Optimal Thinning Algorithm for detection of FCD in MRI Images

Dr.P.Subashini, S.Jansi

Abstract - Thinning is essentially a "pre-processing" step in many applications of digital image processing, computer vision, and pattern recognition. In many computer vision applications, the images interested in a scene can be characterized by structures composed of line or curve or arc patterns for shape analysis. It is used to compress the input data and expedite the extraction of image features. In this paper three different thinning algorithms are applied for MRI Brain Images to estimate performance evaluation metrics of thinned images. Image thinning reduces a large amount of memory usage for structural information storage. Experimental result shows the performance of the proposed algorithm.

Index Terms- FCD, Parallel thinning algorithm, Skeleton, Performance Metrics, and MRI Images.

1 INTRODUCTION

Focal Cortical Dysplasia (FCD), a malformation caused by abnormalities of cortical development has been increasingly recognized as an important cause of medically intractable focal epilepsy. Small FCD lesions are difficult to distinguish from non-lesional cortex and remain overlooked on radiological MRI inspection. Although MRI has allowed the detection of FCD in an increased number of patients, standard radiological evaluation fails to identify lesions in a large number of cases due to their small lesions and complexity of the cortex convolution [1].

The aim of preprocessing is to process the images in raw form and obtain images suitable for detection of FCD. In 2006, the author O.Calliot, worked detecting the FCD and achieved 70% by using histogram method for classifying WM/GM and CSF. In 2009, Jeny Rajan, K.Kannan et al., [2] the median voxel-wise intensity were normalized and morphological operations such as dilation, erosion and connected component analysis were used for removing the scalp and lipid layers from brain MR images. Reducing the false positives cerebellum was removed.

Thinning is a morphological operation that is used to remove selected foreground pixels from binary images. Thinning is somewhat like erosion or opening. It is particularly useful for skeletonization and Medial Axis Transform. It is only applied to binary images, and produces another binary image as output. The thinning operation makes use of a structuring element. These elements are of the extended type meaning they can contain both ones and zeros. The thinning operation is related to the hit-and-miss transform and can be expressed quite simply in terms of it. The thinning of an image *I* by a structuring element *J* is given as

$$Thin(I, J) \quad = \quad I - hit\,andmiss(I, J) \tag{1}$$

Thinning has been used in a wide variety of other applications as well including: medical imaging analysis, bubble-chamber image analysis (a device for viewing microscopic particles), text and handwriting recognition and analysis, metallography (materials analysis), fingerprint classification, printed circuit board design, and robot vision [3].

Thinning can be defined as a process in which outer layers of an object are successively removed until a skeleton of the object is obtained. From the definition of thinning, the two obvious features are Firstly, thinning is an iterative processing. In each step, only outermost layer can be peeled. Secondly, the time used for thinning depends on the size and the shape of the objects in an image. One advantage of thinning is to reduce the data required to represent the topological structure of an object. Because thinning is preprocessing of image, that reduces the processing time in later steps of image processing. In this paper, the various morphological thinning algorithms are tested for detecting the FCD in MRI brain images.

2. Thinning Algorithm

A thinning algorithm usually consists of the iterative removal of contour until the skeleton is formed. The application of the different algorithms leads to different skeleton shapes. There are certain features in the skeleton that characterize the algorithm. Some algorithms are better

- *Dr.P.Subashini, Associate Professor, Department of Computer Science, Avinashilingam University for Women, Coimbatore. Email: mail.p.subashini@gmail.com*
- *S.Jansi, PhD Research Scholar, Department of Computer Science, Avinashilingam University for Women, Coimbatore. Email: jansi.sm@gmail.com*

suited to a particular application than other algorithms, depending on the shaping of the skeleton [4].

Thinning algorithms can be divided into two broad classes namely iterative and non-iterative. Although non-iterative algorithms can be faster than iterative algorithms they do not always produce accurate results. In iterative methods, thinning algorithms produce a skeleton by examining and deleting contour pixels through an iterative process in either sequential or parallel way. Non-iterative (non-pixel based) thinning algorithms produce a certain median or centre line of the pattern to be thinned directly in one pass, without examining all the individual pixels.

