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Image Segmentation and Classification Fields Are Generated Using Binary Random Fields Based on Planar Graph and Neighborhood Spanning Tree

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***Abstract:** Image analysis plays a pivotal role in computer vision, with image segmentation and classification being fundamental tasks in this domain. This abstract presents a novel approach to image processing that leverages Binary Random Fields (BRF) with a foundation in planar graphs and neighborhood spanning trees. This innovative methodology seeks to enhance the accuracy and efficiency of image segmentation and classification, addressing key challenges in computer vision applications. Binary Random Fields (BRF) is probabilistic graphical models that have proven effective in capturing spatial dependencies and contextual information within images. Our proposed method extends the utility of BRF by incorporating planar graph theory and neighborhood spanning trees to refine the segmentation and classification processes. Planar graphs offer a structured representation of image data, preserving topological relationships among pixels, while neighborhood spanning trees provide a hierarchical framework for modeling image regions.*

***Keywords:** Planar Graph Representation, Neighborhood Spanning Trees, image Enhancement Techniques, Raw images.*

I. INTRODUCTION

Texture is frequently printed in terms of the abstraction relationships between constituent values in the literature on picture methods. By mathematically simulating these abstraction relationships, texture associate in Nursingalysis aims to capture the visual qualities of texture in associate degree analytical type. This enables the segmentation of an image into its many textural elements, with each element being categorized according to how well it adheres to the mathematical model of a chosen texture. This method aims to formalize the variables that make the texture models distinct from one another but not fundamentally dissimilar from the other textures not included in the work set by using the quantity and type of work data sets. If a texture is to be recognized in an exceedingly} very scene containing earlier unseen textures, then a fresh approach is required.

The feel models must be forced to capture all of the unique qualities of a texture rather than just the ones needed to distinguish it from other well-known textures.

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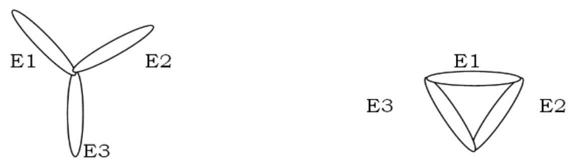
In this chapter, a novel method for segmenting images using binary random values generated within an image-supported neighborhood-spanning tree is presented. For elegant multi-resolution photographs, our method has produced better results than standard region-based segmentation techniques. In the majority of automatic pictorial pattern-recognition and scene analysis challenges, image segmentation is a crucial first step [1, 2][13][15]. One of the most crucial procedures before analyzing the produced picture data is image segmentation. Its main goal is to divide an image into parts that have a sturdy correlation with objects [3, 4][14]16][17]. This chapter describes the generation of random fields for image segmentation supported spanning tree.

II. HELLY FILTER

An imperative property of hyper graph hypothesis is that the alleged Helly property. This property sums up the geometric plan of perceive ability. It gotten from arched pure mathematics and has been summed up to hyper graphs by Berge. A hyper graph has the Helly property if each cluster of hyper edges crossing a pair of (meeting family) includes a non-empty convergence (has an area with a star). Figure 3.3 shows 2 instances of connection hyper edges. Fig 1(a): A group of three hyper edges meeting 2 by 2 with a nonempty crossing point. Fig 1(b): A group of three hyper edges meeting 2 by 2 with a vacant crossing point.



(a). Star. (b). Triangle.

Fig 1: Suppose that the Hyper Graphs Have Only Three Hyper Edges, Then the Hyper Graph (A) Has the Helly Property.

This basic property is of big enthusiasm for hyper graph have faith in. It portrays correct hyper graph categories, as an example, unimodular hyper graphs and adjusted hyper graphs. As a computerized image has geometrical and combinatorial viewpoints the Helly property is basically suited to image making ready. Provides a image an opportunity to be spoken to by its neighborhood hyper graph. Within the event that this hyper graph has the Helly property, the focuses of the celebs portray the traditional neighborhood relations of the celebs. On these lines a star focus is illustrative of the complete neighborhood.

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These focuses can be associate degree adequate portrayal to disentangle worldwide information. In separate pure mathematics it's necessary to outline the grids that satisfy the Helly property. Within the following sections, use solely the 8-neighborhood system of order n.

A. Helly Filter Algorithm

In spite of the very fact that the Helly [5] property is not connected with the physical arrangement of an image, the smoothness of near properties will frequently facilitate one build a hyper graph that fulfills this property while not radically ever-changing the primary image. Within the gift, work a calculation for ever changing an image with the goal that it fulfills the Helly property [6,7].

