

A symmetry based anomaly detection in brain using cellular automata for computer aided diagnosis

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ABSTRACT

Computer aided diagnosis (CAD) is an advancing technology in medical imaging. CAD acts as an additional computing power for doctors to interpret the medical images which leads to a more accurate diagnosis of the disease. CAD system increases the chances of detection of brain lesions by assisting the physicians in decreasing the observational oversight in the early stage of diseases. This paper focuses on the development of a cellular automata based model to find the anomaly prone areas in human brains. Because of the bilateral symmetric nature of human brain, a symmetry based cellular automata model is proposed. An algorithm is designed based on the proposed model to detect the anomaly prone areas in brain images. The proposed model can be a standalone model or it can be incorporated to a sophisticated computer aided diagnosis system. By incorporating asymmetry information into a computer aided diagnosis system, enhances its performance in identifying the anomalies exists in bilaterally symmetrical brain images.

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1. INTRODUCTION

Medical images play a key role in detection and diagnosis of various diseases. Advances in medical image techniques have facilitated to improve accurate diagnosis. Accurate detection of abnormalities in brain is very complex task. Several researches have carried out in this area. The numerous researches over the last few decades in analysing medical images developed automated techniques [1] for diagnosis. The performance of the traditional automated computer diagnosis system is trivial because it has its own barrier as the automated diagnosis system cannot replace doctors to detect the diseases. Unlike automated diagnosis system, where the diagnosis is done by the machines, computer aided diagnosis [2]-[7] is a system by considering the role of radiologists or physicians in diagnosing the lesions. CAD is used to give a second opinion to the physicians to detect the anomalies in brain. The various technologies developed in CAD are catalysing the enhancement of lesion detection in brain images. CAD system can have multiple modules such as anomaly detection, diagnosis and risk assessment etc. The main objective of this paper is to develop a cellular automata (CA) model, which detects the anomaly prone areas in human brain, which can be integrated with a sophisticated CAD system to enhance its performance.

Radiologists are commonly using Magnetic Resonance Image (MRI) to analyse the internal structure of human brain. The existing techniques used for tumour detection uses various methods using MRI images. Texture based feature analysis [8] and water shed algorithm [9] is mainly used for brain tumour detection. Expectation maximization method [10] is used for brain anomalies detection based on bilateral filter [10]. A two stage region of interest segmentation [11] based on multi level threshold [11] and hard

thresholding [12] is used to detect the area of tumours. All these techniques mentioned above used image processing techniques to detect the anomalies. In order to incorporate intelligence along with brain tumour detection algorithms, fuzzy logics [13]-[17] are included, which helps to the detection of more accurate lesions in brain. But training of data is required to incorporate intelligence in anomaly detection algorithms.

The anomaly parts in the brain may be in various size and shape, so the segmentation of anomaly is a challenging task. Integration of anatomical knowledge with anomaly detection techniques, aids the system to uncover the symmetry or asymmetry in the brain structure leads to enhance the system performance in computer aided diagnosis of the brain anomalies. Human brain structure has two apparently similar halves that exhibit high level of bilateral symmetry. But symmetry is violated in the presence of lesions in brain. So the aim of this paper is to explore the degree of asymmetry occurs due to the presence of lesions in the brain and propose an automated technique using cellular automata to detect the anomalies prone area exists in the human brain. Most of the image processing technique used for anomaly detection needs image registration [18] and are prone to inter-individual and inter-equipment variations even under controlled circumstances, leads to erroneous situation to draw inferences based on absolute values directly. So, approaches based on relative values of the anatomical data have high impact in identifying the lesion region in human brain. Symmetry based method is based on statistically significant relative values, may provide more insights for identifying and quantifying the brain lesions in computerized analysis. There are techniques uses symmetry based approach [19]-[26] for detecting brain tumours and for brain tumour segmentation, bilateral symmetry of the brain structure is exploited. Since the symmetry based approach works on anatomical information of the brain, it does not require training of the data. This paper proposes a symmetry based method to identify anomaly prone areas based on cellular automata [27], [28]. Since cellular automata are a parallel computation models, different variants of cellular automata is used in various medical imaging applications such as cellular automata based model for predicting pattern of dengue fever [29] and learning cellular automata [30] for tumour detection in mammography. So, in this paper, an algorithm based on CA is proposed to find out the asymmetry in brain images in constant time. In order to find out more accurate areas, that are prone to anomaly, the neighbourhood information about the asymmetric area also considered. Since CAD system can have multiple modules, the proposed technique can be integrated to a sophisticated CAD system to enhance its performance or it can be used as an independent CAD system to assist the doctors for the brain image interpretation.

