

Design Simulation and Assessment of Cellular Automata Based Improved Image Segmentation System

Raman Gaur¹, Toofan Mukherjee², Sanjay Sharma³, Akash Dadhich⁴

¹M.Tech Scholar, Department of Computer Science & Engineering, SBCET, Jaipur

^{2,3,4}Assistant Professor, Department of Computer Science & Engineering, SBCET, Jaipur

Email: bittu043@gmail.com

Article History	Abstract
<p>Article Submission 25 December 2022</p> <p>Revised Submission 30 January 2023</p> <p>Article Accepted 04 March 2023</p> <p>Article Published 30 March 2023</p>	<p>A variety of methods may be found in the numerous image segmentation techniques. Here a method of text retrieval conducted is typically to produce a collection of localized features. In computer science, object recognition is the problem of automatically "identifying", or classifying, an object. In certain instances, the awareness of artifacts is deeper into image in image segmentation through image processing. The algorithm used for image segmentation has a direct impact on the outcome of the whole approach, therefore it is important to choose carefully. It is important to choose a segmentation method appropriate for a certain framework. There are several ready-to-use segmentation methods, so one by one evaluate the tools to see which works best. Segmentation algorithms have reached such a level of complexity that a research employing them is often considered impractical. The given research undertakes the process of improved graph cut method to select the foreground and background of image through labelling and segmentation of the image. Results have been compared on the performance parameter to analyse the effectiveness of the proposed algorithm for segmentation of the images.</p> <p>Keywords- Images Segmentation, Image Labelling, Image Processing, Growcut Method.</p>

I. INTRODUCTION

Image segmentation is a basic technique that is used in a wide range of vision-related applications. There is no established approach for selecting a segmentation algorithm, nor is there a standardized method for comparing the output of one process to that of another. This problem may enable segmentation to result in incorrect judgments and/or unanticipated outcomes. Image segmentation has shown to be very difficult once again because it does not have a precise meaning. In computer graphics, segmentation is the process of breaking down a collection of pixels into many smaller components. While this idea is quite comparable to the other interpretations of the literature, the criteria itself is sometimes controversial. Segmentation is a sound attempt to emulate a human interpretative behavior known as the identification of patterns. The scope of the problem is greatly increased when segmentation is taken into consideration.

Digital image processing (DIP) is the way to manipulate of images through a computer. DIP is a subfield of signals and structures, but focuses on pictures. It centers around making a picture utilizing PC framework. The contribution of the framework is a mathematical picture and the framework cycle, utilizing fruitful picture calculations and giving a picture as a result. The most popular model is Adobe Photo Shop.

In most techniques, images are treated as 2-D signals. Image is defined as the function of 2-D light intensities $f(x, y)$ where x and y represent the spatial coordinates. F is called the gray level or intensity of the image at any

coordinate pair (x, y) . In this case, when f values of x , y , and amplitude are finite and discrete, the digital image is known. The key components of DIP systems in Figure 1.1 are:

- Image Acquisition
- Storage
- Processing
- Recognition
- Display and Communication interface.

