

# Optimal Cellular Automata Technique for Image Segmentation

Mariena A. A., J. G. R. Sathiaseelan

**Abstract:**Leukemia death secured 10<sup>th</sup> place among the most dangerous death in the world. The main reason is due to the delay in diagnosis which in turn delayed the treatment process. Hence it becomes an exigent requirement to diagnose leukemia in its early stage. Segmentation of WBC is the initial phase of leukemia detection using image processing. This paper aims to extract WBC from the image background. There exists various techniques for WBC segmentation in the literature. Yet, they provides inaccurate results. Cellular Automata can be effectively implemented in image processing. In this paper, we have proposed an Optimal Cellular Automata approach for image segmentation. In this approach, the optimal value for alive cells is obtained through particle swarm Optimization with Gravitational Search Algorithm (PSOGSA). The optimal value have fed in to the cellular automata model and get the segmented image. The results are validated based on the parameters like Rand Index (RI), Global Consistency Error (GCE), and Variation of Information (VOI). The Experimental results of proposed technique shows better results when compared to the previously proposed techniques namely, Hybrid K-Means with Cluster Center Estimation, Region Splitting and Clustering Technique and Cellular Automata. The proposed technique outperformed all other techniques.

**Keywords:** Optimal Cellular Automata, Image segmentation, PSOGSA, VOI, RI, GCE.

## I. INTRODUCTION

Microscopic images are observed to diagnose various diseases. Changes in blood status reveal the development of diseases in a person. In-depth examination of blood is the best way to diagnose leukemia effectively. Leukemia has been detected by segregating the White Blood Cells and analysing it from other elements of blood. Segmentation is the foremost step to analyze an image accurately. Segmenting the white cells from the blood is a tiresome task, yet there are numerous methods for blood cell segmentation. All the existing methods are having inaccurate in segmenting the white blood cells. Cellular automata model have been widely used in the past two years by researchers in the field of image segmentation. In the Cellular Automata model, each pixel can be treated as a cell and the image as a cellular space [1]. The CA model contains cell space, cell status, neighborhood and a set of rules. The neighborhood can be Cellular automata model have been widely used in the past two years by researchers in the field of image segmentation. In the Cellular Automata model, each pixel can be treated as a cell and the image as a cellular space [1]. The CA model contains cell space, cell status, neighborhood and a set of rules.

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The neighborhood can be defined as a region that consists of all adjacent cells. Here each cell having finite number of states. The future state of the central cell will be affected by the previous states of the surrounding cells with set of rules. An image is termed as a two-dimensional CA where each cell and states are represented by pixel and its intensity respectively. Here we apply the same rule to all cells in the area. Cellular automata comprised of two neighbourhoods such as Von Neumann and Moore neighbourhoods that are depicted in Figure I. (a) and I. (b). The diamond-shaped neighborhood [8] is termed as Von Neumann model that can be used to define a set of cells that surround a specific central cell. The neighborhood has five cells that are the four immediate non-diagonal neighbours with the central cell. The square neighborhood [8] that consists of nine cells is called Moore neighborhood [8] that consist of eight surrounding neighbours and the central cell. In a two-dimensional image, the central pixel treated as the current cell and the surrounding pixels considered as the eight neighbours of that pixel.

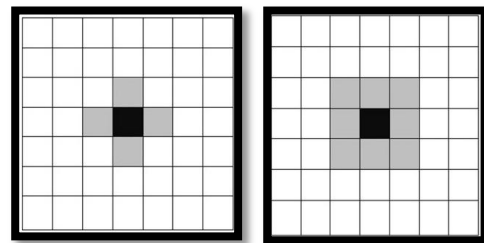


Fig.I (a). Von Neumann. (b) Moore neighborhood

Different researchers have already developed many standard segmentation algorithms in recent decades. However, some researchers have tried CA for image segmentation and obtained better results.

