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Skeleton Generation for Digital Images Based on Performance Evaluation Parameters

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Abstract

Skeletonization is a crucial step in many digital image processing applications like medical imaging, pattern recognition, fingerprint classification etc. The skeleton expresses the structural connectivities of the main component of an object and is one pixel in width. Present paper covers the aspects of pixel deletion criteria in the skeletonization algorithms needed to preserve the connectivity, topology, sensitivity of the binary images. Performance of different skeletonization algorithms can be measured in terms of different parameters such as thinning rate, number of connected components, execution time etc. Present paper focuses on Peak Signal to Noise Ratio, number of connected components, execution time and Mean Square error on Zhang and Suen algorithm and Guo and Hall algorithm.

Keywords*: Skeletonization, Optical character Recognition (OCR), PSNR, MSE, ZS, GH*

1. Introduction

Skeletonization is the process of extracting skeletons by deleting unwanted pixels from an image. It is morphological operation that deletes black foreground pixels iteratively layer by layer until one pixel width skeleton is obtained. It is a procedure of reducing an object to its minimum size [2].Skeletonization is usually applied on binary images which consist of black (foreground) and white (background) pixels. It takes input to be a binary image, and produces another binary image as output as shown in Figure 1.

For a skeletonization algorithm to be effective, it should reduce the images into thin like objects and should retain the topological and geometric properties as well. However, a good skeletonization algorithm must have the following features:

1. The resulting skeletons should maintain connectivity.
2. The resulting skeletons should be of unit pixel width.
3. No excessive deletion of pixels should takes place.
4. It should perform better in terms of execution time.
5. It should ideally compress the data.

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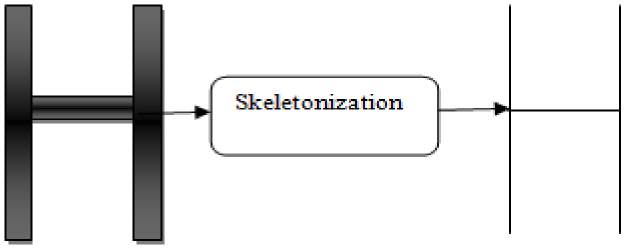


Figure 1. General Concept of Skeletonization

1.1. Need of Skeletonization

Skeletonization is a significant step in many image processing applications for past few decades. Skeletonization of digital images is needed due to following reasons:

1. To reduce amount of data required to be processed [4].
2. To reduce processing time.
3. To extract important features such as critical end-points, junction-points, and connection among the components can be helpful in many applications [4].
4. To reduce unimportant features and unwanted noise.

1.2. Applications of Skeletonization

Skeletonization has been used for variety of image processing applications like:

1. Optical character recognition (OCR) [1,4]
2. Pattern recognition[2]
3. Fingerprint classification[3]
4. Biometric authentication[4]
5. Signature verification[4]
6. Medical imaging[3]

2. Survey of Related Work

Table 1. Related Work

SNo.	Name of the author	Description
1.	Zhang T.Y *et. al.*, [5]	**Pros**: a. Preserves connectivity b. Contour noise immunity. c. Efficient in terms of execution time **Cons**: The resulting skeletons are not of unitary thickness.
2.	Guo Z *et. al.*, [15]	**Pros:** a. Parallel speed is superior. b. Produces very thin medial curves. **Cons:** Produces noisy branches in the skeleton
3.	Zhou R.W *et. al.*, [6]	**Pros**: a. Fast b. Reliable c. High immunity to boundary noise.