For any x element in the domain of I, proceed from step 1 to 3. Let $x \cup \Gamma_{n,\alpha}(x)$ be the edge generated by x in $H_{n,\alpha}$.

Step 1. Compute the set of intersecting families.

Compute A_x the set of edge of $H_{n,\infty}$ associated with the vertices of the neighborhood of x: $A_x = \bigcup_{y \in \Gamma_n(x)} (y \cup \Gamma_{n,\alpha}(y))$. Search in P($A_x$) for the set of interesting families. Build the graph (GI_x) of the intersection of the edge A_x defined by: the set of vertices V= Γ_n **(x),** the set of edges E defined by (Y_1, Y_2) ∈E if and only if $(y_1 \cup \Gamma_{n,\alpha}(y_1)) \cap (y_2 \cup \Gamma_{n,\alpha}(y_2)) \neq \phi$.

Step 2. Search for the set of maximal intersecting families A_x.

Search for the complete maximal sub graphs of the graph GI_x. (This problem is N-P complete but in practice, n is small, and this $\Gamma_n(x)$ has a finite number of neighboring vertices.)

Step 3. Compute the x gray level.

Let $F_{x_1}, F_{x_2}, \ldots, F_{x_l}$ be the set of the maximal intersecting families. (To avoid processing the same family several times, and to process every vertex, present work will deal only with the families whose center of gravity is x, x is the center of gravity of the set of families $F_{x_1}, F_{x_2}, \ldots, F_{x_l}$, if $y \in \Gamma(x)$ for some $y \cup \Gamma_{n,\alpha}(y) \in F_{x_i}$). F_{x_i} is centered on x if the center of gravity of F_{x_i} is x. (x is adjacent to any F_x).If l = 1 (there is only one family with x as a center) and if $x \in F_{x_1}$ then F_{x_1} is a star (the partial sub hyper graph has the Helly property). Else if l >1 of (if l=1 $x \notin F_{x_1}$) build the star as follows. Let $S_x = \bigcup_{i=1,2,\ldots,l} F_{x_i}$, test the variation of the gray level vertices of S_x. If the gap is superior to 2α, the vertex whose gray level is the farthest from the gray level of x is removed from S_x. Repeat the process until the gap becomes acceptable. If x is the center of a star whose edges belong to S_x, it is over. Else, compute the new gray level of x so that x is the center of S_x.

Step 4. Modify the x gray level. Once the entire image has been processed, give to all vertices whose gray levels have changed the values earlier computed.

Step 5. Modify the neighborhood hyper graph.

If some gray values have changed, modify the neighborhood hyper graph associated with the image. Else, it is over. A basic iteration of the Helly filter algorithm [5] (from steps 1 to 3) is shown for a section of an image represented by Fig 2. The vertices (i.e., pixels of the image) used are denoted by x, v1, v2, ……….v24. The vertex x is the vertex to be dealt with. A gray level taken within the range of whole values [0, 255] is associated to each pixel. Let us examine how it proceeds in the case where α =20 for an 8-neighborhood system of order 1. First, let A_x denote the set of hyper edges of the image centered on the pixels v1, v2, …,v8 neighbors of x:

$$A_x = \{E_1, E_2, E_3, E_4, E_5, E_6, E_7, E_8\}$$

$$E_1 = \{v_1, v_{10}\}$$

$$E_2 = \{v_2, v_3, v_{12}\}$$

$$E_3 = \{v_2, v_3, v_4, v_5, v_{13}, v_{14}\}$$

$$E_4 = \{v_3, v_4, v_5, v_{13}, v_{14}, v_{16}\}$$

$$E_5 = \{v_3, v_4, v_5, v_{16}, v_{18}\}$$

$$E_6 = \{v_6, v_{18}, v_{19}, v_{20}, v_{21}\}$$

$$E_7 = \{v_7, v_8, v_{20}, v_{21}\}$$

$$E_8 = \{v_7, v_8, v_9, v_{21}\}$$

Then we build the graph of the intersections of the hyper edges of A_x, denoted as GI_x. It is known that the maximum intersecting families correspond to the maximum complete sub-graphs of GI_x. Thus, the set F_x of the maximum intersecting families in accordance with

$$F_x = \{F_{x_1}, F_{x_2}, F_{x_3}\} \quad \text{With}$$

$$F_{x_1} = \{E_{v_2}, E_{v_3}, E_{v_4}, E_{v_5}\},$$

$$F_{x_2} = \{E_{v_6}, E_{v_7}, E_{v_8}\},$$

$$F_{x_3} = \{E_{v_5}, E_{v_6}\}, \text{ And } \quad F_{x_4} = \{E_{v_1}\}.$$

Thus, the set of pixels S_x is the following:

$$S_x = \{v_1, v_2, v_3, v_4, v_5, v_6, v_7, v_8, v_9, v_{10,} v_{12}, v_{13}, v_{14}, v_{16}, v_{18}, v_{19}, v_{20}, v_{21}\}.$$