The paper has been arranged in such a way that first part familiarizes the theory of cellular automata. Part II climaxes the literature survey of various techniques used for image segmentation. Section III shows the methodology, the results are illustrated in IV<sup>th</sup> part, and finally, the paper is concluded.

## II. LITERATURE SURVEY

Nameirakpam et al. (4) depicted a hybrid approach of clustering and region merging technique for image segmentation. This technique is focused on the density computation. The small segments formed during the clustering are merged in to neighbouring segments in each iteration. The proposed method yields better results in both execution time and accuracy,

Still there is a need to incorporate optimization techniques to optimize the cluster radius. Soumen et al. (6) introduced a technique based on thresholding with watershed for white blood cell detection. The Sobel filter is applied to the frequency domain and apply thresholding on the resulting image. Method secured 93% accuracy with 30 images. The research work has to be improved to work with huge number of datasets. Xin et al. (2) designed a model which contains two modules namely segmentation module and refinement module. In the first module, the background is extracted through k-means and refinement is done by SVM. Yuncong et al. (7) suggested a 3D Otsu segmentation technique in which an acceleration variant is added to reduce the complexity of the Otsu technique. Multiscale representation is used in segmentation is incorporated in order to reduce noise. However, time complexity of the algorithm is high. Zheng et al. (3) proposed a hybrid approach of Otsu based Ant Bee Colony technique for image segmentation. Initially segment the image using Otsu based Ant Bee Colony. The border extractor algorithm has been used for extracting the edges. To detect the ellipse the Ant Bee Colony technique has been used for detecting the ellipse. Experimental results showed that the new technique has obtained better results. Mahaman et al. (5) introduced an approach in which the super pixels are clustered into regions based on global contour cross and mutual selection. Based on the superpixel features region select the best candidate. The merging process is continued until it reached the threshold value. The proposed approach outperforms the other methods still, it does not take the whole image for consideration.

### III. METHODOLOGY

#### A. HKMCCE for Segmentation

The significant peaks of the histogram is gray level values treated as centroids. The resultant cluster number and cluster centroid have given to kmeans technique for processing. Initial centroid computation has been done by using significant peaks of histogram [14].

#### B. Region Splitting and Clustering Technique (RSCT)

With this technique, an image is partitioned into different regions. In each area, pixels with similar intensity values are grouped based on the threshold value and assigned to the comparable cluster. The resulting family of clusters in each surrounding area are combined to form larger clusters [15].

#### C. Cellular Automata

Cellular Automata (CA), first described in 1950 [18, 19]. Cellular Automata works on lattice of cells and it is discrete in time and space [11]. Cellular automata model has been used by many researchers from various fields [12]. In this model each cell has obtained its own state and it changes according to the state of its neighbours [13]. The proposed Cellular Automata technique used theory of Conway's Game of Life. In this theory, population is a group cells that are marked as alive. At each step, the future of each cell was determined by the liveliness of its surrounding neighbours. Any cell with 2 or 3 of its neighbours live than the cell will

survive. An active cell with fewer than two active neighbours dies as a result of under population. Any active cell with two or more active neighbours belongs to the next generation. Any active cell with more than nine live neighbours dies due to overcrowding. Every dead cell with exactly two live neighbours becomes an active cell. Grid initialized with zeros considered as dead cells and ones as active cells. In this work 3\*3 window with greater than the optimal value and less than number of neighbours plus one "active" cells has been used to transform a central pixel to "active" regardless of its prior state. The cellular automaton is treated as a triplet [11] that consists of number of states such as active or dead, dimensions of the grid, neighborhood considered by a cell like Von Neumann and Moore, finally the transition rules.

#### D. Optimal Cellular Automata (OCA) Technique

The Framework consists of three phases initially we acquire the image from the dataset and convert in to binary image then we are finding the optimal value for the number of alive cells. Finally, the optimal value fed in to the cellular automata phase and get the segmented result.