		Cons: It takes more computation time.
4.	Ahmed M *et. al.*, [7]	**Pros**: a. Effective b. Fast c. Can thin any symbol in any language, irrespective of the direction of rotation. **Cons**: Unable to thin two-pixel width lines.
5.	Rockett P.I [9]	**Pros**: a. No excessive erosion b. Produce thin skeletons. **Cons**: Ran 18% slower than A-W algorithm, more execution time.
6.	Tarabek P. [14]	**Pros:** **a.** Z-S algorithm preserves connectivity of the skeletons. **b**. Shows better results in Noise sensitivity measurements. **Cons:** Thinning rate i.e. calculated is not good for vectorization of roads.
7.	Padole G.V [2]	**Pros**: a. preserve the connectivity b. Produce thin skeletons. **Cons**: Edge based iterative thinning algorithm is time consuming as compared to optimized thinning algorithm.
8.	Saeed K. et al. [11]	**Pros**: a. It produces a unit-pixel-wide skeleton. b. Better connectivity in output skeletons. **Cons**: As K3M is iterative thinning algorithm, so it requires much more computing power than other algorithms.
9.	Jagna A. et al. [12]	**Pros**: a. Skeletons are perfectly 8-connected b. Does not results in excessive erosion c. Produces more quality images **Cons**: Not efficient in terms of execution time.
10.	Abu-Ain W. [1]	**Pros:** Performance is high in terms of execution time. **Cons**: Topology problem. Cannot preserve shape sometimes.
11.	Kwon J. [16]	**Pros:** a. One-pixel wide skeleton b. No excessive erosion. **Cons:** Requires more number of iterations.

3. Overview of Skeletonization Algorithms

In general, all the skeletonization algorithms can be classified into two categories as shown in Figure 2:

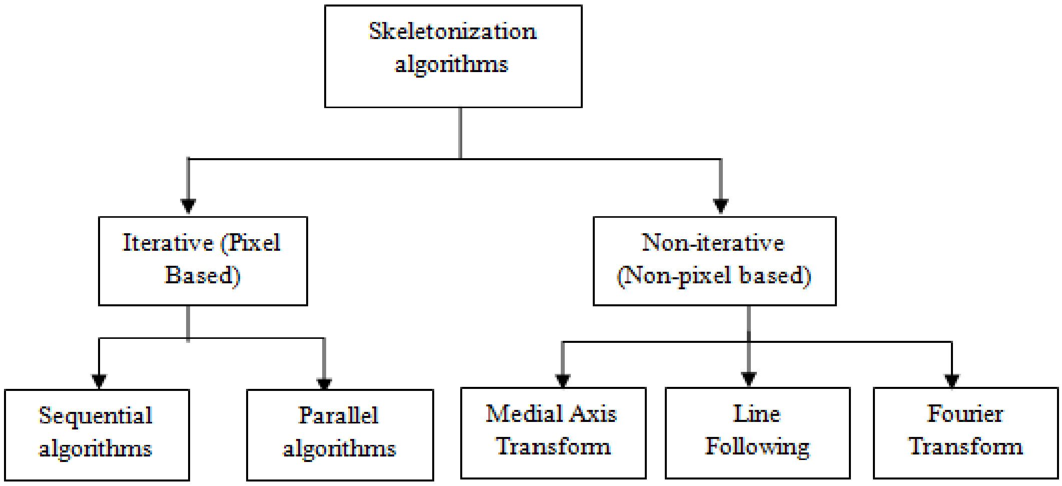


Figure 2. Taxonomy of Skeletonization Algorithms

1. Iterative thinning algorithms: Iterative (pixel based) [1, 2] thinning algorithms examine the individual pixels in a binary image and deletes the boundary pixels of the pattern until a skeleton remains. Iterative thinning algorithms are further divided into two categories: sequential thinning algorithms and parallel thinning algorithms [1, 2].

a. In sequential algorithms, the points selected for deletion are chosen in a predetermined order and this can be possible by either raster scanning i.e. from line to line scan or by contour following [3]. Sequential thinning algorithms preserves the connectivity of obtained skeletons but sometimes they results into unacceptably thick skeletons.

b. On the other hand a parallel thinning algorithm [1, 2] selects pixels for deletion purpose based on the result produced by the previous iterations. For these reasons, these parallel thinning algorithms are appropriate for implementation for parallel processing [3]. Parallel thinning algorithms faces the difficulty of preserving the connectivity of the skeletons. These algorithms are better in terms of computing time or the number of iterations or sub iterations used.