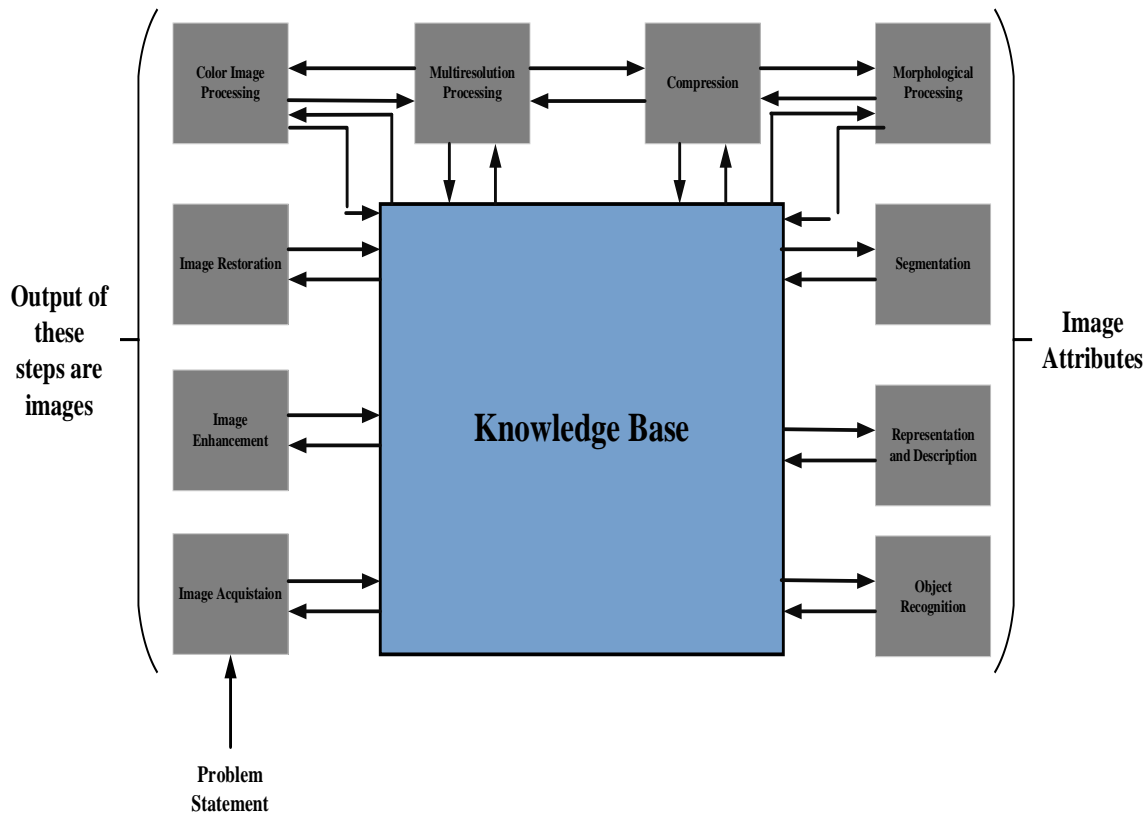


Figure 1.1 Block Diagram of Digital Image Processing System

II. LITERATURE SURVEY

(Ramadan, H., Lachqar, C. and Tairi, H.- 2020) Picture division is perhaps of the most essential errand in PC vision and stays an underlying step of numerous applications. In this paper, we center around intelligent picture division (IIS), frequently alluded to as frontal area foundation partition or item extraction, directed by client connection. We give an outline of the IIS writing by covering in excess of 150 distributions, particularly ongoing works that poor person been studied previously. Besides, we attempt to give an extensive order of them as per various perspectives and present a general and brief examination of the latest distributed works. Besides, we review generally utilized datasets, assessment measurements, and accessible assets in the field of IIS [1].

(Rituparna Sarma and Yogesh Kumar Gupta - 2021) Picture division is the most vital part in picture handling strategies. Various division methods are utilized to section computerized pictures into more modest districts called fragments, comprising of puts of pixels together to investigate significant data from the pictures. Division works on the course of data recovery from the district of interest (ROI). It helps in changing over the advanced picture into more applicable data and simpler to examine. This paper presents a similar examination of existing division procedures and its change to shape new division strategies to conquer a portion of the downsides of the current picture division approaches [2].

(K. Jeevitha, A. Iyswariya, V. RamKumar, S. Mahaboob Basha-2020) Because of the progression of PC innovation picture handling procedures have become progressively significant in a wide assortment of uses. Picture division assumes a significant part in picture handling. Picture division alludes to segment of a picture into various locales that are comparative and different in certain qualities like tone, power or surface. Various calculations and procedures have been created for picture division. This paper explores and incorporates a portion of the innovations utilized for picture division. The different division strategies like Edge Recognition, Limit, District based, Component Based Grouping and Brain Organization Picture Division were talked about in this paper [3].

(Zotin, Alexander, Konstantin Simonov, Mikhail Kurako, Yousif Hamad, Svetlana Kirillova. - 2018) The paper depicts the proposed system to identify the edges of mind cancer from patient's X-ray examine pictures of the cerebrum. At the primary stage, this strategy incorporates some commotion expulsion capabilities further developing highlights that gives better qualities of clinical pictures for solid analysis utilizing Equilibrium Differentiation Upgrade Method (BCET). The aftereffect of second stage is exposed to picture division utilizing Fluffy c-Means (FCM) grouping technique. At long last, Shrewd edge location technique is applied to distinguish the fine edges. During the exploratory review, we utilized pictures containing cerebrum cancers that were portrayed by various area, kind of pathology, shape, size and thickness, as well as the size of the region of the impacted tissue close to the growth space. Discovery and extraction of growth from X-ray check pictures of the mind is finished utilizing MATLAB programming. The got results show a resistivity to a clamor. Additionally, the exactness of division, now and again of cancer pathology, was expanded up to 10-15% in regards to the master gauges [4].