In 1986, Alberto Martin et al [5], analyzed different image processing algorithms by classifying them in logical groups. In this paper, the Template-Based Mark-and-Delete Thinning Algorithms are very popular because of their reliability and effectiveness. This type of thinning processes uses templates, where a match of the template in the image, deletes the center pixel. They are iterative algorithms, which erodes the outer layers of pixel until no more layers can be removed. The Stentiford thinning method is an example of these kinds of algorithms. T.Y.Zhang and C.Y. Suen proposed [6], extracted the skeleton of a picture consists of removing all the contour points of the picture except those points that belong to the skeleton. In 2000, Alfredo Petrosino et al [7], proposed a new parallel thinning algorithm with two subcycles is proposed and compared with other parallel thinning algorithms in terms of 8-connectedness degree, erosion, stability under pattern rotation, and boundary noise sensitivity.

A variety of thinning algorithms such as sequential, parallel, and maximum methods, have been proposed for thinning digital patterns. In a sequential method, the value of a pixel at the nth iteration depends on a set of pixels for some of which the result of nth iteration is already known. In parallel processing, the value of a pixel at the nth iteration depends on the values of the pixel and its neighbors at the (n - 1)th iteration. Thus, all the pixels of the digital pattern can be thinned simultaneously [8].

2.1 Sequential Thinning Algorithm

In a sequential thinning algorithm, the pixels in the bitmap are processed in a sequence, one after the other. Thus the algorithm is able to make use of results obtained so far in the current algorithm together with the state of the bitmap at the end of the last algorithm and apply them to a pixel. The order of execution will therefore affect the final shape of the skeleton. A sequential algorithm may be faster than a parallel algorithm when implemented on serial hardware [4].

2.2 Parallel Thinning Algorithm

In parallel thinning algorithms, pixels are examined for deletion on the basis of results obtained only from the previous iteration. This algorithm have always received more considerable attention in the research area of parallel thinning as they have reduced the computation time in a number of iterations, and that is why they are sometimes called one-pass or fully parallel algorithms[9].

2.2.1 Zhang Suen Thinning Algorithm

Zhang and Suen is a fast parallel thinning algorithm, which yields good results with respect to both connectivity and contour noise immunity. This method gives a better skeleton. Two sub-iterations are there. First sub-iteration removes south or east boundary pixels or north-west corner pixels. Second sub-iteration removes north or west boundary pixels or south-east corner pixels. If at the end of any sub-iteration there are no pixels to be deleted, the skeleton is completed. This method is fast and simple to implement; it counts with two sub iterations in which those pixels fulfilling the rules defined for iteration are removed [10]. The Zhang-Suen algorithm consists of iteratively deleting edge-points, while keeping end-points, and also the shape connectedness should not be occurred[11].

A pixel is a final point if it has a single black neighbor, being the rest all white. A pixel's connectivity is defined as the number of objects it could connect in the original image, and is computed turning round a pixel clockwise and counting how many color changes are produced. The number of changes will be the connectivity, i.e., the number of regions it connects. This algorithm is made by two sub-iterations [5].

In the fist one, a pixel I (i,j) is deleted if the following condition are satisfied:

1. Its connectivity number is one.
2. It has at least two black neighbors and not more than six.

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3. At least one of I(i,j+1), I(i-1,j), and I(i,j-1) are white.
4. At least one of I(i-1,j), I(i+1,j), and I(i,j-1) are white.

In the second sub-iteration the conditions in steps 3 and 4 change.
1. Its connectivity number is one.
2. It has at least two black neighbors and not more than six.
3. At least one of I(i-1,j), I(i,j+1), and I(i+1,j) are white.
4. At least one of I(i,j+1), I(i+1,j), and I(i,j-1) are white.

At the end, pixels satisfying these conditions will be deleted. If at the end of either sub-iteration there are no pixels to be deleted, then the algorithm stops.

2.2.2 Stentiford Thinning Algorithm

Stentiford is a parallel thinning algorithm, which tends to produce lines that follow curves very well, resulting in vectors that most accurately reflect the original image. The objects are connected with a particular pixel.
The Stentiford algorithm can be stated as following [5]:
1. Find a pixel location (i,j) where the pixels in the image match those in template T1. With this template all pixels along the top of the image are removed moving from left to right and from top to bottom.
2. If the central pixel *is not an endpoint, and has connectivity number as 1*, then mark this pixel for deletion.

Endpoint pixel: A pixel is considered as endpoint if it is connected to just one other pixel. That is, if a black pixel has only one black neighbor out of the eight possible neighbors, then it is an endpoint pixel.

Connectivity number: It is a measure of how many objects are connected with a particular pixel.

$$C_n = \sum_{k \in S} N_k - (N_k \cdot N_{k+1} \cdot N_{k+2}) \tag{2}$$

Where, $\mathbf{N_k}$ is the color of the eight neighbors of the pixel analyzed. N_0 is the center pixel. N_1 is the color value of the pixel to the right of the central pixel and the rest are numbered in counterclockwise order around the center.