2. Non iterative thinning algorithms [1, 2]: Non iterative [1, 2] thinning algorithms do not scan individual pixels one by one. Instead, they produces a median line or some centerline of the pattern and then take a decision whether to delete that particular boundary pixel or not. Some popular non-pixel based methods are medial axis transforms, distance transforms, and determination of centerlines by line following [2]. These algorithms show much efficiency in terms of computation time but at the same time these are responsible for creating noise branches in a skeleton.

(a) Medial Axis Transform: Non iterative thinning algorithms are non-pixel based which means they produce a center line or medial line without examining all the pixels. This method is very fast and simple to compute but usually produces noisy skeletons [3, 4].

(b) Line Following: This method computes centreline by following the contours/edges on either side of the pattern [3, 4]. Thus, the skeleton can be formed from connected centrelines.

(c) Fourier Transform: The contour is traced to obtain a closed curve from which the Fourier descriptors can be extracted. Fourier descriptors of the skeleton are obtained and the skeleton can be constructed from a finite set of harmonics [3, 4].

4. Zhang and Suen and Guo and Hall Algorithm

(a) Zhang and Suen Algorithm

Input Image: Pre-processed Image

Output Image: Skeleton of pre-processed image

Sub-iteration 1:

(1) $2 <= B(P1) <= 6$

(2) A (P1) = 1

(3) At least one of P2 and P4 and P6 is white

(4) At least one of P4 and P6 and P8 is white. [5]

Sub-iteration 2:

(1) $2 <= B(P1) <= 6$

(2) A(P1) = 1

(3) At least one of P2 and P4 and P8 is white

(4) At least one of P2 and P6 and P8 is white

After checking all the conditions, the pixel is deleted otherwise not [5].

(b) Guo and Hall Algorithm

Input Image: Pre-processed Image

Output Image: Skeleton of pre-processed image

It uses 3*3 templates for pixel deletion. Let C(P) be the number of 8-connected components of 1's in its neighbourhood.

N (P) =Minimum of (N1(P), N2(P))

N1 (P) = (p1or p2)+(p3or p4)+(p5or p6)+(p7or p8)

N2 (P) = (p2or p3)+(p4or p5)+(p6 or p7)+(p8or p1)

An edge point in the image will be deleted if it satisfies following two conditions:

a) Number of distinct 8 connected components should be one.

b) Number of non zero neighbours should be between 2 and 3.

c) Apply one of the following:

1) (P2vP3vP5)*P4=0 in odd iterations;

2) (P6vP7vP8)*P8=0 in even iterations Where "v" expresses the logic "OR" operation. C (P)=1 means P is 8-simple [15].

In other words, there is only one group of 8-connected 1's around P. Under this condition, deletion of P will not break the connectivity of the elements in the 3*3 window under processing. Condition (a) guarantees P is not a break point. The GH algorithm is better in detecting the end points than the ZS algorithm. The use of N (P) allows one to identify the end points whether or not they have one or two 1's 8-neighbours [15].

5. Performance Measures

There are number of performance measures on the basis of which we can measure various skeletonization algorithms. Some of them are described below:

1. Connectivity Measurement CM [6]: It is used to measure the connectivity in the skeletons that are produced as outputs. This is given by:

$$\boldsymbol{CM}=\sum_{x=0}^{n}\sum_{y=0}^{m}\boldsymbol{S}(\boldsymbol{P}[\boldsymbol{x}][\boldsymbol{y}]) \qquad \textbf{[6]}$$