Calculate the maximum distance between two gray levels of S_x

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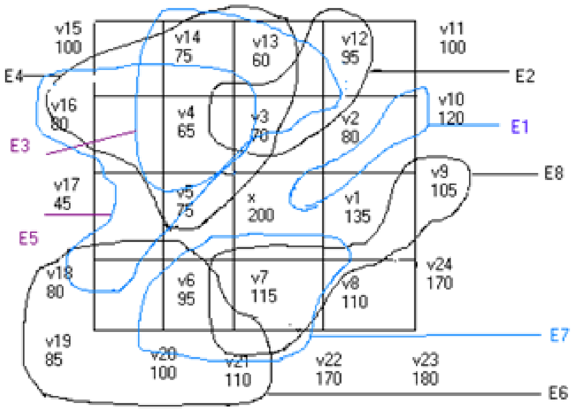

Fig 2: A Figure Representing the Hyper Edges of h1,20 Associated with the Pixels Adjacent to x. They Make up a Set Called ax. Pixel Indices are Ordered According to the Freeman Code.

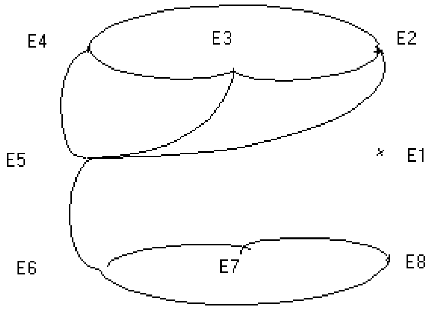

Fig 3. A Figure Representing the Graph Gix of The Measurement of the Hyper edges of Ax

$\Delta I_{max} = I_{max} - I_{min} = I(v_7) - I(v_{13}) = 115 - 60 = 55 > 2\alpha = 40.$

Then remove the pixel whose gray level is the farthest from the one of x, namely v13. It follows that

$$S_x = \{v_1, v_2, v_3, v_4, v_5, v_6, v_7, v_8, v_9, v_{10}, v_{12}, v_{13}, v_{14}, v_{16}, v_{18}, v_{19}, v_{20}, v_{21}\}.$$

And

$$\Delta I_{max} = 115 - 65 = 50 > 2\alpha = 40.$$

Go through this process again until ΔI_{max} is less than 2α. Eventually,

$$S_x = \{v_2, v_6, v_7, v_8, v_9, v_{12}, v_{16}, v_{18}, v_{19}, v_{20}, v_{21}\}.$$

And

$$\Delta I_{max} = 115 - 80 = 35 < 2\alpha = 40.$$

As $x \notin S_x$, its gray level value is given by

$$I(x) = round\left(\frac{I_{max}(S_x) + I_{min}(S_x)}{2}\right) = round(97.5).$$

III. PROPOSED METHOD

In this chapter, a new algorithm is proposed to segment the image into regions by generating binary random fields based on neighborhood spanning trees [8, 9] and planar graphs.

The Non-empty graph G set is an order triple (V (G), E (G), Φ) consist V is called the set of vertices (nodes, points) of the graph, E is said to be the set of edges of the graph and Φ is a mapping from the set of edges E to a set of order or unordered pairs of elements of V. The most common illustration of a graph is by suggests that of a diagram that during which within which} the vertices square measure represent as points and every edge as a line phase connection its finish vertices any try of vertices which square measure connected by a grip may be a graph is termed adjacent vertices. two- dimensional graph is one in all the foremost necessary graphs for image segmentation. A graph G is claimed to be planner, if it are often drawn within the plane while not its edges crossing. Otherwise, G isn't a two-dimensional graph. A two-dimensional graph divides the plane into regions. {a regional neighborhood an square measure a district locality vicinity part a section} is characterized by the cycle that forms its boundary of their regions are connected parts of the plane. Two styles of two-dimensional graphs square measure, one is open two-dimensional graph and another is closed two-dimensional graph. Initial vertex is capable final vertex then it is referred to as closed graph. Initial vertex is not equals to final vertex then it is referred to as open two-dimensional graph.