(S. Yuan, S. E. Venegas-Andraca, C. Zhu, Y. Wang, X. Mao and Y. Luo - 2019) In this paper, the edge location calculation for quantum pictures is proposed. Three stages are comprised: quantum picture smoothing, finding the feature angle and quantum edge following. To execute the above processes, a quantum comparator is planned and quantum circuits for every one of the means are given. The proposed quantum edge discovery calculation takes advantage of quantum parallelism [5].

III. PROPOSED METHODOLOGY

Totally automatic approaches of segmentation are continuously improved, but there can be no fully automatic image analysis method, generally with guaranteed outcomes. Therefore, semiautomatic segmentation systems which enable the user to solve moderate and difficult segmentation jobs through small effort are more popular. A number of strong interactive image segmentation algorithms have recently been proposed based on graph cuts and random pathways. The resulting segmenting quality and the user effort seem significantly to outperform earlier approaches. The contribution to this effort is double. First, we offer a new interactive cellular automated segmentation approach with various positive features.

1. Able to do tasks of somewhat difficult segmentation
2. Is simple to build and makes parallel implementation effective.
3. Creates images of any size of $N \times 1$ (computer time does not rely on the amount of labels)
4. Realizes multi-label segments of image.
4. Is extendable, enables the development of new family of distinct characteristic segmentation algorithms.
5. Is fully interactive - the user monitors the segmentation computation process and at all times can make changes and corrections; Secondly, we wish to draw attention, aside from the theory of the graph to alternative alternative views of the problem of segmentation.

Cellular automata are varied and full of resources, which we believe will enable creative and novel methods for interactive image segmentation.

These methods have been divided into two categories - conceived and developed particularly for medical images for generic image manipulation. In fact, most strategies may be used in both sectors successfully.

MagicWall

A common image editor selection tool today. It collects colour statistics from the user-specified image and segmented using pixels, the colour attributes of which fall inside certain tolerances for the collected data.

Smart Paint

It is an interactive region-based division approach based on the segmentation of the hierarchical image through slide systems. It employs a connecting and collecting method to define a zone of items. The technique uses a hierarchical slide algorithm to automatically integrate the natural flux of image sections with a user-focused, cumulative expansion interface to collect the regions of interactive interest. This approach coordinates interaction between humans and computers to remove areas of interest from complex backdrops with mouse strokes.

Smart Scissors

A limit-based method that calculates the cost-less path between user-specified boundary points. It treats each pixel as a graph node and utilises algorithms to calculate limits in the quickest possible way. A speedier variation of intelligent region-based scissors leverages image tobogganing and then interprets homogeneous regions as graphic nodes.

Graph Cut

It is a technique of combinatory optimization used for the image segmentation task. Every pixel is a network node. The image is represented as a graph. For two labels (i.e., object and background), maxflow/min-cut algorithms can be effectively calculated for globally optimal pixel labelling (with regard to a stated cost function). It is possible to use this technique for N-dimensional images. The remaining pixels will be labelled automatically using the object and background seed pixels provided by the user defined.

GrabCut

It expands the graph cut using an iterative graph cutting mechanism. The user creates the rectangle around the subject - this allows the final object/background label to be first approximated. Then each iteration step collects colour statistics, reweights the image graph, and finally graph cut method to calculate new segmentation which is refined keeping in view of current segmentation. When iterations come to an end, additional seeds, like original graph cutting, can refinish the results of segmentation. Medical images have distinct qualities of their own. Often, they are grey levels; in their structure and look they are considerably different from the objects commonly used in image-editing, which should be segmented. This is perhaps why a great deal of study has been done in the development of unique and effective segmentation methods for the field of medical imaging. Segmentation methods such as Graph Cuts, on the other hand, may be used effectively to medical images.

Watershed transformations are used in conjunction with user markers to segment gray-level images in the marker-based modification of the Watershed. The transform Watershed considers the image to be a relief with the pixel luminosity indicated or with the absolute value of the image gradient. Finally landscape valleys filled with water and reach mountains. The first labels which must be split from each other identify markers placed in the image.

