustering methods and conventional methods for better visualization using without and with refined bitplane of Figures 3-5.

Figures 3-5 of satellite images which is extracted and showed separately for better clustering purpose. In the paper, we experimented with the above edge detection techniques which may miss true edges. With the application of clustering techniques, i.e. conventional, clustering methods, better segmented image with clusters of RIFCM have been obtained. Hence a proposed method can be used for depth computation which carries minimum time consumption of an image and the results also has been proved in Sections 4 and 5.

Figure 8 gives the epsilon values of H, FW, FWV and D images using without and with refined bitplane algorithm for four conventional methods (Canny, Sobel, zero-based, Robert-cross) with values for hills image of without refined bitplane to with
refined bitplane, ranging from 161-128 and Robert-cross 74 with minimum Otsu of without refined bitplane, 97 for Canny Otsu of with refined bitplane and for freshwater image, ranging from 125-92 for without refined bitplane to with refined bitplane. But for conventional 99 of zero-based using without refined bitplane and 61 of zero-based using with refined bitplane and as such there is no stable reduction in epsilon values of conventional methods using without and with refined bitplane and the same is applied for FWV and D images also.

The PSNR rating should be least value compared to RMSE, which should be the highest value of all. Performance analysis of conventional and clustering methods has been used with their RMSE and PSNR values. And the results shows that out of eight methods, a clustering method, RIFCM which is a proposed method yields better quality rating. And it gives 56.54 percent for FWV, 77.23 percent for freshwater (conventional methods), and 44.86 percent (H), 59.19 percent (FW), 31.63 percent (FWV), 56.83 percent (D) of clustering methods performances of without and with refined bitplane images. And on comparison, our proposed method (RIFCM) yields best results towards conventional methods which varies for one image to other image and also variations can be possible for without and with refined bitplane and vice versa and other clustering methods which is clearly shown in Figures 9 and 10 of (a)-(d) (H – hills, FW – freshwater, FWV – freshwatervally, D – drought) images of 40-60 percent as a performance factor of PSNR, RMSE values.

Figure 11 show images calculated without bitplane (WORBP) and with bitplane (WRBP) for traditional/conventional (1 out of 4 – the best) and clustering methods (5). With histogram analysis, a graphical representation of images that results in terms of allocation and deviation have been processed by giving better visualization of a proposed method RIFCM out of all nine methods.
Figure 11 discusses the performance analysis of histogram for four images using mean value ("original mean") and this metric also proves that RIFCM, a proposed method yields better visualization using refined bitplane method for interpretation of images of all eight methods.

The metric of DB index and D index has been used in Tables I-VI where higher the DB index value and lower the D index value gives best clustered image. The overall comparison of indexes of the clustering methods using with refined bitplane and without refined bitplane of four images has been represented. And the results here again proved that our proposed method gives an efficient performance of RIFCM using refined bitplane compared to other conventional and clustering methods. The DB index and D index can be applied for clustering methods and not to conventional methods as the analysis of metrics discussed in the previous sections of the paper.

**Figure 4.**
(a)-(f) Original, clustering methods and a proposed method using without refined bitplane images of drought, freshwater, freshwatervally and hills.
(a)-(f) Refined, clustering methods and a proposed method using with refined bitplane images of drought, freshwater, freshwatervally and hills.

Comparative study of RIFCM

Performance of conventional methods with epsilon values of without and with refined bitplane images of hills, freshwater, freshwatervally and drought.
Table VI deals with the four conventional and four clustering methods where a proposed methodology which has proved and yielded better performance with minimum time in computing the depth. The time complexity of original image is 48.57 percent, conventional image takes 56.34 percent FCM takes 53.23 percent and RCM is 25.51 percent. And as a result, the performance of RIFCM with refined bitplane takes minimum time (≤ original image) compared other clustering and conventional methods.
5. Analysis of results

For analysis, comparison of sliced image with OT has been used for conventional edge detection methods, clustering methods for depth computation. And a proposed refined bitplane with clustering methods with OT is applied to an image for better cluster of images as given in Figure 2.