Spanning tree is graph without cycles. Our first theorem is known as Kircho's Matrix-Tree Theorem [10, 11], and dates back over 150 years. We are interested in counting the number of spanning trees of an arbitrary undirected graph G = (V,E) with no self-loops. In this chapter frequency is calculated for each neighborhood spanning tree or planar graph on 3x3 templates within source image. Based on these frequencies Image is segmented.

A. Methodology

The projected technique consists of 5 steps. the primary step deals with order of putting the weights on a 3x3 neighborhood. The second step computes the sample area by conniving the weights for every neighborhood scanning tree and flat graph. The third step computes the event of interests for segmentation by tally the frequency of prevalence of every neighborhood Spanning tree or flat graph on 3X3 sample area. Fourth step computes the likelihood of every event beneath constraints of likelihood. Fifth step computes the mean and variance and replace every constituent by corresponding variance and select smart threshold [12] for segmentation.

Within the gift chapter, the binary Image weights square measure delineated by exploitation snake like topology. From this the weights of neighborhood spanning trees square measure computed. Neighborhood Spanning trees square measure type a singular combination. Then the frequency of prevalence of every neighborhood-spanning tree is computed. Supported these frequencies, random numbers square measure generated by specifying whether or not neighborhood tree or flat graph is within the mask or not. Supported this likelihood, calculate mean and variance by mathematical formulae. Selected smart threshold technique and phase the image. This technique offers smart classification of pictures.

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The comparisons with hyper graph show that the projected technique will provide additional correct segmentation ends up in each high and low background level regions whereas conserving delicate boundary data with high accuracy.

IV. EXPERIMENTAL RESULTS

In this section, the novel technique for generation of binary random fields for image segmentation and boundary detection for image classification is compared with existing hyper graph technique. In step with the experimental results shown in section four.4.1 to 4.4.9, hyper graph theory and novel technique found boundaries with success. However hyper graph technique fail to find outer edges of pictures and it can't filter the noise for the tiny objects with over imbrication, see 4.4. It produces thicker edges then novel technique. Hyper graph theory fail to supply smart boundaries for advanced pictures. during this section numerous styles of take a look at pictures like Lena River, S.V. Ranga Rao, Blood cells, Rocks and artificial pictures with 100%, 20%, 30%&40% of mathematician , speckle and variance noises are thought of. The experimental results ar made and international threshold values are given in table four.1 and therefore the graph is drawn. Underneath the seeing, the novel technique made higher results than hyper graph technique (see four.6.1 to4.6.3). As per the applied math, estimation novel technique provides higher best results for artificial noise pictures. Supported the results conclusions ar created.