2. RESEARCH METHODS

2.1. Cellular Automata

Cellular automata are computational model consists of an array of cells. Each cell in a CA acts as a processing element. It is a parallel computation model. The neighbourhood of a CA indicates the group of cells in which the CA rules act upon to update a cell state at unit time step. The input data can be stored as states in a CA. The state of each cell can updates in unit time steps based on a local rule which are characterised by the neighbourhood in synchronous fashion. The rule of the CA is a transition function, which takes neighbourhood and the state of a cell at a time step as parameters and returns the new state of that cell in the next time step. CA is used for modelling complex systems. Stephen Wolfram has done an extensive study on two dimensional cellular automata. Two dimensional CA can have various neighbourhoods. In order to find out the anomaly prone areas in a brain image in constant time complexity, a modified cellular automata model called radius boundary CA (RBCA) is proposed.

2.1.1. Radius Boundary CA

The proposed RBCA is a two dimensional cellular automata contains grid of cells. RBCA works based on a reference cell, which is the middle cell in the two dimensional grid termed as $C_{i,j}$. The neighbourhood of the cell $C_{i,j}$ varies in each radius. The radius in an RBCA refers to the distance of the neighbourhood cell with respect to the cell $C_{i,j}$ in all directions i.e., the number of cells traversed from $C_{i,j}$ to the neighbourhoods of $C_{i,j}$ which are the boundary cells in each radius. Table 1 shows the radius structure in an RBCA, R_1 indicates a neighbourhood cell in radius 1 and R_2 indicates neighbourhood cell in radius 2 with respect to the cell $C_{i,j}$. Based on $C_{i,j}$, the cells in each radius interact in parallel.

Table 1. RBCA’s radius structure

R ₂	R ₂	R ₂	R ₂	R ₂
R ₂	R ₁	R ₁	R ₁	R ₂
R ₂	R ₁	<i>C_{i,j}</i>	R ₁	R ₂
R ₂	R ₁	R ₁	R ₁	R ₂
R ₂	R ₂	R ₂	R ₂	R ₂

2.2. RBCA Model for Anomaly Detection

In the proposed RBCA based CAD model for detecting anomaly prone areas in brain, a region based approach is used. The brain image is converted into a two dimensional array based on intensity. The intensity of each pixel varies from 0 to 255. The centroid of the image is calculated in the middle axis. The centroid of the image is treated as the middle cell in RBCA and each pixel value in the two dimensional array are considered as cells in the RBCA. The neighbourhood cells of the centroid in various radius distinguish the region. The set of neighbourhood for the centroid varies according to the radius. Since the brain image is bilaterally symmetrical, in order to ensure the bilateral symmetry, the corresponding cells in each radius based on the centroid are computed. Based on a threshold, asymmetry is calculated in each region. The location of the asymmetric region also can identify based on the region. Figure 1 shows a sample affected brain image.