In Figure 2, the statistical moments with their respective thresholds has been carried out to get refined bitplane images. In Figure 3-5, image representation of nine methods has been processed. In Figures 6 and 7 comparisons are made by taking OT as the epsilon value resulting in a minimum value for better clustering of a proposed algorithm (RIFCM) of all methods (9).

The Otsu threshold value gives the Otsu value as 161-128 (H), 125-92 (FW), 174-131 (FWV) and 132-97 (D) using without refined bit planes and with refined bit plane.

**Notes:** (a) Hills; (b) freshwater; (c) freshwatervally; (d) drought

**Figure 9.**
(a)-(d) Performance analysis with RMSE and PSNR values of conventional methods for original and refined bitplane images
For the original images using without refined bit plane, the $t$-value of H is 45.96 percent (Robert), FW is 79.2 percent (zero-based), FWV is 56.89 percent (zero-based), D is 68.18 percent (Robert-cross) and with using refined bitplane, the $t$-value of H is 75.78 percent (Canny), FW is 66.30 percent (zero-based), FWV is 91.60 percent (Robert-cross), D is 67.01 percent (Canny) for conventional methods. On comparison, there is no stable reduction in epsilon/Otsu values of WORBP and WRBP. And the Otsu threshold value of clustering methods gives for H is 47.82 percent (RFCM), FW is 56 percent (RFCM), FWV is 40.53 percent (RIFCM), D is 45.45 percent (RIFCM) using WORBP and with WRBP, the $t$-value of H is 44.53 percent (RIFCM), FW is 59.78 percent (RIFCM), FWV is 48.85 percent (RIFCM), D is 59.79 percent (RIFCM). Here on
Figure 11.
Histogram analysis using mean of without refined bitplane and with refined bitplane for clustering methods of hills, freshwater, freshwater valley, and drought images.

<table>
<thead>
<tr>
<th>Hills</th>
<th>FCM</th>
<th>RCM</th>
<th>IFCM</th>
<th>RFCM</th>
<th>RIFCM</th>
</tr>
</thead>
<tbody>
<tr>
<td>DB-INDEX-WORBP</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>40.95146</td>
<td>93.82038</td>
</tr>
<tr>
<td>DUNN INDEX-WORBP</td>
<td>0.900001</td>
<td>0</td>
<td>0</td>
<td>0.023238</td>
<td>0.189155</td>
</tr>
<tr>
<td>DB-INDEX-WRBP</td>
<td>0</td>
<td>0.184944</td>
<td>15.70054</td>
<td>0.193631</td>
<td>0.193631</td>
</tr>
<tr>
<td>DUNN INDEX-WRBP</td>
<td>0</td>
<td>8.525729</td>
<td>0.211887</td>
<td>0.021204</td>
<td>0.016745</td>
</tr>
</tbody>
</table>

Table I.
Comparison of DB and Dunn indexes of the clustering methods using refined bitplane and without using refined bitplane algorithm of hills.

<table>
<thead>
<tr>
<th>Freshwater</th>
<th>FCM</th>
<th>RCM</th>
<th>IFCM</th>
<th>RFCM</th>
<th>RIFCM</th>
</tr>
</thead>
<tbody>
<tr>
<td>DB-INDEX-WORBP</td>
<td>45.20328</td>
<td>Infinity</td>
<td>20.70054</td>
<td>33.20328</td>
<td>43.20328</td>
</tr>
<tr>
<td>DUNN INDEX-WORBP</td>
<td>0.153186</td>
<td>0</td>
<td>3.211887</td>
<td>0.043186</td>
<td>0.093186</td>
</tr>
<tr>
<td>DB-INDEX-WRBP</td>
<td>14.70054</td>
<td>0</td>
<td>0.40423</td>
<td>0.399804</td>
<td>19.70054</td>
</tr>
<tr>
<td>DUNN INDEX-WRBP</td>
<td>0.125887</td>
<td>0</td>
<td>2.211887</td>
<td>4.910032</td>
<td>0.02116</td>
</tr>
</tbody>
</table>

Table II.
Comparison of DB and Dunn indexes of the clustering methods using refined bitplane and without using refined bitplane algorithm of freshwater.
comparison of Otsu values of WOBP and WRBP, our proposed method (RIFCM) using WRBP gives stable reduction of noise free image of thresholding (40-60 percent) to all four images with other clustering methods of both WOBP and WRBP. In fact for some images, WOBP is minimum compared to WRBP as in FW as 70-79 values. Hence again proved using Otsu/epsilon metric, our proposed methodology gives better filtered image which is used for further reconstruction of images.