The Random Walker

It is analytically determined by the likelihood for a random Walker to reach one of the previously labelling pixels, provided a small number of pixels with user-defined seed labels (label numbers may be larger than 2). The segmentation of the image is achieved when each pixel is assigned to the label for which the highest probability is calculated this method presents a singular solution for segmentation into connected segments, which is resistant against 'weak' borders. A reliability rating is also determined for each pixel of membership.

Interactive Region Growth

It is a descendant with classical approaches of image segmentation. Object of interest is initially indicated the seed pixel after that it is iteratively summed to the increasing zone by the next pixels, while complying with the criteria for a certain zone of homogeneity. The principal difficulty is to 'leak' the developing area across 'small' limits. This approach only works on the object and background of two labels. The results of the image editing procedures presented were examined. The authors have proven clearly that graph-based approaches enable superior segmentation results, with less effort than others. One of the few disadvantages of graph-based methods is that the graphics are difficult to expand on a multi-label job, and they lack flexibility.

New restrictions on the object's soft segmentation limitations set by users cannot be easily applied. As for the smart layer, the advantage of its technology on classic 'magic wall' is number of user interactions and speed, based on the examples the authors provide. It is unlikely that intelligent paint would be able to solve challenging

segmentation problems, given the algorithm described and the results reported. Another debatable thing is precise object boundary evaluation, because an initial over segmentation of the finest segmentation is achieved that cannot correlate with real object boundaries. Random walkers are the best way in discussing of medical images. It puts the segmentation and region behind both in terms of quality and segmentation resilience. The segmentation quality is similar to the graph cuts but random walkers can discover the solution to the number of labels > 2 . But its installation is slow and not an easy task. Furthermore, extending the method to obtain certain specific algorithm features is not straight forward (i.e., configurable limit smoothness).

Multi-labelling

Multi-labelling tasks can be solved using minute graph algorithms however we are not aware of any attempt at applying this multi-labelling method for interactive image segmentation. We employ a straightforward interactive user method users specify certain pixels of images that correspond to objects (we will name them seed pixels) to be segregated from one another. The objective is automatically allocating labels for other image pixels, rather to achieve the user's segmentation outcome. For the resolution of pixel etiquette, our process uses cellular automatics. The process is iterative and provides the user with feedback during the segmentation.

The method proposed enables (but does not need) human input to provide dynamic interaction and feedback between the user and the computer during a labelling process. In places where the segmentation is difficult to compute, but no further user effort is required where the Segmentation is automatically calculated correctly, this can correct and guide the algorithm with the user input. We would like to describe important elements of our method:

1. Able to do tasks of somewhat difficult segmentation
2. Operation on images with size $N \geq 1$.
3. Multi-labelling is carried out. (the number of labels does not effect directly the computing time);
4. Is expandable to allow the design of new segmentation algorithm families with specified features.
5. Interactivity
6. The understanding and execution of the method is straightforward.
7. Using mobile automates may be quickly.

Ulam and von Neumann introduced Technical Basic cellular automatons by Ulam and von Neumann. As a result, the models of many dynamic systems, including image denotification and edge detection are employed in various applications. A mobile device is supported by a grid of $p \in P \subseteq Z^m$, generally a discreet algorithm in time and space. A (bidirectional, deterministic) cellular automator is threefold:

$$T = (H, M, \delta)$$

where H is an unspecific *state set*,

M is the neighbourhood system, and

$\delta: H^M = H$ (rule). In accordance with neighbourhood state t at the time of the preceding step t , this function calculates cell status in the time step of $t+1$.

Where M are the von Neumann and Moore neighborhoods:

$$M(p) = \{q \in Z^m: \|p - q\|_1 = \sum_{i=1}^n |p_i - q_i| = 1\}; \quad (\text{Von}) \quad (3.1)$$

$$M(p) = \{q \in Z^m: \|p - q\|_\infty = \max_{i=1,m} |p_i - q_i| = 1\}; \quad (\text{Moore}) \quad (3.2)$$

The cell state H_p is triplet (l_p, θ_p, C_p) where

l_p = label of the current cell,

θ_p = strength of current cell and cell feature vector

C_p , = cell feature vector of defined image. Also assume that $\theta_p \in [0,1]$

As digital image is array of $k \times m$ pixels in two dimensional. So unlabelled image with cellular automaton in which cellular space P is defined by the $k \times m$ array with initial states for $\forall_p \in P$ are set to:

$$l_p = 0, \theta_p = 0, C_p = RGB_p; \quad (3.3)$$

where RGB_p is the three-dimensional vector of pixel's p color in RGB space.

