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Hypergraph-based Algorithm for Segmentation of Weather Satellite Imagery

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Abstract:

Objective: Classification of cloud images through segmentation of automated satellite images to improvise the level of accuracy. **Method Analysis:** To classify cloud images the hyper graph model uses the idea of maximally bonded subsets that is endowed with integer valued metric are applied to receive the classifications. The widely used hyper graph model is Intensity Neighborhood Hyper graph (INHG) and representation model in this article is Intensity Interval Hyper graph (IIHG). **Findings**: The results obtained through this process is proved to be more accurate and the time complexity is O(n) in weather prediction. Similarly, the results received through IIHG, which also provides the same computational complexity where all the pixels to be processed with less time. **Enhancement:** The proposed methodology increases the accuracy level of prediction with less computation time and this work can be enhanced by including pattern recognition in automated processing.

Keywords: Hyper Graph, INHG, IIHG, Satellite Imagery, Segmentation

1. Introduction

As on date, there is a good amount of knowledge to understand and interpret cloud structure in earth atmosphere. An expert observer derives considerable information of the details inherently available in the shades of monochrome (gray scale 0 through 255) cloud images. These days, though, expert meteorologists due to their varied (and increasing) assignments are in need of automated intelligent computing systems for interpreting satellite imagery which are extremely valuable for ship-board and air craft applications.

Segmentation of satellite imagery is the first important step towards developing an automated interpretation system of cloud features. Combinations of neural networks with expert systems[1] and with thresh olding techniques[2] were developed for segmentation of satellite imagery. An alternative approach is taken up in this article, using hyper graphs with in and distance metric.

Graphs and hyper graphs have emerged as tools in the development of such customized intelligent systems. Hyper graph-based image representation models are useful in applications such as image segmentation, edges detection, noise removal and image compression. The major principle behind compression is interrelationship of nearby pixels would provide more redundant information[3]. Various technologies such as photography-metric camera, TLS (Terrestrial laser scanner) were used to obtain high resolution images to monitor the behavior and dynamic behavior of cloud structure. To classify large volume of data Principal Component Analysis is also used but it is widely implemented with an integrated environment[4]. Remote sensing also made extensive assistance in natural disasters like flood monitoring and assessing of damage. The flood extents were predicted through MODIS data through mapping of data. Other techniques such as supervised classification were also used to classify[5].

A widely-used hyper graph model in applications is the INHG[6-9] The representation model used in this

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article is the IIHG[10]. Two stand-out advantages in the IIHG model are: (i) its O(n) computational complexity (compared to O(n^3) in the INHG) and (ii) it leaves no pixel unprocessed.

A major evolvement of this paper is a hyper graph-based segmentation method that outputs a segmented imagery free from insignificantly small cloud parts.

2. Mathematical Preliminaries

A *simple hypergraph*[11] is an ordered couple H = (V, E) where: (i) V is a non empty finite set and (ii) E is a set of non empty subsets of V such that $\cup_{X \in E} X = V$. Each member of V is a *vertex*; and each member of E is a *hyperedge* (or, an *edge*).

The Cartesian square N × N which mentions the set of N positive integers. Let $(x_1, y_1), (x_2, y_2) \in N \times N$, we define $\rho((x_1, y_1), (x_2, y_2)) = \max\{|x_1 - x_2|, |y_1 - y_2|\}$. The function ρ is said to be chessboard metric if it is a function on N × N with any non empty subset of N × N metric[12].

In chessboard metric consider V be a finite non empty subset of N × N metric. Assume that A be the non empty subset of V and the finite sequence $x_1, \ldots, x_k$ of distinct elements of A is a *hyper path* in A if $\rho(x_i, x_{i+1}) = 1$ for each $i = 1, \ldots, k-1$. A is a *bonded set* if there is a hyper path between every pair of distinct vertices in A.

In a set V consider 2^{V*} be the denote the set of all non empty subsets. Let $A, X \in 2^{V*}$ such that $A \subseteq X$. Then A is *maximally bonded* in X (or, A is a *maximally bonded subset* of X) if:

(i) A is bonded
(ii) Whenever Y is a subset of X that contains A properly (i.e. $A \subset Y \subseteq X$ and $A \neq Y$), then Y is not bonded.

Proposition 2.1
Let V be a finite non empty finite subset of N × N, provided with the chessboard metric ρ. Take $A, B \in 2^{V*}$. Then

(i) $\rho(A, B) \geq 1$ iff $A \cap B = \varphi$.
(ii) Let A and B be bonded. Then $A \cup B$ is bonded if and only if $\rho(A, B) \leq 1$.