#### E. Particle Swarm Optimization with Gravitational Search Algorithm (PSOGSA)

In Gravitational Search algorithm the population details has not been shared by the agents to the co-agents. The velocity and acceleration of the agents are updated by incorporating the global searching capability and the local searching ability of PSO and GSA respectively [20].

$$F_{ij}^d(q) = \text{Gra}(q) \frac{M_{pi}(q) \times M_{aj}(q)}{R_{ij}(q) + \alpha} (x_j^d(q) - x_i^d(q)) \quad (1)$$

Where,  $p_i(q)$  is the agent  $i$ 's passive gravitational mass,  $\text{Gra}(q)$  is gravitational constant at time  $q$ ,  $\alpha$  is a small constant,  $a_j(q)$  is agent  $j$ th active gravitational mass and Euclidian distance between two agents  $i$  and  $j$  is  $R_{ij}(q)$ .

$$\text{Gra}(q) = \text{Gra}(0) \times \exp(-\beta \times \text{iter}/\text{maxiter}) \quad (2)$$

$$a_{ci}(q) = \frac{f_i^d(q)}{m_i^d(q)} \quad (3)$$

The following two equations (4) and (5) has been used to update the velocity and position of agents.

$$V_i^{q+1} = F \times V_i^q + C_1 \times \text{rando} \times a_{ci}(q) + C_2 \times \text{rando} \times (\text{glBest} - x_i^q) \quad (4)$$

Where  $F$  is a weighting function,  $\text{rando}$  is a random number within zero and one,  $a_{ci}(q)$  is the acceleration of agent  $i$  at iteration  $q$ ,  $V_i$  is agent  $i$ 'th velocity at iteration  $q$ ,  $C_1$  is a weighting factor, and  $\text{glBest}$  is the best solution. The position has been updated in each run.

$$x_i^{q+1} = x_i^q + V_i^{q+1} \quad (5)$$

Initially, all agents are randomized and considered as a candidate solution. The force and gravitational constant are computed using equation (1) and (2). With every iteration the best solution is updated to date. Agents in the vicinity of optimal solutions try to grab the other agents moving around them. The agents travel so slowly until all the agents are reached very close to the optimum solution [9].

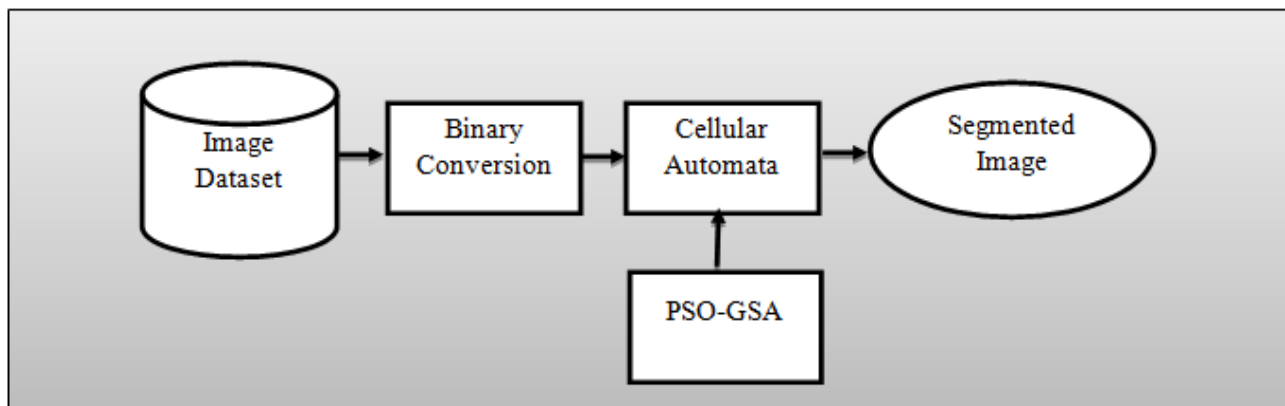


Fig. II. Proposed OCA framework

**Optimal Cellular Automata Technique**

Input: Blood smear Image

Output: Segmented Image

Step1: Read the image.