The ultimate objective is to assign a potential K label to each pixel. The seed cell labels are established properly when the user initiates the segmentation by defining the segmentation seeds, while their strength is determined by the strength of the seed. This establishes the cellular automaton's initial state.

Grow Cut

We can utilise biological metaphor to provide an intuitive explanation for the above pseudocode. Pixel-labeling can be treated as the growth and the fight for K bacterial dominance. The bacteria begin to spread out and strive to occupy the entire image from the seed pixels. Therefore, we termed the "**Grow Cut**" approach. The rules of development and competition in bacteria are obvious: every cell strives to 'assault' its neighbours at every discrete time step. The assault force is determined by the cell strength of the attacker, the distance, and the distance between the C_q and C_p functional vector of the attacker and of the defender. The defending cell is 'conquered' and its label and strength are modified if the assault is stronger than defensive strength. The upshot is that the most powerful germs occupy the nearby locations and are gradually being disseminated across the image. The process proceeds until automatically converges into a stability in which cell states change.

The basic arrangement is fairly simple and yet may be segmented with excellence. The resulting segment limit can, however, be jagged in some images. If it's a problem to collect tiny detail from the border (i.e. in healthcare applications), it can be acceptable or even necessary but it can be an undesired artefact to edit a general high resolution image graph. We suggest an expansion of the automaton to attain a smoother limit.

Two additional conditions modify the local transition rule. First of all, the cell, which has too many enemies, is not able to assault its neighbours by foes (p) as $T1$ is. The second: the enemy's cell (p) — $T2$ — is forced into the weakest enemy, irrespective of the strength of the cell. The number of the enemies shall be

$$enemies^t(p) = \max_{l=1,k} \left(\sum_{q \in N(p), l_q^t \neq l_p^t} 1 \right) \quad (3.4)$$

This is the most encountered segmentation job in image processing. All of the terms above are also true for the labels $K > 2$.

This is done with 'object' and 'background' pins. The initial labels and intensities of each seed pixel are defined by every paint stroke of the brush. The automatic evolution begins when the initial seeds are set. The first, unfulfilled user labelling is typically enough to automatically finish the entire segmentation, but never always. During the calculation of the cell labels, the user can monitor progress and, if necessary, correct and steer the labelling process interactively.

With each paint stroke the states of the pixels underneath change with automatic development changes. This approach permits regions of interest to be extracted by means of simple mouse strokes from complicated backdrops. Note that it is not only possible to alter this after the segmentation is completed but also in the centre of the segmentation calculation. The fact that seeds do not necessary provide hard segmentation restrictions is a major difference from approaches based on graph cutting. In other words, user brush strokes do not just need to designate the areas of firm background, but can instead continually alter the pixels, for example "more foreground" or "a bit more background."

The segmentation from the user part is therefore more versatily controlled and the process is tolerating to imprecise paint strikes. This is particularly helpful for the precise segmentation of items such as flowers or plant sheets. The 'strength' of the seed is governed by the initial strength the brush strokes of the user. During evolution, hard restrictions designate pixels which cannot be changed and readily reached by setting the strength to 1. seed cells. The initial strength value of soft limit values is more than 1, or the current cell strength is only increased or decreased by some value. Contrary to graphing, it can help to improve segmentation in disorderly areas by the addition of seeds to an already properly divided area (i.e., at the border). This applies particularly when the exact border is estimated in a fuzzy or disguised area.

IV. RESULTS ANALYSIS

Database Utilized in Implementation of Improved Grow-Cut

This process has been done with help of MATLAB software using designed graphical user interface. The system has been simulated using different images of flowers with different background. The process has been explained in figures explained below. The process has been simulated with different types of images.