Thereby using our approach has proved to be better than the old techniques. And the performance of images may be > or < RIFCM to four clustering methods for without refined bit plane but for four methods always > RIFCM using refined bitplane algorithm.

Table III.
Comparison of DB and Dunn indexes of the clustering methods using refined bitplane and without using refined bitplane algorithm of freshwatervally

<table>
<thead>
<tr>
<th>Freshwatervally</th>
<th>FCM</th>
<th>RCM</th>
<th>IFCM</th>
<th>RFCM</th>
<th>RIFCM</th>
</tr>
</thead>
<tbody>
<tr>
<td>DB-INDEX-WORBP</td>
<td>0.828179</td>
<td>Infinity</td>
<td>0.723001</td>
<td>10.09157</td>
<td>42.33182</td>
</tr>
<tr>
<td>DUNN INDEX-WORBP</td>
<td>6.208979</td>
<td>0</td>
<td>0.08112</td>
<td>0.054797</td>
<td>0.045893</td>
</tr>
<tr>
<td>DB-INDEX-WRBP</td>
<td>0.201419</td>
<td>0.281419</td>
<td>0.4</td>
<td>0.399804</td>
<td>0.281655</td>
</tr>
<tr>
<td>DUNN INDEX-WRBP</td>
<td>4.03718</td>
<td>4.43718</td>
<td>0.021228</td>
<td>4.910032</td>
<td>0.02001</td>
</tr>
</tbody>
</table>

Table IV.
Comparison of DB and Dunn indexes of the clustering methods using refined bitplane and without using refined bitplane algorithm of drought

<table>
<thead>
<tr>
<th>Drought</th>
<th>FCM</th>
<th>RCM</th>
<th>IFCM</th>
<th>RFCM</th>
<th>RIFCM</th>
</tr>
</thead>
<tbody>
<tr>
<td>DB-INDEX-WORBP</td>
<td>10.02157</td>
<td>13.70054</td>
<td>0.323001</td>
<td>13.25991</td>
<td>12.66384</td>
</tr>
<tr>
<td>DUNN INDEX-WORBP</td>
<td>0.053186</td>
<td>0.111887</td>
<td>0.02112</td>
<td>0.028717</td>
<td>0.029364</td>
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<tr>
<td>DB-INDEX-WRBP</td>
<td>0.90423</td>
<td>0.428179</td>
<td>0.428866</td>
<td>0.428866</td>
<td>1.00423</td>
</tr>
<tr>
<td>DUNN INDEX-WRBP</td>
<td>0.90116</td>
<td>4.208979</td>
<td>0.021067</td>
<td>0.017018</td>
<td>0.08116</td>
</tr>
</tbody>
</table>

Table V.
Overall comparison of DB and Dunn indexes of the clustering methods using refined bitplane and without using refined bitplane algorithm of hills, freshwater, freshwatervally and drought images