3. Repeat steps 1 and 2 for all pixel locations matching T1.
4. Repeat steps 1-3 for the rest of the templates: T2, T3, and T4. T2 will match pixels on the left side of the object, moving from bottom to top and from left to right. T3 will select pixels along the bottom of the image and move from right to left and from bottom to top. T4 locates pixels on the right side of the object, moving from top to bottom and right to left.
5. Set white the pixels marked for deletion.

2.2.3 OPTA Thinning Algorithm

The One Pass Thinning Algorithm (OPTA) was proposed in 1986 [12]. In this algorithm, there are no sub iterations in each iteration. The OPTA algorithm uses ten predefined windows to carry out the thinning procedure. The OPTA algorithm uses two kinds of different sized windows to prevent the deletion of two-pixel thick lines. The main advantage of OPTA algorithm is that only one pass is needed to delete all of the outermost layer points on the boundary of the object. That will reduce the processing time.

OPTA – a parallel thinning algorithm, which produce the skeleton of the images. This algorithm exhibits good effects for straight lines. The One Pass Thinning algorithm is a typical template matching algorithm [13]. For each pixel, extract 10 neighborhood pixels, comparison with eight elimination templates and two retention templates, then judge the center pixel to be deleted. A new thinning algorithm reforms the elimination templates and retention templates of OPTA algorithm [14]. OPTA algorithm is applied on raster scanned binary images, using a set of 10 thinning patterns of 3×3 and 3×4 predefined elements, and produces the skeleton of their objects[15]. The OPTA algorithm is faster than the Zhang-Suen algorithms. But the skeletons of this algorithm are not as good as Zhang-Suen and Stentiford algorithms.

3. Results and Discussions

The images are thinned by three different algorithm as described in the above section. In order to measure the performance of the algorithms, metrics such as PSNR, SNR, MSE, Precision, Recall, Sensitivity and Specificity are obtained for MRI brain images by applying Zhang Suen, Stentiford, and OPTA thinning algorithms.

PSNR is defined as the ratio of peak signal power to average noise power

$$PSNR(db) = 10\log_{10}\left(\frac{D^2 MN}{\sum_{i,j}\left(x(i,j) - y(i,j)\right)^2}\right)$$

(3)

for $0 \le i \le M-1 \text{ and } 0 \le j \le N-1$, where D is the maximum peak-to-peak swing of the signal (255 for 8-bit images). Assume that the noise $x(i,j) - y(i,j)$ is uncorrelated with the signal.

SNR is defined as the ration of average signal power to average noise power and for an MxN image is

$$SNR(db) = 10\log_{10}\left(\frac{\sum_{i,j} x(i,j)^2}{\sum_{i,j}\left(x(i,j) - y(i,j)\right)^2}\right)$$

(4)

for $0 \le i \le M-1 \text{ and } 0 \le j \le N-1$. Let x (i, j) represent the value of the ith row and jth column pixel in the original image x and let y (i, j) represent the value of the corresponding pixel in the output image y. The local error is $e(i,j) = x(i,j) - y(i,j)$ and the total square error rate will be as in equation

$$MSE = \frac{\sum_i \sum_j e(i,j)^2}{MxN}$$

(5)

Precision can be seen as a measure of exactness or fidelity. High precision means a relevant result. Precision is defined as:

$$Percision = \frac{TruePositives}{FalsePositives + TruePositives}$$

(6)

Recall is a measure of completeness. A high recall means a lot of useless results to sift through. Recall is defined as:

$$\mathrm{Re}call = \frac{TruePositives}{FalseNegatives + TruePositives}$$

(7)

Sensitivity measures the proportion of actual positives which are correctly identified.

$$Sensitivity = \frac{TruePositives}{TruePositives + FalseNegatives}$$

(8)

Specificity measures the proportion of negatives which are correctly identified.

$$Specificity = \frac{TrueNegatives}{TrueNegatives + FalsePositives}$$

(9)

Figure1 shows the original image and the optimal thinning images obtained by different thinning algorithms. Table1 shows the evaluation metrics for different thinning algorithms. From the Table1 it is observe that the performance of the Stentiford algorithm is better than the other algorithms. In this table, the result obtained by Stentiford thinning algorithm gives lowest error rate (38.94) compared to the other two algorithms for MRI brain images. This method accurately reflects the original image.