- Flower Dataset (Three different samples)
- Complex background images

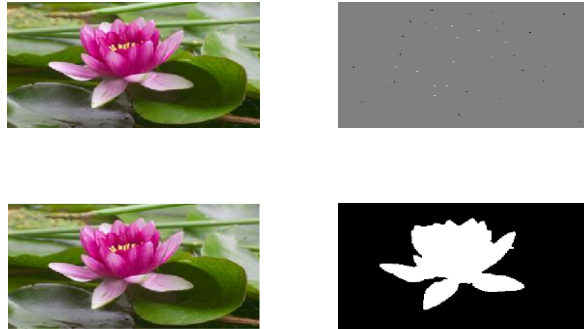


Figure 4.1 Output of Segmentation Using Improved Grow Cut Algorithm

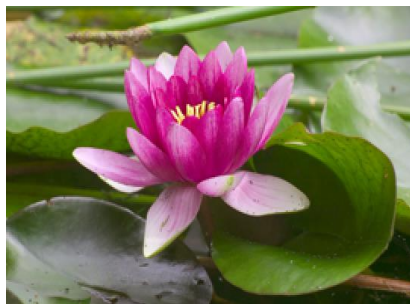


Figure 4.2 Input Image Used for Segmentation with Normal Background

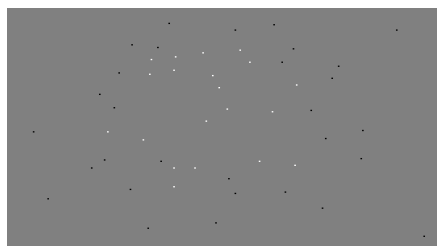


Figure 4.3 Generation of Label Image for Sample Image Using Labelling Algorithm



Figure 4.4 Output of Segmentation with Labelled Image with Grow Cut Algorithm

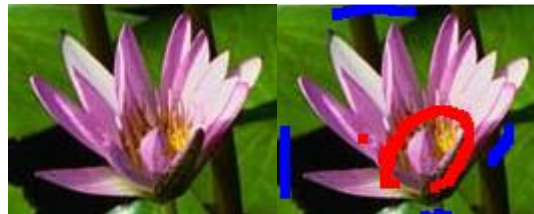


Figure 4.5 Analysis on Sample2 of Flower Image



Figure 4.6 Output of Segmentation with Random Selected Label Image



Figure 4.7 Output analysis between two segmented images with created label images



Figure 4.8 Output of Segmentation for Complex Background Image with Proposed Algorithm



Figure 4.9 Output of Segmentation with Another Sample having Medium Complexity



Figure 4.10 Manual Selection of Background and Fore Ground Pixels for Label Image



Figure 4.11 Output of Segmentation Using Improved Selection of Foreground and Background Pixels



Figure 4.12 Input Image with Complex Background for Creation of Label Image

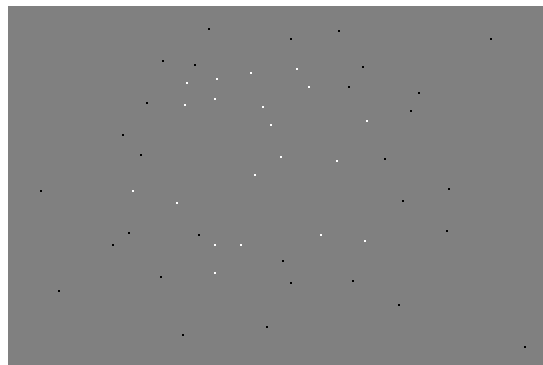


Figure 4.13 Manual Creation of Label Image for Complex Background Image



Figure 4.14 Output of Segmentation Using Proposed Algorithm for Complex Background Image with Improved Label Image

The images have been implemented for segmentation for all images using customized label images. The algorithm has been successfully implemented for these images. It was observed that the algorithm performed decently for normal background images, but the efficiency and effectiveness of segmentation was affected when complex

background and incorrect labels images were entered. The mathematical expressions have been explained as follows-

The commonly used neighborhood systems N are the von Neumann and Moore neighborhoods:

1) Von Neumann neighborhood

$$N(p) = \{q \in Z^n: \|p - q\|_1 = \sum_{i=1}^e |p_i - q_i| = 1\} \quad (4.1)$$

2) Moore neighbourhood

$$N(p) = \left\{q \in Z^n: \|p - q\|_\infty = \max_{h=1,n} |p_i - q_i| = 1\right\} \quad (4.2)$$

The state Sp of the cell p is actually triple in our case, where lp is the label of the existing cell p , p is the current cell p strength and C_p is the functional vector. In the original Grow Cut an image can be seen as a specific configuration of a cell automation, where the pixels of the image define cell space. For every unlabelled pixels of the image p , the initial states for $\forall p \in P$ are set to

$$l_p = 0, \theta_p = 0, C_p = RGB_A \quad (4.3)$$

The initial states of the background seed pixels are set to:

$$l_p = -1, \theta_p = 1, C_p = RGB_p \text{ Where } lp=1 \text{ denotes foreground, } -1 \text{ denotes background.}$$