Step2: Convert the color image in to binary image.

Step3: Pad the image boundary with ones.

Step4: Compute the Optimal value through PSOGSA

Step5: **for each** 3\*3 grid from the image repeat step 6 through step 9.

Step6: Take the difference between the sum of the neighbourhood values and the current pixel.

Step7: Check whether it is greater than the optimal and lower than the total number of neighbourhood.

Step8: **If** yes, update the current pixel with one.

Step9: **Otherwise**, replace the current pixel with zero.

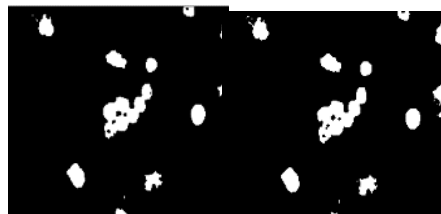
Step 10: final output is the resultant image

**IV. PERFORMANCE ANALYSIS AND EXPERIMENTAL RESULTS**

In this paper, we have effectively developed a method for extracting white blood cells using OCA technique. The performance of this method is analysed by using 50 blood smear images and is shown in Figures 3, 4 and 5. We calculated the performance of the proposed work based on the parameters like RI[15], VOI [15] and GCE[15]. BSI1 is shown in Fig. III (a).The segmented image obtained by using HKMCCE [15] is presented in III (b). The result of RSCT is illustrated in Fig.III(c). Fig.III (d) is the result of CA and III (e) is the result of OCA. The proposed OCA technique surpassed all other techniques.



Fig.III. (a) BSI 1 III. (b) HKMCCE III.(c) RSCT



III. (d) CA III.(e) OCA

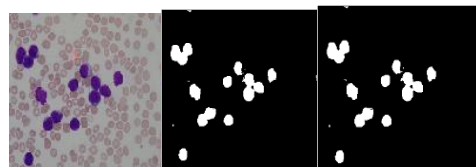
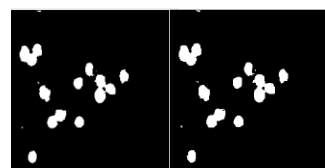


Fig.IV.(a) BSI 2 IV.(b) HKMCCE IV. (c) RSCT



IV.(d)CA IV. (e) OCA

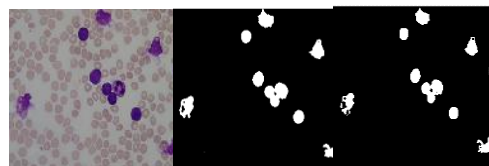
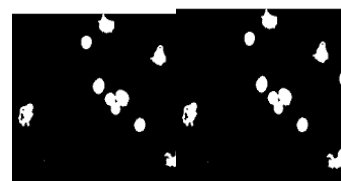


Fig.V.(a) BSI 3V.(b) HKMCCE V.(c) RSCT



V.(d) CA V.(e) OCA

Table I. Experimental results of RI.

Techniques	BSI1	BSI2	BSI3
HKMCCE	0.9281	0.8461	0.7866
RSCT	0.9287	0.9176	0.9188
CA	0.9358	0.9322	0.9242
OCA	0.9710	0.9775	0.9785