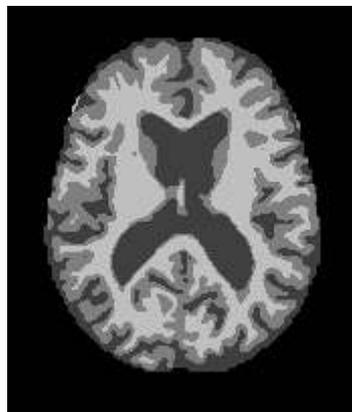


Figure 1. Sample affected brain image

Table 2. RBCA model

R ₄	R ₄	R ₄	R ₄	R ₄	R ₄				
R ₄	R ₃	R ₃	R ₃	R ₃	R ₃	R ₃	R ₃	R ₃	R ₄
R ₄	R ₃	R ₂	R ₂	R ₂	R ₂	R ₂	R ₂	R ₃	R ₄
R ₄	R ₃	R ₂	R ₁	R ₁	R ₁	R ₁	R ₂	R ₃	R ₄
R ₄	R ₃	R ₂	R ₁	<i>C_{i,j}</i>	R ₁	R ₂	R ₃	R ₄	R ₄
R ₄	R ₃	R ₂	R ₁	R ₁	R ₁	R ₂	R ₃	R ₄	R ₄
R ₄	R ₃	R ₂	R ₂	R ₂	R ₂	R ₂	R ₃	R ₄	R ₄
R ₄	R ₃	R ₃	R ₃	R ₃	R ₃	R ₃	R ₃	R ₄	R ₄
R ₄	R ₄	R ₄	R ₄	R ₄	R ₄				

Under the assumption that the brain image is bilaterally symmetric with respect to the middle axis, the centroid is calculated. Both the sides of the axis are symmetrical in nature. So, in order to check the level of asymmetry exists in the image, based on the centroid, calculate the level of asymmetry by comparing the values of the respective cells in both the sides of the axis. Table 2 shows the RBCA model, where *C_{i,j}* is treated as centroid ie, middle cell and the cells in the column which contains *C_{i,j}* is treated as the axis of the image. Region based comparison is used in this technique. The region is identified based on the radius. In each radius, the cells in each row marked with same colour based on the middle cell are compared for the symmetry. The RBCA model is also a parallel computation model because the cells in each radius are independent and based on the middle cell, parallel access to cells in each radius is possible. In order to make the RBCA model as a parallel computation model, the computation process is discussed below. Assuming the co-ordinate of the centroid as (*i, j*).

Comparison required in radius 1:

The middle level cells: $(i, j - 1)$, and $(i, j + 1)$

Top level cells: $((i - 1)(j - 1)$ and $(i - 1)(j + 1))$

Bottom level cells: $((i + 1)(j - 1)$ and $(i + 1)(j + 1))$

Comparison required in radius 2:

The middle level cells: $((i, j - 2)$ and $(i, j + 2))$,

$((i - 1)(j - 2)$ and $(i - 1)(j + 2))$,
 $((i + 1)(j - 2)$ and $(i + 1)(j + 2))$.

Top level cells: $((i - 2)(j - 1)$ and $(i - 2)(j + 1))$,

$((i - 2)(j - 2)$ and $(i - 2)(j + 2))$.

Bottom level cells: $((i + 2)(j - 1)$ and $(i + 2)(j + 1))$,

$((i + 2)(j - 2)$ and $(i + 2)(j + 2))$

So, total comparison operations required in this RBCA model vary according to the radius. In each radius, the total number of comparisons required is calculated based on the above computations. Assume that r is the radius with respect to the centroid,

Top level (r) level, the number of comparisons required: r comparisons

Bottom level (r) level, the number of comparisons required: r comparisons

Middle level, the number of comparisons required: $(2 * r) - 1$ comparisons

The cells in the top and bottom levels of each radius with respect to the centroid, in the asymmetric region are compared with its neighbourhood cells to check the level of asymmetry to ensure more accuracy.

2.2.1. Algorithm 1: check the asymmetry in a brain image

Step 1: Find the centroid of the given image, after orientation of the symmetric plane in the space.

Step 2: Let a be the two dimensional array, which stores the integer values of the image, i, j be the centroid of the image

Step 3: Let r be the radius of the image from the centroid

Step 4: For each radius, $r = 1$ to *boundary* do in **Parallel**

Step 5: For each row, $k = 0$ to r do in **Parallel**

Step 5.1: if k is not equal to r

Step 5.1.1: Compare the values of $a((i - k)(j - r))$ and $a((i - k)(j + r))$

Step 5.1.1.1: if the difference is greater than threshold

Assign zero to the image location, holds the greater value.

Step 5.1.2: Compare the values of $a((i + k)(j - r))$ and $a((i + k)(j + r))$

Step 5.1.2.1: if the difference is greater than threshold,

Assign zero to the image location, holds the greater value

Step 5.2: Else

Step 5.2.1: For each column, $l = 0$ to r do in **Parallel**

Step 5.2.1.1: Compare the values of $a((i - k)(j - l))$ and $a((i - k)(j + l))$

Step 5.2.1.1.1: if the difference is greater than threshold,

Assign zero to the image location, holds the greater value

Step 5.2.1.2: Compare the values of $a((i + k)(j - l))$ and $a((i + k)(j + l))$

Step 5.2.1.2.1: if the difference is greater than threshold,

Assign zero to the image location, holds the greater value.