<table>
<thead>
<tr>
<th>Hills, freshwater, freshwatervally, drought</th>
<th>FCM</th>
<th>RCM</th>
<th>IFCM</th>
<th>RFCM</th>
<th>RIFCM</th>
</tr>
</thead>
<tbody>
<tr>
<td>DB-INDEX-WOBP-H</td>
<td>1.000000011</td>
<td>0</td>
<td>0</td>
<td>40.95145695</td>
<td>93.82037953</td>
</tr>
<tr>
<td>DUNN INDEX-WOBP-H</td>
<td>0.900000794</td>
<td>0</td>
<td>0</td>
<td>0.02328018</td>
<td>0.189155049</td>
</tr>
<tr>
<td>DB-INDEX-WOBP-FW</td>
<td>0.153186224</td>
<td>0</td>
<td>0.184943573</td>
<td>15.70054299</td>
<td>0.19363085</td>
</tr>
<tr>
<td>DUNN INDEX-WOBP-FW</td>
<td>0.201418501</td>
<td>0.281418501</td>
<td>0.404230011</td>
<td>0.399804003</td>
<td>0.281654653</td>
</tr>
<tr>
<td>DB-INDEX-WOBP-FWV</td>
<td>4.03718</td>
<td>4.43718</td>
<td>0.021228</td>
<td>4.910032</td>
<td>0.02001</td>
</tr>
<tr>
<td>DUNN INDEX-WOBP-FWV</td>
<td>6.208979478</td>
<td>0</td>
<td>0.081119794</td>
<td>0.054796802</td>
<td>0.045893055</td>
</tr>
<tr>
<td>DB-INDEX-WOBP-D</td>
<td>10.02156639</td>
<td>13.70054299</td>
<td>0.323001077</td>
<td>13.25991243</td>
<td>12.66384388</td>
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<tr>
<td>DUNN INDEX-WOBP-D</td>
<td>0.053186224</td>
<td>0.111886938</td>
<td>0.021119794</td>
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<td>0.081159794</td>
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<tr>
<td>DB-INDEX-WOBP-FWV</td>
<td>0.90423</td>
<td>0.42817936</td>
<td>0.428865632</td>
<td>0.428865632</td>
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<tr>
<td>DUNN INDEX-WOBP-D</td>
<td>0.901159794</td>
<td>4.208979478</td>
<td>0.021067026</td>
<td>0.017018079</td>
<td>0.081159794</td>
</tr>
</tbody>
</table>
And the results says as a reduction of 79.50 percent (161-128-H), 73.6 percent (125-92-FW), 75.28 percent (174.131-FWV) and 73.48 percent (132-97-D) with a best PSNR rating as discussed in Section 3 of RIFCM using refined bitplane in comparison of all nine methods’ performances with a rating of 40-60 percent as quality factor for the proposed algorithm of satellite images. Tables I-VI consider the metric of DB index and D index which also gives 93.82038-0.189155 (H), 43.20328-0.093186 (FW), 42.33182-0.045893 (FWV), 12.66384-0.029364 (D) using WORBP and 0.193631-0.016745 (H), 19.70054-0.02116 (FW), 0.281655-0.02001 (FWV), 1.00423-0.08116 (D) using WRBP algorithm and thereby satisfying the condition as high the DB index value and low the D index value, the better the image is clustered. The results proved that our proposed method proves the condition of again another metric, DB index.

We computed results of time complexity in terms of seconds using conventional, clustering methods using refined bitplane of depth computation for further process. First, we divided the images into planes using refined bitplane and reducing the noise by applying on images. The different mathematical statistical methods like mean, standard deviation, variance and their PSNR values were applied on the bit-plane to calculate the efficiency of the refined bitplane method. The output of conventional, FCM, RCM, IFCM and RFCM techniques gives clustered results of four images. But the proposed algorithm RIFCM, yields best results of four images using refined bitplane algorithm compared to other methods. SIFT invariant features which aim for local features to register models to scanned depth scenes and achieved high registration accuracy has resulted in terms of percentages as 107.14 percent for WORBP and WRBP of hills and freshwater, but 100 percent for WORBP and WRBP of freshwatervally where for a drought image, 93.75 percent in terms of percentage of time in secs. And on comparison of nine methods, the time complexity in seconds of $H[14-15, 0.15-0.14]$, $FW[0.14-0.15, 0.15-0.15]$, $FWV[0.15-0.15, 0.16-0.14]$ and $D[0.15-0.16, 0.16-0.13]$ which states that time taken to compute depth is “<” for WRBP and “>” for WORBP which is stable for the proposed methodology (RIFCM) which has proved the objective of the paper in comparison with other clustering methods and conventional methods which wont give constant result for WORBP/WRBP.