Where

$$S\ (P[x]\ [y]) = \begin{cases} \mathbf{1}, & \boldsymbol{if\ CN}(\boldsymbol{P}[\boldsymbol{x}][\boldsymbol{y}] < 2 \\ \mathbf{0}, & \boldsymbol{otherwise} \end{cases} \quad \textbf{[6]}$$

Where CN is defined as current neighborhood function and is defined as follows:

$$\boldsymbol{CN\ (P_0)} = \sum_{x=1}^{8}(\boldsymbol{P_x} * \boldsymbol{Q_x}) \qquad \textbf{[6]}$$

Connectivity can be measured in terms of:

a. Number of Connected Components [14]: It basically counts the total number of separated regions or components as shown in Figure 3. It is used to measure whether obtained skeleton is connected or not.

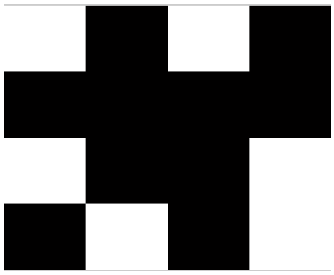


Figure 3. Image with 4 Components (NOC=4)

2. Thinning Rate (TR): The degree to which an image can be thinned or completely thinned can be possibly measured in terms of thinning rate as shown in Figure 4 [15].

The thinning rate is given by the equation:

$$\boldsymbol{TTC}=\sum_{x=1}^{n}\sum_{y=1}^{m}\boldsymbol{TC}\ (\boldsymbol{P}[\boldsymbol{x}][\boldsymbol{y}]) \qquad \textbf{[14]}$$

Where:
TTC indicates total triangle count.
n, m are dimensions of input image.
P[x] [y] are the black pixels with coordinates x,y
TC indicates triangle count.

The TR is defined as follows:

$$\boldsymbol{TR}=1-\frac{\boldsymbol{TTC_T}}{\boldsymbol{TTC_O}} \qquad \textbf{[14]}$$

Where:
TTC stands for total triangle count
TTC_T stands for total triangle count of thinned image
TTC_O stands for total triangle count of original image

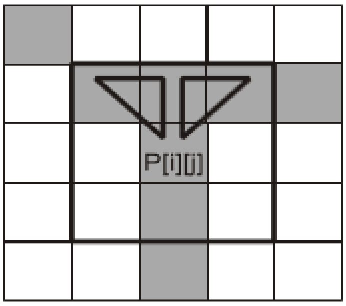


Figure 4. Triangle Count=2 [14]

3. Mean Square Error [16]: Mean square error calculates the difference between the original input image and the skeletonized image. For example: If we have two images and that images are identical in every aspect then MSE between the images is considered to be zero. Lesser the MSE better is the quality of the image. MSE can be defined as follows:

$$\boldsymbol{MSE}=\frac{1}{mn}\sum_{x=0}^{m-1}\sum_{y=0}^{n-1}[I(x,y)-K(x.y)]^2 \quad [16]$$

4. Peak Signal to noise ratio (PSNR)[16]: Peak signal to noise ratio is usually abbreviated as PSNR, it is used to measure the quality of reconstructed image or we can say skeletonized image [16].

If the MSE in case of any images is zero, then PSNR value reaches to infinite.
Larger the PSNR better is the quality of the image. PSNR is defined by:

$$PSNR = 20 * \log_{10}(MAX_I) - 10 * \log_{10}(MSE) \quad [16]$$

5. Execution Time: It is the total time taken to execute a program or code completely. Execution time can be found by tic-toc command. Place tic; before the first line of code and toc; after the last line of the code.