Step 5.2.2: End for

Step 5.3: Compare the values of left, right and middle cell for zero,

Step 5.3.1: If all the three values are zero,

Assign zero to middle cell, 255 otherwise.

Step 6: End of step 5

Step 7: End of step 4

2.2.2. Description of the Algorithm

The algorithm to find out the asymmetry exists in bilaterally symmetric brain images are proposed in Algorithm 1. Assume that a T2-weighted brain is converted into a two dimensional array, a with integer values ranging from 0 to 255. The intensity of each pixel is converted into integer values. Step 1 find out the centroid of the image and column of the array which contains the centroid is considered as middle axis of the image. Step 2 assign the image into a two dimensional array a . Step 4 initializes the radius, r from the centroid to the boundary of the image. In step 5, for loop is used to check each row from 0 to, where r is the radius. In each radius, there are three levels of comparisons such as top level, bottom level and middle level is required. Since the number of comparisons required in each level is different, step 5 is used to check whether the selected row is equivalent to radius level or not. If it is not in radius level, steps from 5.1.1 to 5.1.2 are used for middle level comparisons. In each radius, $(2 * r) - 1$ comparisons are required in the middle level with the corresponding cells in each row. If the respective values are not equal, based on a threshold, assign a 0 in the location where the symmetry is breaking, to indicate the asymmetry. Step 5.2 is used for the else condition, ie, top and bottom level comparisons in each radius. The top and bottom level, r number of comparisons required. In step 5.2.1, for loop is used to access each column values. In each case, the algorithm checks for the asymmetry. Step 5.3 checks the left and right neighbourhood values of each cell for asymmetry, if the neighbourhood cells are also asymmetric, mark the cell value as 0 to indicate anomaly prone area. So, with this algorithm, the asymmetric areas, which are prone to anomaly, can be identified.

3. RESULTS AND ANALYSIS

In order to perform the experimental work to implement the above mentioned algorithm to identify the asymmetry exists in bilaterally symmetric images; T2 - weighted images are used. Matlab-version 2018 is used for the implementation of the above mentioned algorithm. Considered affected brain images. The image is converted into a two dimensional array, the values of the array varies from 0 to 255 based on the intensity of each pixel in the image. Experiments have done on different standard brain images. Figure 2 and Figure 3 shown the sample input and output.

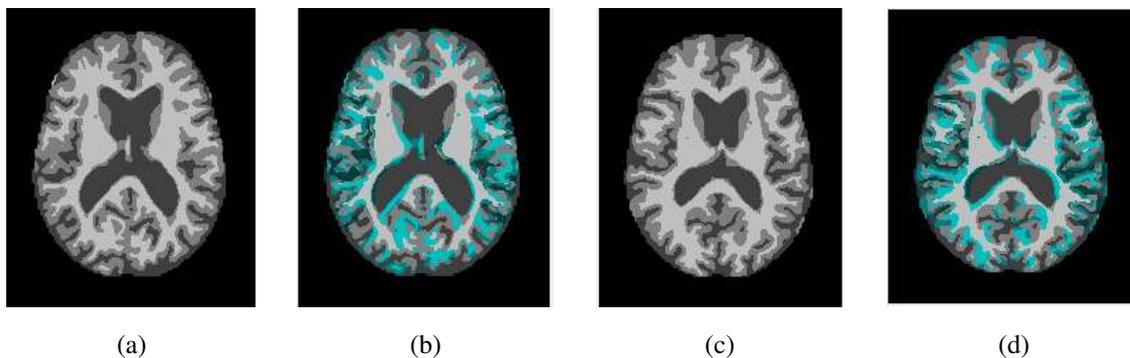


Figure 2. (a) Affected brain, (b) Anomaly prone areas detected, (c) Affected brain, (d) Anomaly prone areas detected

