DISTANCE MEASURE BASED AFFINITY-PROPAGATION FOR CLASSIFYING REMOTE SENSING IMAGES: A COMPARATIVE ANALYSIS

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ABSTRACT

By the reason of uplifted number of ethereal channels and an upraised quantity of information, the classification of remote sensing image is backbreaker. There would be a rigid hindrance to uplift the potencies and certainty of those methods, distinctly in the absence of training data and with monitored- clustering. In order rectify the above mentioned imperfections and determined classification a Jensen distance based affinity propagation clustering algorithm is proposed for classifying remote sensing images.

Keywords: Distance measures, Image Classification.

1. INTRODUCTION

AClassification is incorporated to accredit the analogous levels accordance to the accumulation of consistent and compatible characteristics. Categorization is encompassed on the basis of special features like texture and density. There are two methods categorized such as pixel by pixel classification and per-field classification allied with segmented area methodologies. Monitored categorizations inculcated training sites to find out and learn about samples of finite element. Image processing software is used to derive the statistical characterization of every information sensing and recording are considered to be the ultimate activities of remote sensing. A physical carrier is required to transmit the events to the sensors via medium. Remote sensing is generalized as an information carrier in terms of an electromagnetic wave. The outcome is analyzed by determining a scene of the image by a foreign sensing system. Remote sensing images are assorted as digitalized images that are where the requirement of image processing software is uplifted to rectify flows like commutative dislocation of images and indistinct arrangement of pixels. Such factors that affect the performance of the process have to be taken into account.

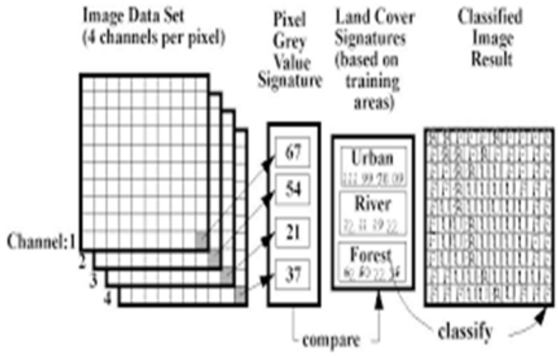

Fig-1 Sample Process of Classification system

2. RELATED WORKS

The following table describes the classification methods and Accuracy of the Existing works in table 1

Table 1 Related Works

Author Name	Method	Accuracy
Luhe Wan et.al	LUCC	85.2 %
B P Ganasria and G S Dwarakisha	Parallelepiped Algorithm, Minimum Distance to Mean Algorithm and Maximum Likelihood Algorithm	90.5%
Kianoush Suzanchi and, Ravinder Kaur	LULCC	88.2%
Ibrahim Rizk Hegazy and Mosbeh Rashed Kaloop	Markov chain analysis	90.5%
Brian W. Szuster and Qi Chen	support vector machine in a weighted or layered classification	91.4%

3. THE PROPOSED WORK

The concepts utilized in the present intelligent system for effective image classification are detailed in this section and various distance measures are based on affinity propagation clustering architecture, as shown in fig- 2:

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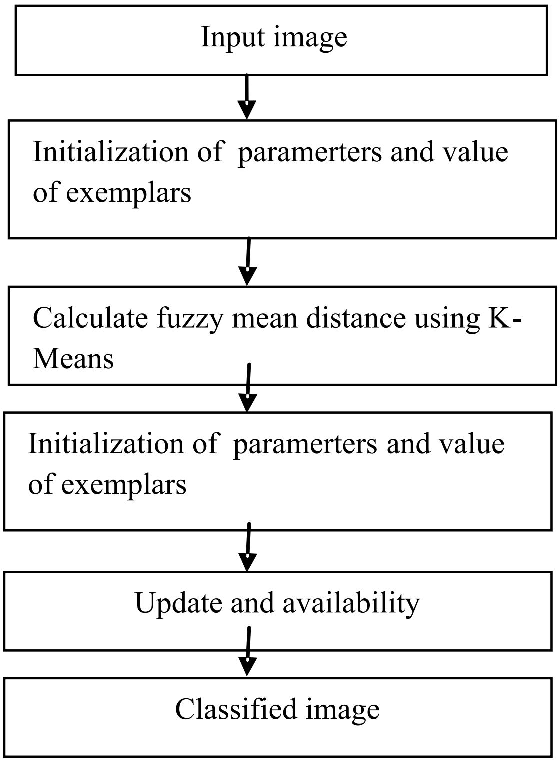

Fig-2 System Architecture

3.DISTANCE-MEASURES BASED AFFINITY PROPAGATION

In this scheme, the Euclidean distance is deliberate from each class mean to all other classes. The endeavour is to maximize this remoteness on the whole, to ensure that unlike classes are reserved separate from one another. In this functioning, they maximize the minimum distance between the classes. Instead they could maximize the middling or midpoint distance between the classes:, but this holds the danger of accepting a subset which has some classes very close to one another, but go undetected because some are very far apart.

A. **K-means clustering algorithm with Euclidean Distance**

Let X={x_1,x_2...x_k} be set of data and M={m_1,m_2....m_k}

1) Select a number (K) of cluster centers - centroids at random
2) Assign every item to its nearest cluster center using Euclidean distance

$$S_i^{(t)} = \{x_j : \| x_j - m_i^{(t)} \| \le \| x_j - m_{i^*}^{(t)} \| \text{ for all } i^* = 1, \dots, k\}$$

3) Move each cluster center to the mean of its assigned items

$$m_i^{(t+1)} = \frac{1}{|S_i^{(t)}|} \sum_{x_j \in S_i^{(t)}} x_j$$

4) Repeat steps 2,3 until convergence or change in cluster assignment less than a threshold.