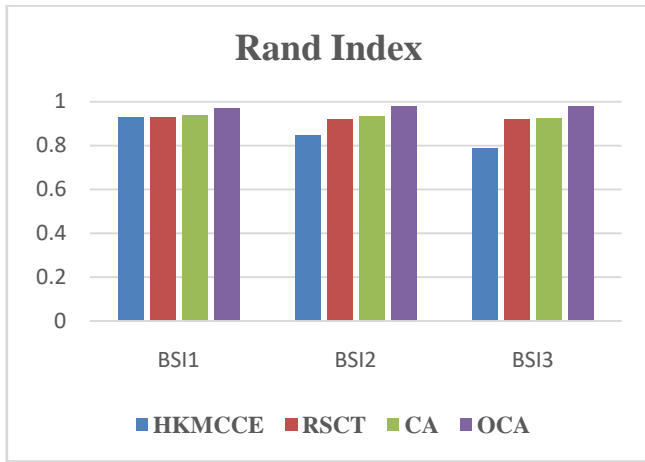


Fig.VI. Results of Rand Index

Table II. Performance Analysis on VOI

Image	BSI1	BSI2	BSI3
HKMCCE	0.3641	0.6191	0.3079
RSCT	0.3472	0.1985	0.2144
CA	0.3278	0.1886	0.1985
OCA	0.1726	0.1382	0.1428

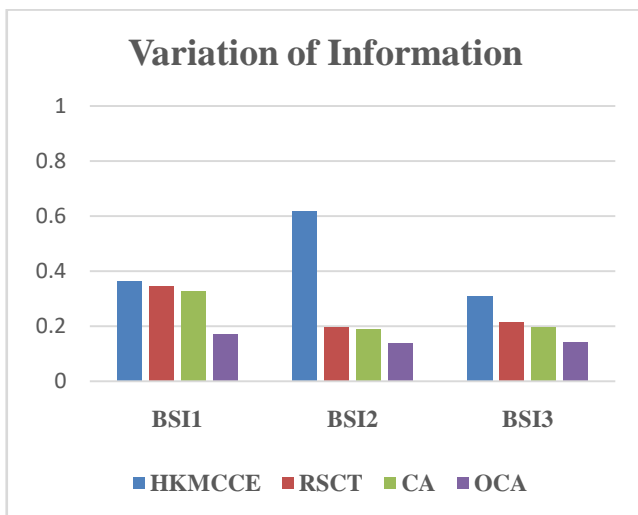


Fig.VII. Results of VOI

Table III. Performance Analysis on GCE

Image	BSI1	BSI2	BSI3
HKMCCE	0.0468	0.0603	0.0743
RSCT	0.0361	0.0485	0.0377
CA	0.0313	0.0347	0.0341
OCA	0.0245	0.0192	0.0186

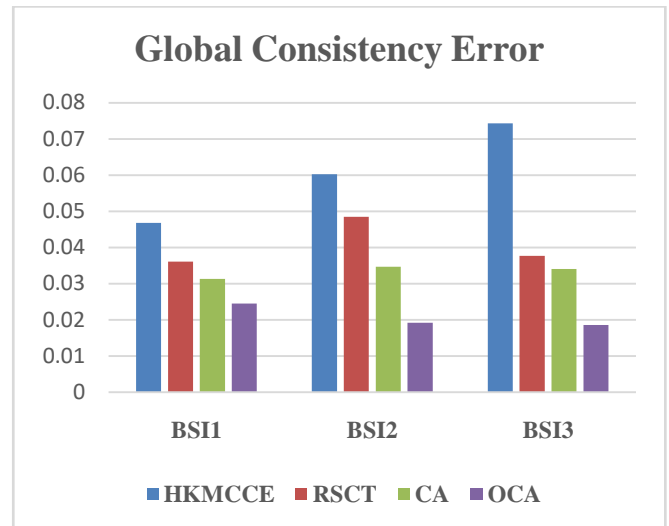


Fig.VIII. Results of GCE

V. CONCLUSION

In this paper, an Optimal Cellular Automata (OCA) technique has proposed to extract WBC from the blood image. Here the optimal value for the alive cell obtained through PSO-GSA technique and it is input in to the Cellular Automata model to get the resultant image. The Proposed OCA method overcomes the standard segmentation techniques by enhancing the performance in terms of Rand index which is increased by 7% global consistency error decreased by 2% and Variation of information decreased by 15%. The experimental results obtained better results for RI, GCE, and VOI. The proposed work can be extended for color images as a future work.

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