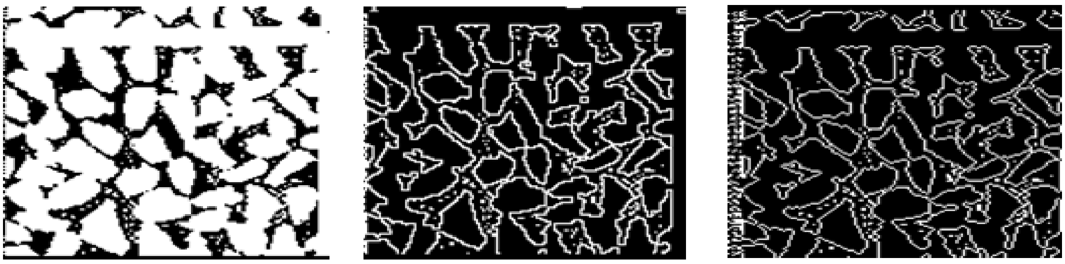
A. Results on Lena images

(a) Lena (b) Hyper (c) Novel

B. Results on S. V. Ranga Rao images

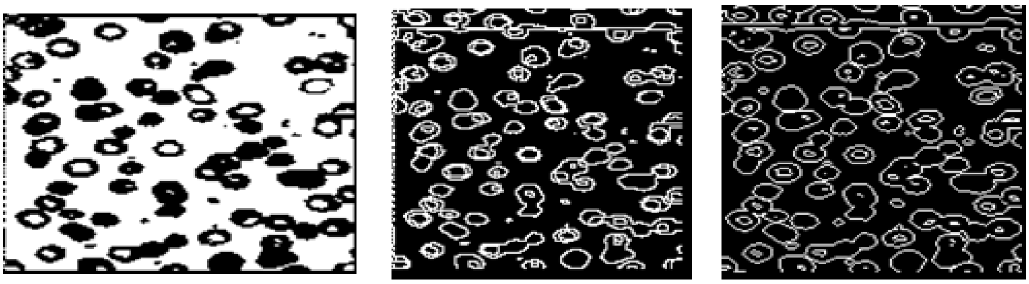
(a) S. V. Ranga Rao (b) Hyper (c) Novel

C. Results on Rocks Images



(a) Rocks (b) Hyper (c) Novel

D. Results on Blood Cells Images



(a) Blood cells (b) Hyper (c) Novel

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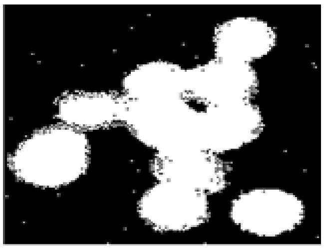
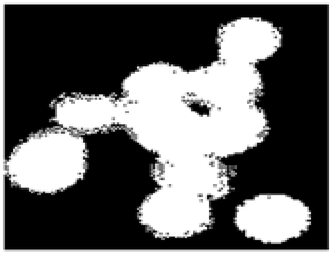
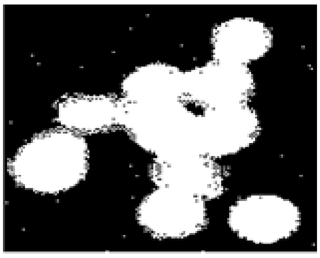
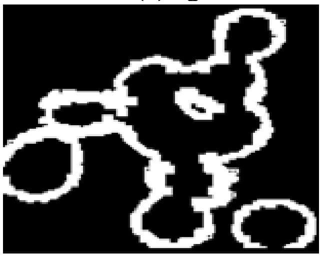
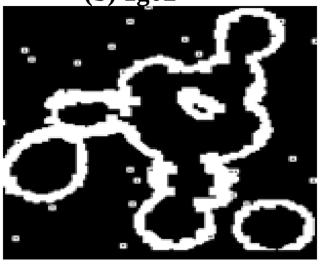
E. Original bmp image with Gaussian noise of 10%, 20%, 30%

