CELLULAR AUTOMATA-BASED ALGORITHM AND ITS APPLICATION IN MEDICAL IMAGE PROCESSING

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ABSTRACT

This paper presents cellular automata algorithms for medical image processing. Mammogram images are comprehensively carried out to determine the hypothesis spots of breast cancer. In this respect, the main cellular automata algorithm and its variation are presented and studied to deal with binary and grayscale images. The results of the proposed algorithms are promising and helpful for physician and doctors in diagnosis of the breast cancer in further steps.

***Index Terms*—** Cellular automata, mammogram image processing

1. INTRODUCTION

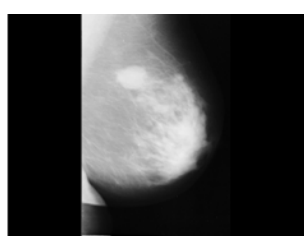
Cellular automata (CA) are a discrete spatiotemporal system whose behavior is specified in terms of local interactions. They appear as natural tools for image processing due to their local nature and simple parallel computation implementation. In this respect, there are a number of papers which generally discuss cellular automata for image processing. Hernandez et al. [1] presented CA for elementary 2-D image enhancement. Wongthanavasu et al. [2] presented 3-D CA for edge detection on binary and grayscale images and compared its performance evaluation to well-known edge operators. Rosin [3] presented algorithms for training cellular automata for image processing. Besides these, there are some papers discussed medical image processing. Cheng et al. [4] presented methods for mass detection and classification. Viher et al. [5] presented cellular automata algorithms for follicle image recognition.

This paper presents a cellular automata-based algorithm and its variation for white spot detection in mammogram. It starts by introducing cellular automata fundamentals necessary for understanding the proposed algorithms. Then, applications in noise removal, edge detection, and white spot detection in mammogram image for the breast cancer diagnosis are presented.

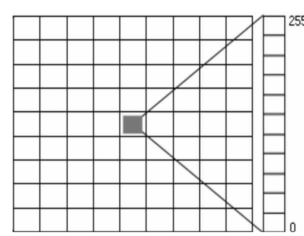
2. CELLULAR AUTOMATA

Let I denote the set of integer. A 2-D cellular space is a 4-tuple, (IxI, V, N, f), where IxI is a set of cartesian product of two integer sets, V is a set of cellular states, N is the type of neighborhood, and f is the local transition function from V^n into V. The relevant neighborhood function is a function from IxI into 2^{IxI} defined by $g(\alpha) = \{\alpha+\delta_1, \alpha+\delta_2, \ldots, \alpha+\delta_n\}$, for all $\alpha \in IxI$, where δ_i $(i = 1,2,\ldots,n) \in IxI$ is fixed. The neighborhood state function of a cell α at time t is defined by $h^t(\alpha) = (v^t(\alpha+\delta_1), v^t(\alpha+\delta_2), \ldots, v^t(\alpha+\delta_n))$. For 2-D von Neumann neighborhood, the neighborhood state function of the central cell (α) is defined by: $h^t(\alpha) = (v^t(\alpha+(0,0)), v^t(\alpha+(0,1)), v^t(\alpha+(1,0)), v^t(\alpha+(0,-1)), v^t(\alpha+(-1,0))$, where $v^t(\alpha+(0,0)$ is current state of the central cell, $v^t(\alpha+(0,1)$ ($v^t(\alpha+(0,-1))$ for the north (south) cells, $v^t(\alpha+(1,0)$ ($v^t(\alpha+(-1,0))$ for the east (west) cells.

Now we relate the neighborhood state of a cell α at time t to the cellular state of that cell at time $t+1$ by $f(h^t(\alpha)) = v^{t+1}(\alpha)$. The function f is referred to as the 2-D CA rule and is usually given in the form of a state table, specifying all possible pairs of the form $(h^t(\alpha), v^{t+1}(\alpha))$. Figure 1 shows 2-D digital image and 2-D CA.



(a) 2-D digital image.



(b) 2-D cellular automata.

Figure 1. 2-D digital image vs. 2-D CA.