Proposition 2.2
Let V be as in Proposition 1, and let $A, X \in 2^{V*}$ with $A \subseteq X$. Suppose that A is maximally bonded in X. Then $\rho(A, X\text{-}A) > 1$.

Proposition 2.3
If A and B (with $A \neq B$) are maximally bonded in X, then $A \cup B$ is not bonded.

The proofs of 2.1 through 2.3 are straightforward.

3. Intensity Interval Hyper graph (IIHG) Representation of an Image

A noise free digital gray level image which is labeled as I is mathematically denoted by the function I: V→ W (here $V \subseteq N \times N$), where let $a = (x, y) \in V$, I (a) called as the gray scale intensity value of the pixel 'a' located at $(x, y) \in N \times N$, such that it is natural to provide an image I which is a non-empty finite subset V of N × N. Consider V be equipped with chessboard metric ρ. Assume that L be any positive integer, L ≤ 254 and q = [255 − 255(mod L)]/L. The Set:

(a) $E_1 = \{a \in V \mid 0 \leq I(a) \leq L\}$,
(b) $E_k = \{a \in V \mid (k-1)L + 1 \leq I(a) \leq kL\}$ for $k = 2, \ldots, q$,
(c) $E_{q+1} = \{a \in V \mid qL + 1 \leq I(a) \leq 255\}$.

Let $E = \{E_t: t = 1, \ldots, q+1;\ E_t \neq \varphi\}$. The hyper graph H = (V, E) on the set V (the image), and so H is a hyper graph representation of the image I. H is the *Intensity Interval Hyper graph* (IIHG) associated with the image I. No two hyperedges of this H intersect.

4. The Proposed Algorithm

The input image is a finite non empty subset V of N × N, each vertex in V representing a unique pixel of the image, with no repeated representations. The algorithm is summarized below in the following flow diagram which is mentioned as Figure 1.

5. Results of Experiments

The following table gives a hint of the promising performance of the IIHG + maximally bonded sets method. A comparison has been done with the thresh olding neural networks technique of[2] which is presented as a chart from Figure 2.

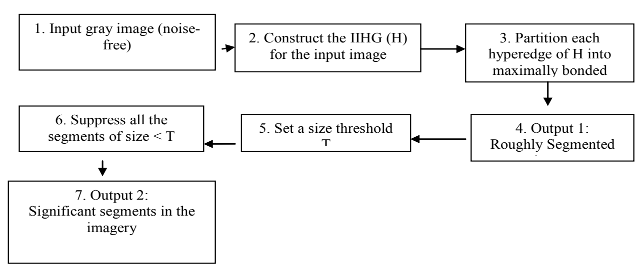

Figure 1. The IIHG algorithm flow diagram.