Original Image	Zhang-Suen Thinning Image	Stentiford Thinning Image	One Pass Thinning Image

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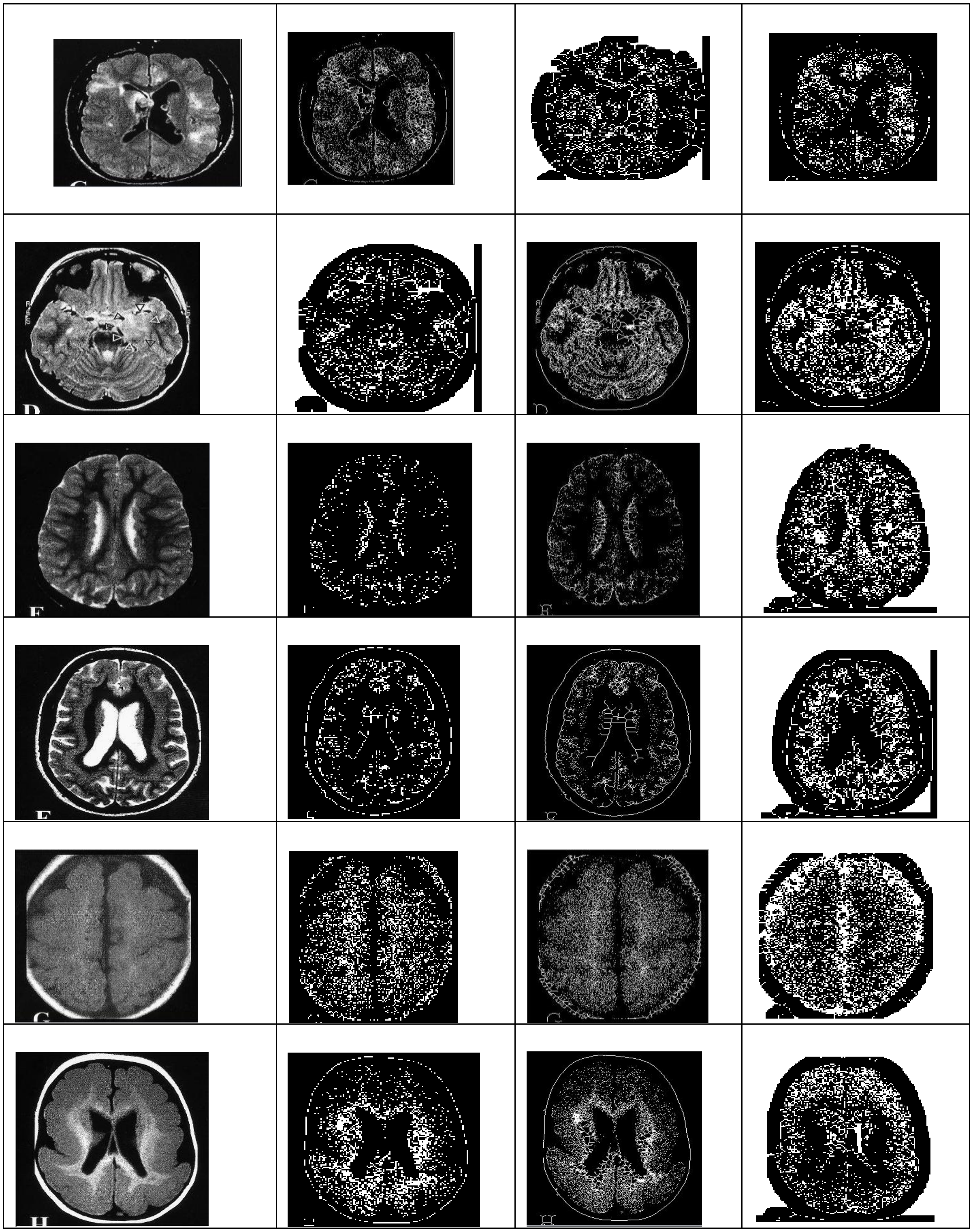