3. CA-BASED ALGORITHMS

As stated previously, cellular automata techniques appear as a natural tool for image processing due to their local nature and simple parallel computing implementation. In this section, we present one main algorithm and investigate its variation as methods for processing mammogram images. The methods will correspond to edge detection and noise removal for both binary and grayscale images, while the last one will correspond to spots detection for breast cancer diagnosis. Examples of the application of these cellular automata techniques to real mammogram images will be presented, which together with the results will show the performance characteristic.

The main cellular automata algorithm for k gray levels of digital images is on the basis of a bi-dimensional cellular automata (IxI, V, N, f) with $V = \{0, 1, 2, \ldots, k-1\}$, where k is a number of states, N is the type of neighborhood (e.g. n neighbors), while the local transition function f is from V^n into V. The proposed algorithm is shown in (1) following:

$$f((\nu^t(\alpha+\delta_1), \nu^t(\alpha+\delta_2),\ldots,\nu^t(\alpha+\delta_n))) = \begin{cases} E(\alpha), & \text{if } \max\limits_{j=0}^{k-1} N(C_j)=C_{target} \text{ and } sum(\nu^t(C_{target})) > k-1 \\ B(\alpha), & \text{otherwise} \end{cases} \quad (1)$$

where C_j is the j^{th} class of the pixel values (states) in its neighborhood $(h^t(\alpha))$ for $j = 0, 1, 2,..,m$ and $\nu^t(\alpha+\delta_i) \in C_j$.
$N(C_j)$ is a number of neighbors of α which fall into class C_j.
$sum(\nu^t(C_{target}))$ is summation of $\nu^t(C_{target})$.
C_{target} is the majority class containing maximal number of neighbors.
$\nu^t(C_{target})$ denotes all of $\nu^t(\alpha+\delta_i) \in C_{target}$.
$E(\alpha)$ is the edge pixel value.
$B(\alpha)$ is the background pixel value.
k is a number of states.

For class arrangement, histogram distribution will be utilized to suggest the range of each class.

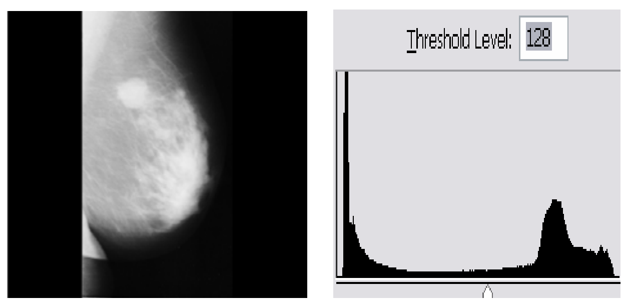
3.1. Gray level edge detection

The objective of the edge detection techniques is to enhance the magnitude of the local differences in gray level values between regions of the images. Over regions which are different, changes must be made to enhance the edges. The proposed variation of (1) which deals with this task is shown in formula (2) for Von Neumann's neighborhood, four classes and 256 gray levels as following:

$$f((\nu^t(\alpha+\delta_1), \nu^t(\alpha+\delta_2),\ldots,\nu^t(\alpha+\delta_5))) = \begin{cases} 255, & \text{if } \max\limits_{j=0}^{3} N(C_j) = C_{target} \text{ and } sum(\nu^t(C_{target})) > 255 \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

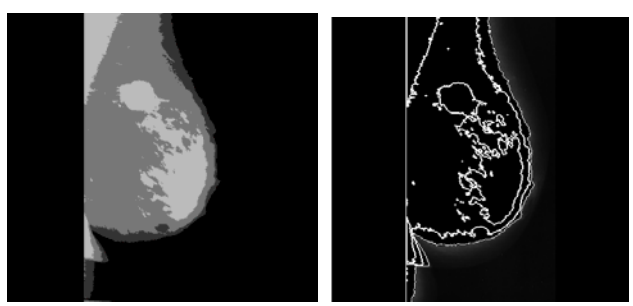
where C_j is the j^{th} class of the pixel values in its neighborhood $(h^t(\alpha))$ for $j = 0, 1, 2, 3$ and $\nu^t(\alpha+\delta_i) \in C_j$.
$N(C_j)$ is number of neighbors of α which fall into class C_j.
C_{target} is the majority class containing maximal number of neighbors $(\nu^t(\alpha+\delta_i) \in C_{target})$.
$sum(\nu^t(C_{target}))$ is summation of $\nu^t(C_{target})$.
$\nu^t(C_{target})$ denotes all of $\nu^t(\alpha+\delta_i) \in C_{target}$.