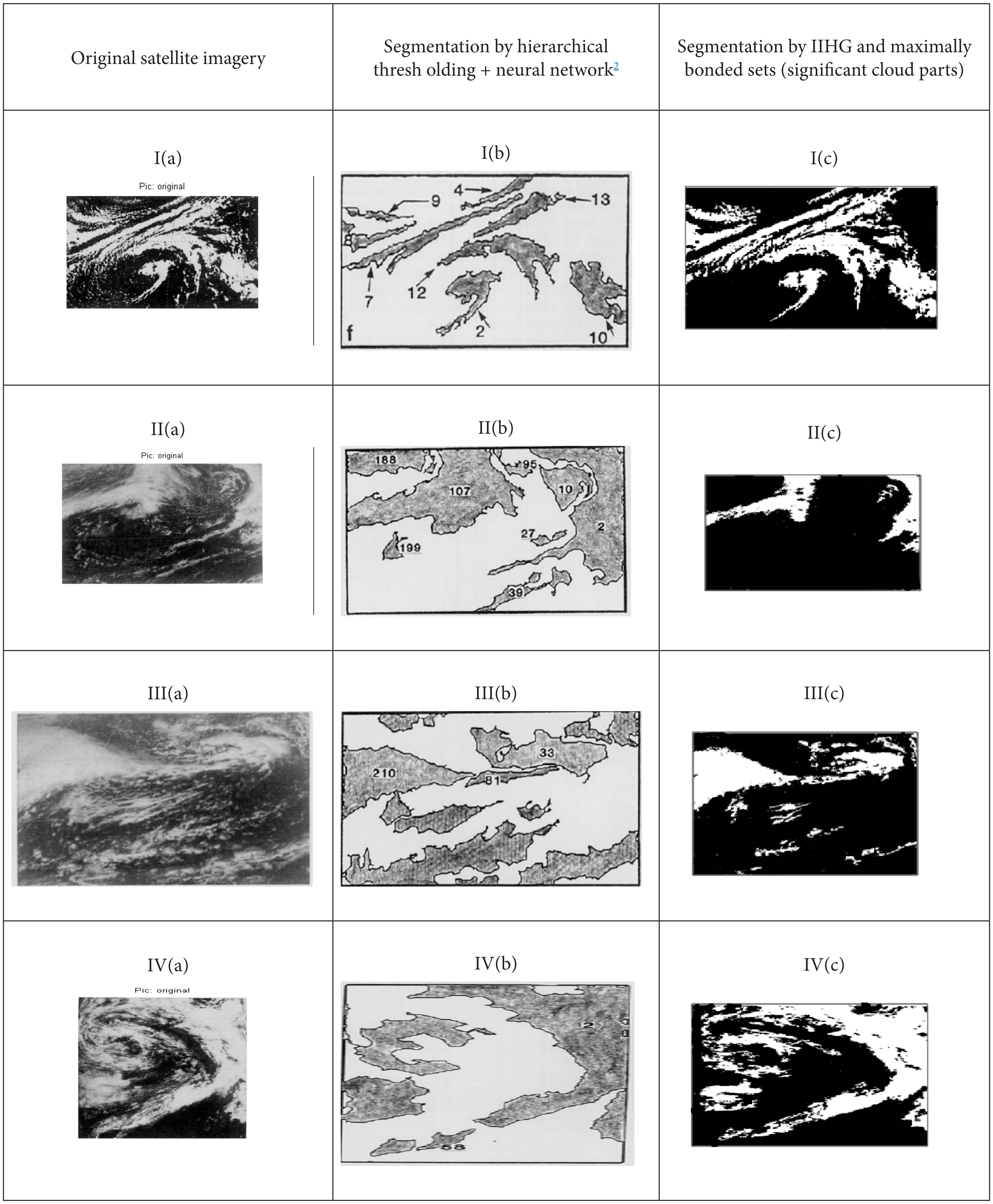

Figure 2. Comparison Chart. **(a)** original satellite imagery **(b)** cloud portions shaded dark **(c)** cloud portions shaded bright.

6. Algorithm Features

(i) The total count of computations in the algorithm is λn, having $1 \le \lambda \le 255$. Consider $f(n) = n$ and with $g(n) = \lambda$ n. Since $n \to \infty$, the limits of $f(n) / g(n)$ is $1 / \lambda$, and that of $g(n)/ f(n)$ is λ. Because of having both λ and $1/ \lambda$ are finite and nonzero, O(n) is the time complexity of proposed algorithm.

(ii) Each hyperedge is finite, and so consists of only finitely many maximally bonded subsets. Each maximally bonded subset is extracted in a finite number of steps using propositions 2.2 and 2.3. From these it is clear that the algorithm converges.

(iii) For standard sizes (from 80×120 to 256×256), the run time is less than 30 seconds. For satellite imagery (size exceeding 256×256), run time is under 120 seconds.

(iv) The proposed algorithm needs no additional weighting measure, and the IIHG always has a low number of hyperedges to process, for any image.

(v) However, the IIHG algorithm does not offer any built-in method to tune L, and human perception is a significant factor in choosing L for a given image. So a good range for an image can be found only after repeated tests using several values of L in its specified range ($1 \le L \le 254$).

7. Future Scope

(i) Segmented satellite images have to be analyzed for features of interest to application specialists like meteorologists and image processing experts. Hyper graphs have substantial potential for image analysis because images are essentially organization of objects and hyper graphs are essentially mathematical expressions of relations that are indispensable for organizations of objects.

(ii) Pattern recognition is a requirement for automated interpretation. Hyper graph properties like transversals, dominating sets and isomorphism have one common thread running through them, and that is recognition of organizational pattern of objects. So such properties can be integrated in the quest for developing an automated interpretation system.

8. Concluding Remarks

At the base of hyper graphs are sets and relations, and hyper graphs accommodate relations of any order. So hyper graphs are excellent tools in applications that have scope for sets and relations (that is, objects and their organizational patterns).

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