The following are the steps of the suggested segmentation algorithm:

- 1) The user can get object seed (pixel) set SO and background seed (pixel) set SB by using a mouse-operated brush of white (for object) and blue (for background) color.
- 2) The image is partitioned into many separate sections using a watershed method based on color information.
- 3) The new neighborhood system is used, with the regions obtained in step 2 serving as the cellular automata's cells. This neighborhood system is then subjected to the Grow Cut algorithm.
- 4) The Grow Cut algorithm is used to do automatic edge correction on the segmentation result from step 3. The enhanced Grow Cut, which is based on the watershed algorithm, has a more rougher segmentation result boundary. The automatic edge correction is conducted in order to shorten the user's interactive times.

Table 4.1
Comparison with Existing Work

Image Number	Original Grow Cut	Proposed method without edge correction	Proposed method edge correction
1)	18.953 s	0.266 s	0.516 s
2)	18.828 s	0.234 s	0.547 s
3)	13.567 s	0.187 s	0.515 s
4)	14.694 s	0.203 s	0.469 s

Table 4.2
Precision, Recall and Time

	Prec.	Recall	Time
Ground-truth	—	—	~ 3600 s
Conventional scribbles (after the 1st iteration)	85%	76%	2389 s
Bounding box by sphere (after 3 iterations)	92%	90%	251 s
Label transfer by SIFT flow (after 3 iterations)	88%	92%	1019 s

This exploration proposes a segmentation calculation in view of the Grow Cut of two different scale charts. Watershed calculation in view of variety data has been utilized to parcel the picture into various locales which will be the cells of the cell automata. Then, at that point, the Grow Cut calculation is performed on this area scale chart. At last edge revision in light of Develop Cut of pixel-scale diagram is utilized on the limit of the division result. Near investigations with the Develop Cut techniques have been finished and trial results exhibited that the proposed strategy outflanks Develop Cut technique both on running time and rightness of division.

V. CONCLUSION

Image segmentation is a fundamental method utilised in many vision-related applications. There is no standard way for comparing the output of one procedure to that of another, nor is there a method for selecting a segmentation algorithm. A typical way of text retrieval used here is to generate a collection of localised features. Object recognition is the problem of automatically "identifying" or classifying an object in computer science. In some cases, image segmentation using image processing allows for a richer understanding of artefacts. The picture segmentation method has a direct impact on the overall output of the technique, so it's crucial to choose wisely. It is critical to select a segmentation method that is appropriate for a certain framework. There are various ready-to-use segmentation methods available; assess each tool one by one to find which one works best. Segmentation methods have become so complicated that using them in research is typically deemed impracticable. The presented study uses an enhanced graph cut approach to pick the foreground and background of an image by labelling and segmenting the image. The effectiveness of the suggested algorithm for picture segmentation was evaluated by comparing the results on the performance parameter.

REFERENCES

- [1]. Ramadan, H., Lachqar, C. & Tairi, H. A survey of recent interactive image segmentation methods. *Comp. Visual Media* **6**, 355–384 (2020). <https://doi.org/10.1007/s41095-020-0177-5>.
- [2]. Rituparna Sarma and Yogesh Kumar Gupta. A comparative study of new and existing segmentation techniques. *IOP Conf. Series: Materials Science and Engineering*, 1022 (2021) 012027, doi:10.1088/1757-899X/1022/1/012027.
- [3]. K. Jeevitha, A. Iyswariya, V. RamKumar, S. Mahaboob Basha , V. Praveen Kumar. A REVIEW ON VARIOUS SEGMENTATION TECHNIQUES IN IMAGE PROCESSING. *European Journal of Molecular & Clinical Medicine* ISSN 2515-8260 Volume 7, Issue 4, 2020.
- [4]. Zotin, Alexander, Konstantin Simonov, Mikhail Kurako, Yousif Hamad, Svetlana Kirillova. (2018) "Edge detection in MRI brain tumor images based on fuzzy C-means clustering." *Procedia Computer Science* 126: 1261–1270.
- [5]. S. Yuan, S. E. Venegas-Andraca, C. Zhu, Y. Wang, X. Mao and Y. Luo, "Fast Laplacian of Gaussian Edge Detection Algorithm for Quantum Images," 2019 IEEE International Conferences on Ubiquitous Computing & Communications (IUCC) and Data Science and Computational Intelligence (DSCI) and Smart Computing, Networking and Services (SmartCNS), Shenyang, China, 2019, pp. 798-802.
- [6]. Magdalene C. Unajan Magdalene C. Unajan, Member, IAENG, Bobby D. Gerardo, Ruji P. Medina "A Modified Otsu-based Image Segmentation Algorithm (OBISA) "Proceedings of the International MultiConference of Engineers and Computer Scientists 2019 IMECS 2019, March 13-15, 2019, Hong Kong.
- [7]. Seemawazarkar, Bettahally N. Keshavamurthy, Ahsan Hussain (2018) "Region-based segmentation of social images using Soft KNN algorithm", 6th International conference on smart computing and communications, *Procedia computer Science*, 125: 93-98.
- [8]. Nguyen MongHien, Nguyen ThanhBinh and Ngo Quoc Viet, "Edge detection based on Fuzzy C Means in medical image processing system," 2017 International Conference on System Science and Engineering (ICSSE), Ho Chi Minh City, 2017, pp. 12-15, doi: 10.1109/ICSSE.2017.8030827.
- [9]. Patel, Isha & Patel, Sanskruti. (2019). Analysis of Various Image Segmentation Techniques for Flower Images. 6. 1936-1943.