In implementing (2) in an original mammogram image being supervised by the histogram information (Fig.2) for the class arrangement, the results were shown in Figure 3.



(a) Original mammogram. (b) Histogram.

Figure 2. Original mammogram and its histogram.



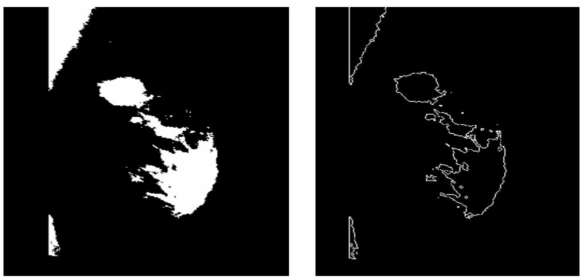
(a) Four class image. (b) Edge map result.

Figure 3. (a) Four classes of image, and (b) result of edge detection.

It is remarkable that the cellular automata algorithm simply provides the best edge maps shown in Figure 3(b).

3.2. Binary edge detection

In case of edge detection on binary image, the cellular automata algorithm in (2) is directly applied to binary image efficiently. It is no need to be changed. Figure 4 shows the promising result of the algorithm dealing with binary images. The edge result exhibits the superb quality with one pixel wide and edge has no break.



(a) Original binary image. (b) Edge result.

Figure 4. Edge result as dealing with binary image.

3.3. Noise filtering

The objective of the noise filtering is to reduce the local differences in gray level values between regions of the images. Over regions which are similar, no changes must be made, in order to avoid the destruction of the main characteristics of the image. The proposed variation of cellular automata algorithm given in (1) using von Neumann's neighborhood and two states dealing with this task is shown in formula (3) as follow:

$$f((\nu^t(\alpha+\delta_1),\nu^t(\alpha+\delta_2),\ldots,\nu^t(\alpha+\delta_5)) = \begin{cases} \max(\nu^t(C_{target})), & \text{if } \max_{j=0}^{3} N(C_j) = C_{target} \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

where C_j is the j^{th} class of the pixel values in its neighborhood $(h^t(\alpha))$ for $j = 0, 1, 2, 3$ and $\nu^j(\alpha+\delta_i) \in C_j$.

$N(C_j)$ is number of neighbors of α which fall into class C_j.

C_{target} is the majority class containing maximal number of neighbors $(\nu^j(\alpha+\delta_i) \in C_{target})$.

$\nu^j(C_{target})$ denotes all of $\nu^j(\alpha+\delta_i) \in C_{target}$.

$max(\nu^j(C_{target}))$ is the maximal state of $\nu^j(C_{target})$.

Figure 5 shows an original binary mammogram with salt and pepper noise at 2%. The noise filtering result using one iteration of implementing such an algorithm is shown in Figure 6. In this respect, the cellular automata algorithm provides the promising result.

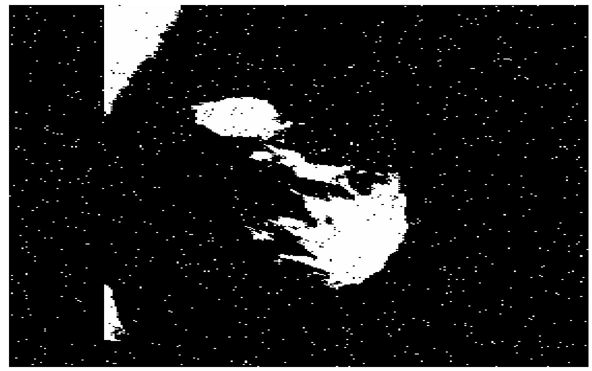


Figure 5. Binary image with salt and pepper noise (2%).