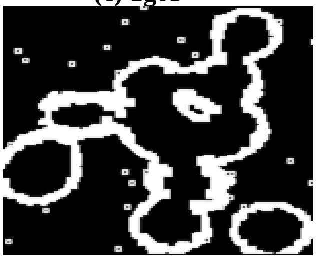

(a) 1g01

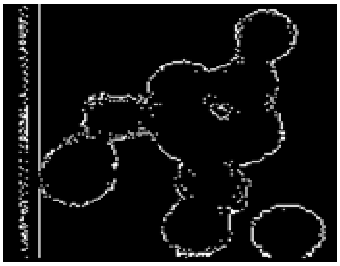

(b) 1g02

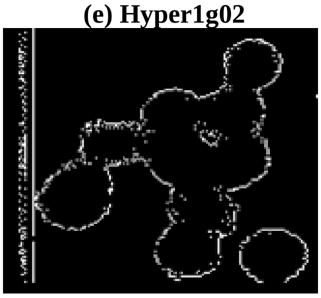

(c) 1g03

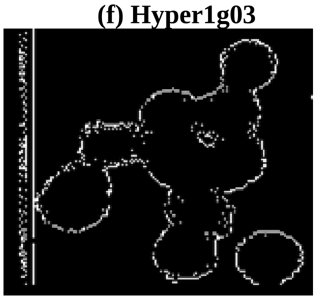

(d) Hyper1g01


(e) Hyper1g02

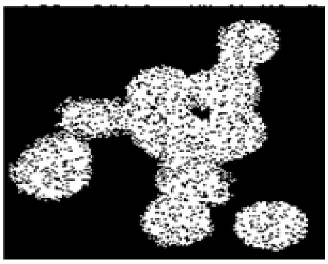

(f) Hyper1g03

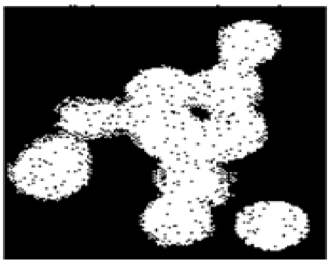

(g) Novel1g01

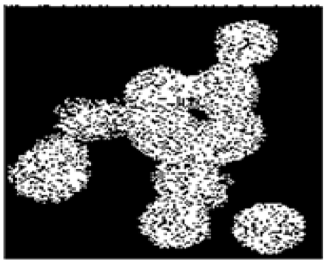

(h) Novel1g02

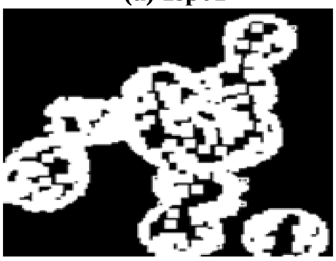

(i) Novel1g03

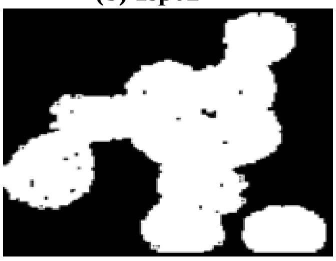
F. Original Bmp Image with Speckle Noise of 10%, 20%, 30%

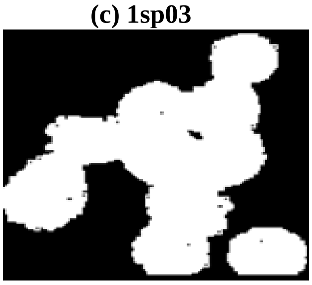

(a) 1sp01

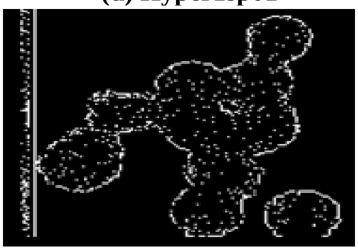

(b) 1sp02

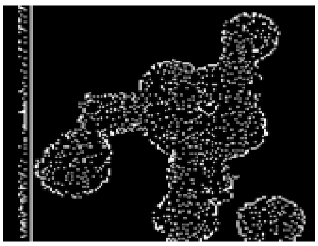

(c) 1sp03

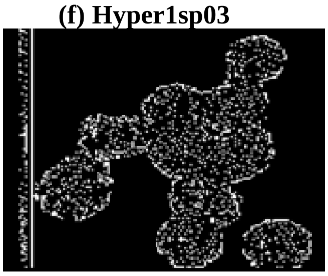

(d) Hyper1sp01


(e) Hyper1sp02


(f) Hyper1sp03


(g) Novel1sp01


(h) Novel1sp02


(i) Novel1sp03

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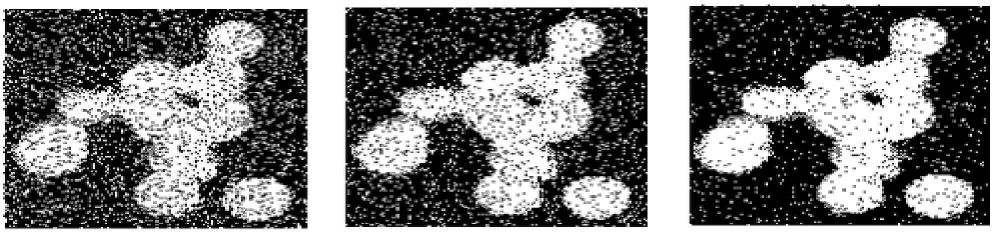
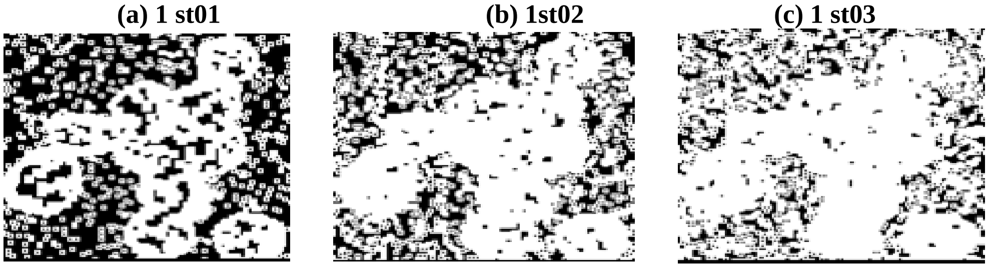
G. Original Bmp Image with Speckle Noise of 40%