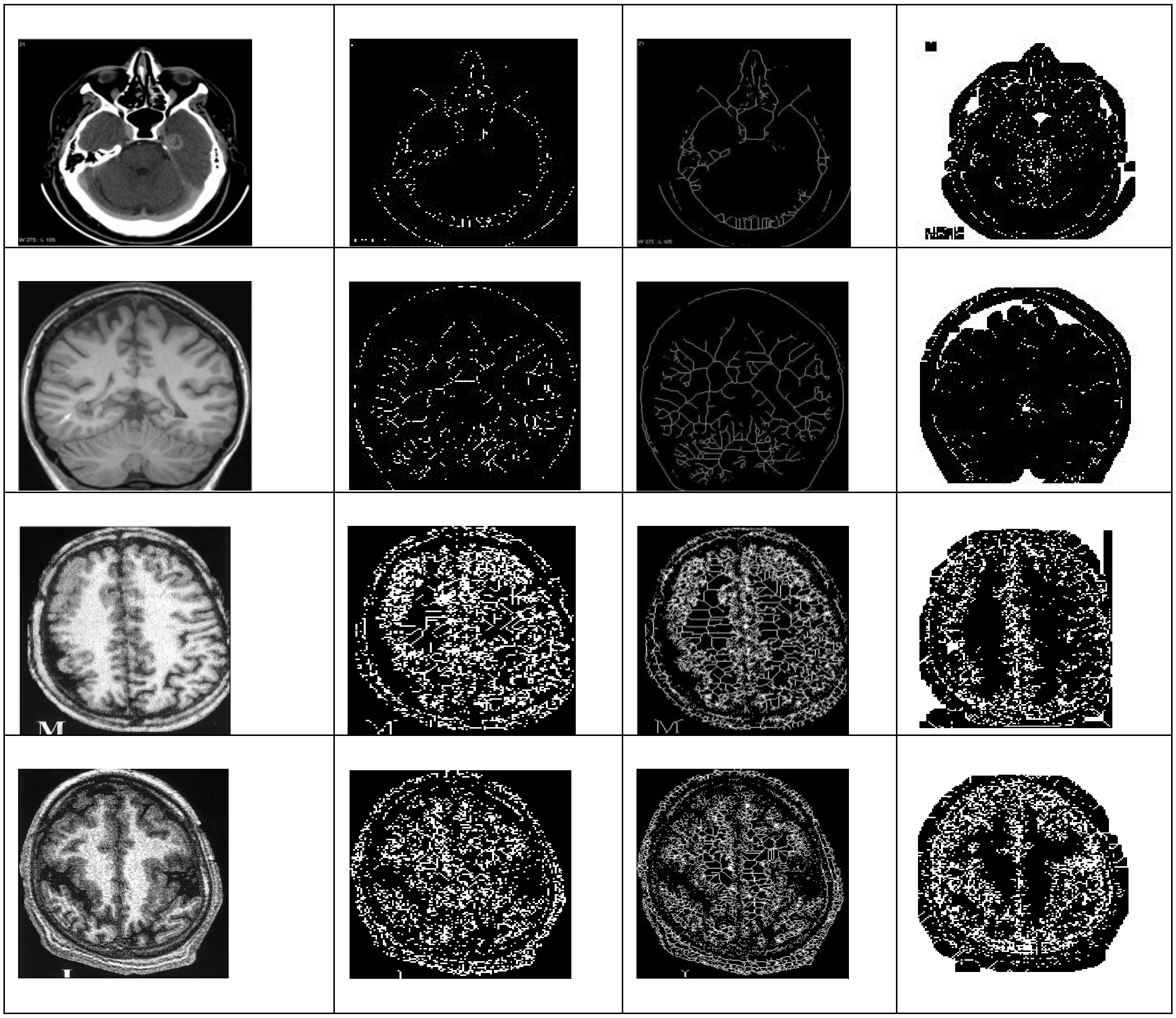

Figure1: The optimal thinning algorithms for MRI images.

Performance Metrics	Zhang-Suen Algorithm	Stentiford Algorithm	One Pass Thinning Algorithm
PSNR	11.827	13.278	8.617
SNR	27.155	30.695	24.916
MSE	66.075	56.228	94.706
Precision	0.833786	0.943074	0.538253
Recall	0.7859	0.7989	0.63082
Sensitivity	0.785981	0.798519	0.696344
Specificity	0.275113	0.593124	0.15661

Table1: Performance metrics of various algorithms.

Conclusion

In this paper, the three different thinning algorithms are applied for obtaining the optimized thinned image and the performance metrics are evaluated. From the above table, the average of performance metrics for the Stentiford thinning algorithm gives lowest error rate (56.228) compared to the other two algorithms for MRI brain images. This method accurately reflects the original image. In this algorithm, the objects are connected with a particular pixel. The experimental result shows the Stentiford algorithm is the better when compared to the other two algorithms.

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