- [10]. Luxit Kapoor, Sanjeev Thakur,” A Survey on Brain Tumor Detection Using Image Processing Techniques”, 2017 7th International Conference on Cloud Computing, Data Science & Engineering – Confluence,IEEE 2017,pg. 582-585.
- [11]. Chao-Lun Kuo, Shyi-Chyi Cheng, Chih-Lang Lin, Kuei-Fang Hsiao, Shang-Hung Lee,”Texture-based Treatment Prediction by Automatic Liver Tumor Segmentation on Computed Tomography”, 2017 IEEE.
- [12]. M. Moghbel, S. Mashohor, R. Mahmud, and M. Iqbal Bin Saripan, “Automatic liver tumor segmentation on computed tomography for patient treatment planning and monitoring,”EXCLI Journal, vol. 15, pp. 406–423, 2016.
- [13]. Kapil Kumar Gupta,Dr. Namrata Dhanda,Dr. Upendra Kumar,” A Comparative Study of Medical Image Segmentation Techniques for Brain Tumor Detection”, 4th International Conference on Computing Communication and Automation (ICCCA),2018 IEEE, pg. 1-4
- [14]. Xiaoqiang Ji, Yang Li, Jiezhong Cheng,Yuanhua Yu,MeijiaoWang, “Cell Image Segmentation Based on an Improved Watershed Algorithm”, 8th International Congress on Image and Signal Processing (CISP),IEEE 2015, pg. 433-437
- [15]. Priyanka Kamra, Rashmi Vishraj, Kanica, Savita Gupta,” Performance Comparison of Image Segmentation Techniques for Lung Nodule Detection in CT Images”, International Conference on Signal Processing, Computing and Control (ISPCC), IEEE 2015,pg. 302-306.
- [16]. Yu, H. S.; Yang, Z. G.; Tan, L.; Wang, Y. N.; Sun, W.; Sun, M. G.; Tang, Y. D. Methods and datasets on semantic segmentation: A review. *Neurocomputing* Vol. 304, 82–103, 2018.
- [17]. Chen, X. J.; Pan, L. J. A survey of graph cuts/graph search based medical image segmentation. *IEEE Reviews in Biomedical Engineering* Vol. 11, 112–124, 2018.
- [18]. Jain, S.; Laxmi, V. Color image segmentation techniques: A survey. In: *Proceedings of the International Conference on Microelectronics, Computing & Communication Systems. Lecture Notes in Electrical Engineering, Vol. 453*. Nath, V. Ed. Springer Singapore, 189–197, 2017.
- [19]. Zhu, H. Y.; Meng, F. M.; Cai, J. F.; Lu, S. J. Beyond pixels: A comprehensive survey from bottom-up to semantic image segmentation and cosegmentation. *Journal of Visual Communication and Image Representation* Vol. 34, 12–27, 2016.
- [20]. Yao, R.; Lin, G.; Xia, S.; Zhao, J.; Zhou, Y. Video object segmentation and tracking: A survey *arXiv preprint arXiv:1904.09172*, 2019.