(a) 1sp04 (original) (b) Hyper1sp04 (c) Novel1sp04

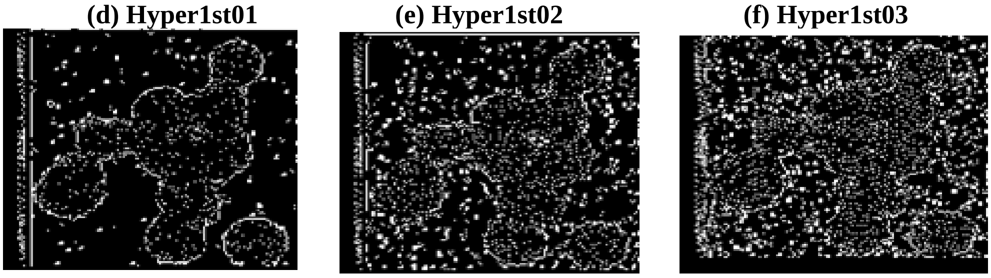
H. Original Bmp Image with Standard Deviation Noise of 10%, 2 0%, 30%



(a) 1 st01 (b) 1st02 (c) 1 st03

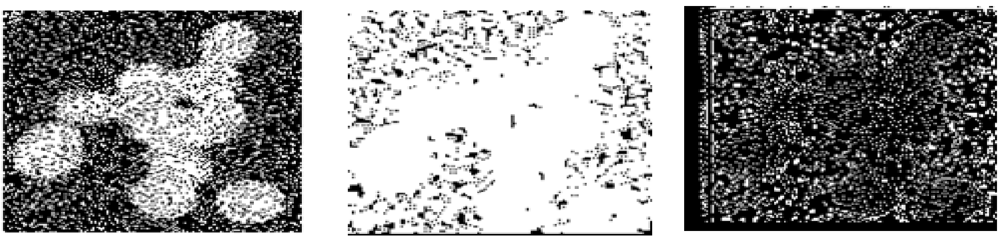


(d) Hyper1st01 (e) Hyper1st02 (f) Hyper1st03



(g) Novel1st01 (h) Novel1st02 (i) Novel1st03

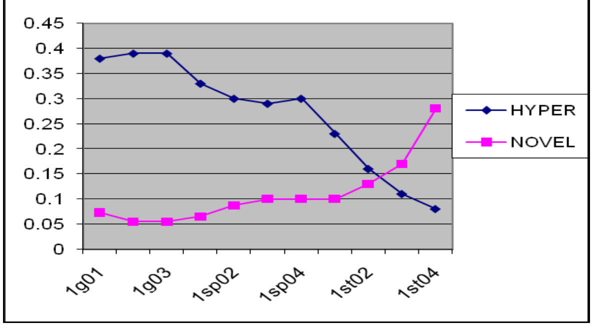
I. Original Bmp Image with Standard Deviation Noise of 40%



(a) 1st04 (original) (b) Hyper1st04 (c) Novel1st04

Table- 1.

IMAGES	HYPER	NOVEL
1g01	0.38	0.073
1g02	0.39	0.055
1g03	0.39	0.055
1sp01	0.33	0.065
1sp02	0.3	0.087
1sp03	0.29	0.1
1sp04	0.3	0.1
1st01	0.23	0.1
1st02	0.16	0.13
1st03	0.11	0.17
1st04	0.08	0.28



Graph-1

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V. CONCLUSIONS

The hyper graph approach combines the outputs of all the weak, erratic, and specialized segmenters to produce approximations of the true boundaries of images that are better than the approximations produced by any single unaided segmenter. This strategy has the important advantage of working far more consistently than any of the entity segmenters and won't fail disastrously because each entity segmenter is dependent on one sort of image or another. However, one segmenter fails while another one succeeds. This is the true significance of the success of the new methodology.

The price of this incorporated move toward is undoubtedly an increased computational strain expressed as extended processing times and more storage responsibilities. These issues are merely technical, though. The availability of similar processors in the near future, older arithmetic units, quick algorithms, simplified code, and increased memory sizes all promise to alleviate these problems in the field of computer science. This issue in the psychobiological arena is resolved by the organic brain's enormous store capacity and built-in parallel city. The hyper graph theory enables all combinatorial mathematical circumstances. The current study has promoted solutions to fundamental image processing issues like segmentation, which is predicated from this model. Not improving the recital of these algorithms is the primary objective, but only to imply that this new move toward can be successful move toward to image processing.

With this application, one can conclude that the hyper graph associated with an image enables one to process a picture using very basic presumptions. The segmentation method using weak operators has a cost that increases computational load, results in longer processing times, and needs more storage. In the future, an algorithm can be expanded to reduce the aforementioned complications. By employing criteria for a hyper graph to satisfy the Helly property, the regularity standard, flexibility, parameters, and conclusion rules, among other things, the combinatory algorithm provided can undoubtedly be improved in a variety of ways. By creating simple binary random fields supported by neighborhood spanning trees and planate graphs, a replacement segmentation mechanism has been provided to overcome these drawbacks.