<table>
<thead>
<tr>
<th>Time in seconds of WORBP/WRBP</th>
<th>Original time/refined bitplane</th>
<th>Canny</th>
<th>Sobel</th>
<th>Zero-based</th>
<th>Robert-cross</th>
<th>FCM</th>
<th>RCM</th>
<th>IFCM</th>
<th>RFCM</th>
<th>RIFCM</th>
</tr>
</thead>
<tbody>
<tr>
<td>WORBP-HILLS</td>
<td>0.14</td>
<td>0.13</td>
<td>0.16</td>
<td>0.16</td>
<td>0.14</td>
<td>0.15</td>
<td>0.15</td>
<td>0.16</td>
<td>0.15</td>
<td>0.15</td>
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Table VI. Depth computation of nine methods using without and with refined bitplanes
This approach thereby gives a reduction in time complexity of depth computation as given in Table V in detail under Section 4 which use SIFT invariant feature method and the existing tool\(^7\) and refined bitplane filter algorithm.

From Figure 1, we derive four rules for the achievement of minimum time complexity of depth computation using WORBP and WRBP for four images. Rule 1: the WRBP < T < WORBP at the stage of preprocessing. Hence lesser the value of Threshold, more enhanced image will be the output for further cluster of images [R1-Max-Min]. Rule 2: the histogram analysis using mean value metric says that minimum the mean value, the intensity pixels will be high [R2-Min-Max]. Rule 3: the PSNR, RMSE values metric says between 40 and 60 rating the performance, the better quality images of the proposed satellite images has been proved as > RMSE and < PSNR [R3-Max-Min]. Rule 4: the DB index and D index metric proves that > the DB index < D index [R4-Max-Min].

Rule 1 + Rule 2 + Rule 3 + Rule 4 = yielded minimum time complexity for depth computation of hills, freshwater, freshwatervally and drought satellite images.

Hence, the comparison is for the satellite image of hills, freshwater, freshwatervally and drought extracted from (URLs under references) the proposed four rules. As a whole, the objective of the paper yielded minimum time complexity for depth computation using proposed algorithm (RIFCM) with refined bit plane algorithm. In future, output of the clustered image can be considered for further refined future reconstruction of images for better visualization/decision analysis/interpretation of images.

6. Conclusion
The contribution of the paper deals with proving the superiority of RIFCM with RBP in clustering with other clustering methods and other supporting metrics with and without refined which integrates judiciously RIFCM with RBP. The formulation is geared towards minimizing time complexity of depth computation of satellite images with respective to hills, freshwater, drought, freshwatervally. Several new measures are defined based on rough sets to evaluate the performance of RIFCM using refined bitplane algorithms with other methods and techniques with minimum time complexity. Finally, the superiority of the RIFCM using RBP is demonstrated, along with a comparison with other related algorithms, on a satellite images with NASA.org images (hills, drought) and national geographic photographic images (freshwater, freshwatervally). Some of the metrics (Min epsilon, Min-Max PSNR-RMSE, Max-Min histogram analysis, Max-Min DB and D index) and time complexity of depth computation used for evaluating the supremacy of the RIFCM with RBP algorithm may be used in a suitable combination of clustering of satellite image for further reconstruction.

Thereby, clustering our proposed algorithm proved better depth computation with minimum time complexity with the four rules of four different satellite images. And in future, the author aim is to apply clustered images for further process of reconstruction of images.

References


Input data URLs

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Further reading


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Swarnalatha Purushotham is an Assistant Professor (Selection Grade), in the School of Computing Sciences and Engineering, VIT University, at Vellore, India. She is pursuing her PhD degree in intelligent systems. She has published more than 20 papers in international journals/international conference proceedings. She is having 12 years of teaching experiences. She is a member of ACM, IEEE, IACSIT, CSI, IACSIT, IEEE. Her current research interest includes image processing, remote sensing and artificial intelligence. Swarnalatha Purushotham is the corresponding author and can be contacted at: pswarnalatha@vit.ac.in

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