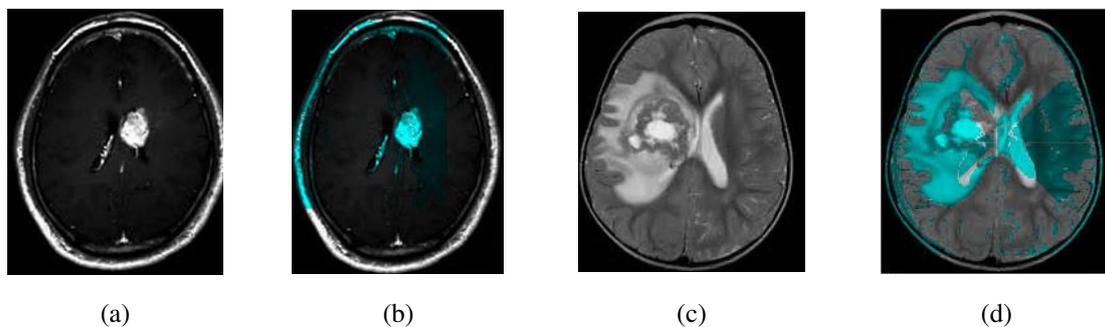


Figure 3. (a) Affected brain, (b) Anomaly prone areas detected, (c) Affected brain, (d) Anomaly prone areas detected

The RBCA model proposed here is a parallel computational model. The computations in each radius perform in parallel and the comparison operations in the top level, bottom level and middle level in each radius also performs in parallel. So, the time complexity of the above mentioned algorithm is constant. In each region, ie, radius, the algorithm checks for the immediate neighbourhood for the asymmetry resulted in detection of more accurate anomaly prone area. With this proposed model, even very minimal level of asymmetry also can be detected, which helps the physicians to identify the area in which more focus needs to be carried out. So doctors can interpret the brain images properly, that result in a proper diagnosis of the disease by reducing observational oversight of the doctors.

3.1. Comparison with Existing Techniques

Since the proposed method is a symmetry based method, unlike the qualitative analysis on brain anomaly detection, image registration, training the data is not required. Symmetry based approach is based on relative data, so the dependency of the pixel variations can be minimized. Most of the symmetry based techniques used for anomaly detection used extensive comparisons, which leads to high time complexity. The works which uses bounding box techniques, [18]-[22] to detect anomaly based on symmetry needs $O(n^2)$ time, where n is the input size. Whereas RBCA model requires only constant time to find the anomaly prone areas. So the proposed RBCA model is a more efficient model based on symmetry to detect brain lesions. Figure 4 shows the time complexity comparison of other techniques and RBCA model. The graph in the green colour indicate the $O(n^2)$ time and the graph in the red colour indicate the constant ie, $O(1)$ time complexity.

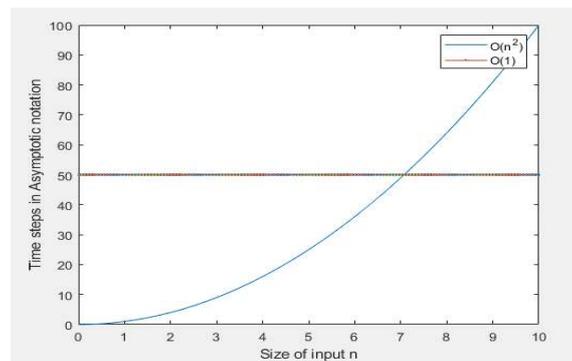


Figure 4. Time complexity comparison

4. CONCLUSION

CAD system is considered as a complementary computing power to diagnose the disease with more accuracy. CAD increases the chances of detection of diseases by assisting the physicians in decreasing the observational oversight in the early stage of diseases. CAD can be assembled as packages and implemented. The RBCA model proposed in this paper helps the physicians to identify the area in which more focus needs to be carried out. Most of the cases the small lesions may be missed by the doctors, in corporation of asymmetric information along with the CAD system enhance the performance of the system by reducing the observational oversight. The proposed RBCA model can be integrated with a sophisticated CAD system or may work as a standalone CAD system to find the anomaly prone areas in human brain. Since the proposed model is based on cellular automata, in constant time complexity, the RBCA model detects anomaly prone areas in human brains.

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