Figure 6. Binary image after noise removal.

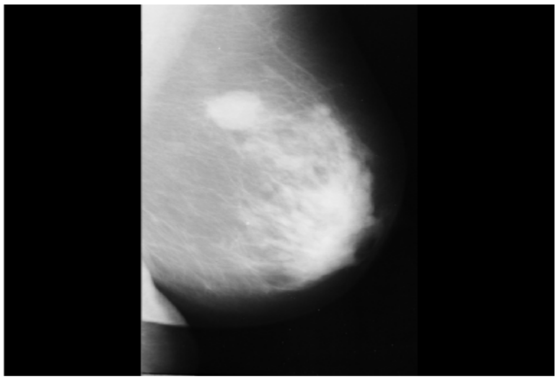
3.4. Spot detection

The objective of the spot detection is to assist the physicians and doctors in locating the hypothesis spots for breast cancer. The shape and spread region of the spots play a vital role for further steps of analysis and have to be comprehensively taken into account. In this regard, a set operator is presented to provide such an affect as following:

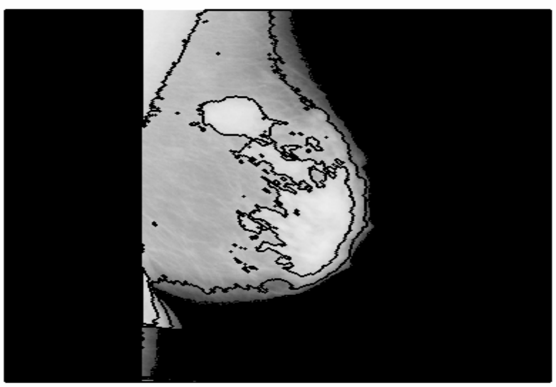
$$W = X - Y \quad (4)$$

where X denotes an original image investigated,
Y denotes an edge map due to formula (2), and
W denotes the resulting image.

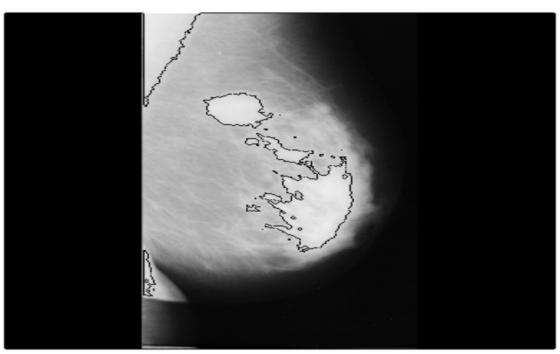
The difference (-) of two sets (images) is simply the subtraction of pixel values between two images (sets) in the same coordinate. By implementing such an operator in an original image (Fig. 7(a)) with respect to Y the results of formula (2) on grayscale and binary images, the resulting white spots detection were shown in Figure 7 (b) and (c), respectively.



(a) Malignant breast cancer.



(b) Spots detection due to (2) for grayscale.



(c) Spot detection due to (2) for binary image.

Figure 7. Mammogram image processing with white spot detection: (a) original malignant breast cancer, (b) cancer spot detection due to (4) for grayscale, and (c) due to (4) for binary image.

5. CONCLUSIONS AND DISCUSSIONS

The behavior of cellular automata is fascinating not only from a theoretical perspective but also from an experimental perspective. The uniformity of cell space offers the beauty and elegance of results. However in real life modeling non-uniformity of cells space may offer better in sights. In this work we have presented uniform cellular automata algorithms for elementary medical image processing. More specifically, cellular automata algorithms dealing with noise filtering, edge detection, and white spot detection for mammogram image in breast cancer diagnosis are presented and investigated. The results are promising, and quite encouraging in determining other tasks. In this regard, we have more investigations on application for mammogram image processing and hope report in the near future.

6. REFERENCES

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