B. **K-means clustering algorithm with Canberra distance**

Let X={x_1,x_2...x_k} be set of data and M={m_1,m_2....m_k}

1) Select a number (K) of cluster centers - centroids at random
2) Assign every item to its nearest cluster center using Sorensen distance

$$S_j^{(t)} = \left\{x_j : \frac{\| x_j - m_j \|}{\| x_j + m_j \|} \text{ for all } j = 1, \dots, k\right\}$$

3) Move each cluster center to the mean of its assigned items

$$m_i^{(t+1)} = \frac{1}{|S_i^{(t)}|} \sum_{x_j \in S_i^{(t)}} x_j$$

4) Repeat steps 2,3 until convergence or change in cluster assignment less than a threshold.

K-means clustering algorithm with Jensen distance

Let X={x1,x2...xk } be set of data and M={m1,m2....mk}

1) Select a number (K) of cluster centers - centroids at random.

2) Assign every item to its nearest cluster center using Canberra distance

$$S_j^{(t)} = \left\{x_j : \frac{\| x_j - m_j \|}{\| x_j \| + \| m_j \|} \text{ for all } j = 1, \dots, k\right\}$$

3) Move each cluster center to the mean of its assigned items

$$m_i^{(t+1)} = \frac{1}{|S_i^{(t)}|} \sum_{x_j \in S_i^{(t)}} x_j$$

4) Repeat steps 2, 3 until convergence or change in cluster assignment less than a threshold.

4. RESULTS AND DISCUSSION

This segment discusses and analyse the outcome of Euclidean Distance-based affinity Propagation (ED-AP), Canberra-Distance based Affinity Propagation (CD-AP), Jensen -Affinity based Propagation (JS-AP) to classify images with similar functionalities based on Quick bird Dataset.

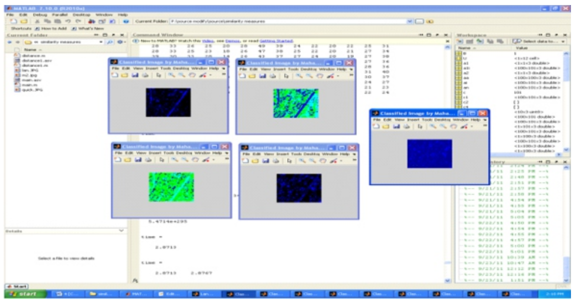

Fig- 3 Results of ED-AP (Quick bird Dataset)

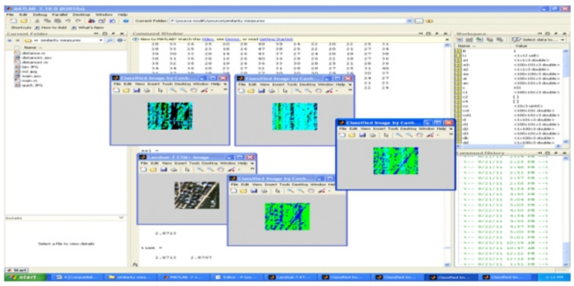

Fig- 4 Results of CD-AP (Quick bird Dataset)

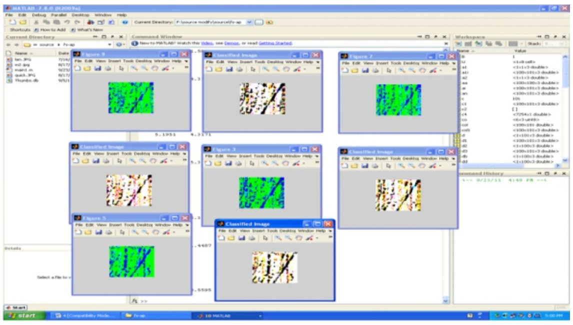

Fig-5 Results of JS-AP (Quick bird Dataset)

Table-2 Performance of Quick bird Dataset

Parameter	ED-AP	CD-AP	MFS-AP
Execution numbers	1	1	1
Execution time	86	64	
Overall accuracy	73.58	76	83.25
Kappa value	0.688	0.734	0.832
APA	76.60	78.96	86.43
AUA	72.55	75.89	81.34
ASMAI	0.584	0.592	0.722

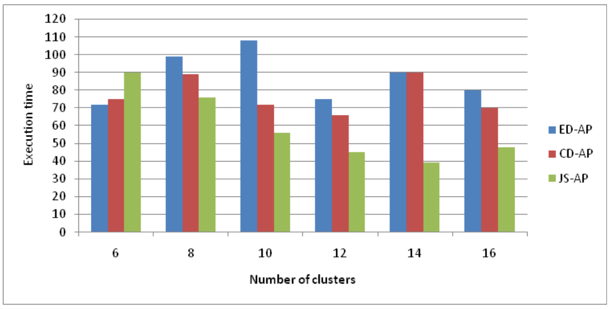

Fig-6 Comparison Chart

5. CONCLUSION

The clustering performance of the three algorithms has been evaluated using Quick bird Remote sensing dataset. The classification results have demonstrated the effectiveness of the proposed algorithms in discovering structures in image data. The classification Algorithm has led a Jensen distance-based affinity propagation clustering algorithm that is better than other existing algorithms.

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