The results for noisy images produced by this new technology are accurate. The values table and graph demonstrate how very useful it is for picture classification by constructing intelligent borders. Numerous additional opportunities for segmentation in unsupervised mode are made available. The user can understand the outcomes of this formula as being immediate because it is simple enough. Because a binary image might not have all the information necessary for some applications, such satellite images and texture images. Pictures in monochrome display more information than those in binary. Monochrome images are suitable for representing complex images. In order to overcome these limitations, we plan to present a substitute water shed methodology for grey level picture segmentation and classification in the further research.

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REFERENCES

1. G.Matheron, Elements pour UneTheorie des MilieuxPoreux, Paris, 1967
2. L. Vincent. AlgorithmesMorphologiques _a Base de Files d'Attenteet de Lacets: Extension aux Graphes. PhD thesis, Ecole des Mines, Paris, May 1990.
3. F.Meyer, “Contrast Feature Extraction “, in special issue of Practical Metallographic, J.L Chermant, Ed (Rfederer-Verlag, Stuttgart, 1978) Pp.374-380.
4. Dubes .R And Jain A. K Validity studies in clustering methodologies, Pattern Recognition 11, 235-254, 1979. https://doi.org/10.1016/0031-3203(79)90034-7
5. An Efficient Algorithm for Helly Property Recognition in a Linear Hypergraph, H. Cherifi
6. Universit´e de Bourgogne. LIRSIA. BP 47870 21078 Dijon Cedex, France. S. Ub´eda INSA-Lyon. CITI, 20, ave A. Einstein F-69 Villeurbanne Cedex, France.
7. Helly property, clique graphs, complementary graph classes, and sandwich problems, Mitre C. Dourado Priscila Petito Rafael B. Teixeira Celina M. H. de Figueiredo, Articles • J. Braz. Comp. Soc. 14 (2) • 2008 • https://doi.org/10.1007/BF03192558 https://doi.org/10.1007/BF03192558
8. https://users.renyi.hu/~gyarfas/Cikkek/12_Gyarfas_ANoteOnHypergraphsWithTheHellyProperty.pdf
9. Bretto and B. Laget, Neighborhood Hypergraph and Image Analysis, in signal Process. II, 5-9 September 1994, Fontainebleau.
10. Bretto, J. Azema, H. Cherifi, and B. Laget. IEEE Transaction on Combinatorics and Image Processing. France, 1997. https://doi.org/10.1006/gmip.1997.0437
11. R.W. Ehrick and J.P. Foith. A view of texture topology and texture description. Computer Graphics and Image Processing, 8:174-202, 1978. https://doi.org/10.1016/0146-664X(78)90048-5
12. Threshold selection,” IEEE Trans.syst., man,cybern., vol. SMC-9, no.1 pp.38-52,jan.1979. https://doi.org/10.1109/TSMC.1979.4310072
13. Satish, P., Srinivasulu, S., & Swathi, Dr. R. (2019). A Hybrid Genetic Algorithm Based Rainfall Prediction Model Using Deep Neural Network. In International Journal of Innovative Technology and Exploring Engineering (Vol. 8, Issue 12, pp. 5370–5373). https://doi.org/10.35940/ijitee.l3777.1081219
14. Thatha, V. N., Babu, A. S., & Haritha, D. (2019). Research of Clustering Algorithms using Enhanced Feature Selection. In International Journal of Engineering and Advanced Technology (Vol. 9, Issue 2, pp. 4612–4615). https://doi.org/10.35940/ijeat.b5115.129219
15. Bokhare, A., & Metkewar, P. S. (2019). Benchmarking of Graph Partitioning Tools and Techniques. In International Journal of Recent Technology and Engineering (IJRTE) (Vol. 8, Issue 4, pp. 775–787). https://doi.org/10.35940/ijrte.d7369.118419
16. Singh, B. P., & Barik, R. (2023). Image Segmentation Based Automated Skin Cancer Detection Technique. In Indian Journal of Image Processing and Recognition (Vol. 3, Issue 5, pp. 1–6). https://doi.org/10.54105/ijipr.h9682.083523
17. Sharma, Dr. K., & Garg, N. (2021). An Extensive Review on Image Segmentation Techniques. In Indian Journal of Image Processing and Recognition (Vol. 1, Issue 2, pp. 1–5). https://doi.org/10.54105/ijipr.b1002.061221

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