6. Noise Sensitivity (NS): This criteria measures how much as skeleton is immune to noise. It is very significant feature of skeletonization algorithms because it determines both topology and shape preservation of the skeleton [14]. NS can be defined as follows:

$$NS=\sum_{x=1}^{n}\sum_{y=1}^{m} N(P[x][y]) \qquad [14]$$

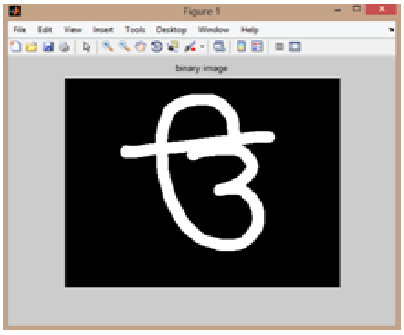
$$N(P[x][y])=\begin{cases} 1 & if\ CN(P[x][y]) > 2 \\ 0 & otherwise \end{cases} \quad [14]$$

Where:
P[x] [y] are black pixels with coordinates x,y
n, m are dimensions of an image

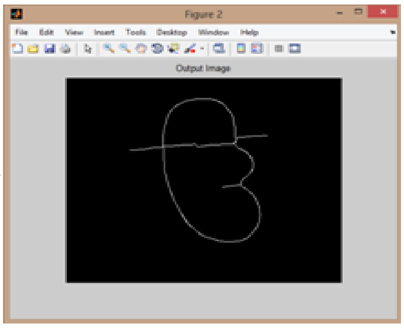
CN is connectivity number which counts the total number of color in neighbourhood of pixel P[x][y] [14].

6. Skeletonization Algorithms

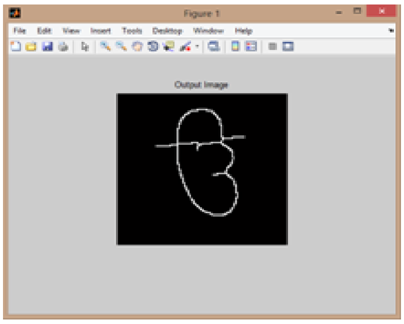
In the present paper we are applying Zhang and Suen algorithm, Guo and Hall algorithm in order to measure performance evaluation parameters such as thinning rate, PSNR,MSE, Execution time and number of connected components etc. Present section describes some of the outputs of Zhang and Suen and Guo and hall algorithm and Zhang and Suen modified algorithm skeletonization is shown in Figure a, b, c, d respectively.



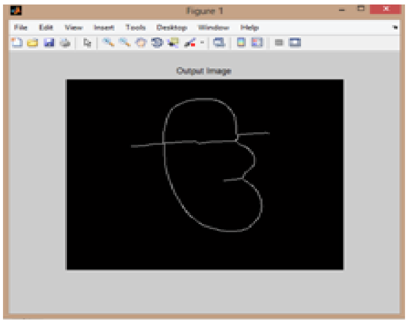
(a) Input Image



(b) ZS skeletonization



(c) GH skeletonization

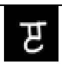
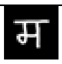


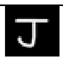
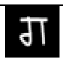
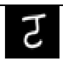
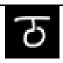
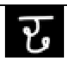
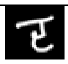
(d) ZS modified skeletonization

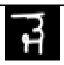
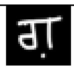
7. Results of ZS in Comparison to GH Algorithm

Present section describes outputs of Zhang and Suen algorithm and Guo and Hall algorithm in terms of following parameters such as: number of connected components, execution time, PSNR, MSE.

Table 2. Comparative Analysis of Algorithms on the Basis of Parameters

						PARAMETERS						
	PSNR			MSE			Execution Time			Connected Components		
Image	**ZS**	**GH**	**ZS Modified**	**ZS**	**GH**	**ZS Modified**	**ZS**	**GH**	**ZS Modified**	**ZS**	**GH**	**ZS Modified**
	33.90	32.85	33.91	33.25	32.88	33.24	0.90	45.7	0.96	1	1	1
	32.85	32.81	32.87	33.42	32.77	33.43	0.91	34.2	0.93	1	1	1
	32.95	32.92	32.97	34.91	33.01	34.89	0.74	34.2	0.72	1	1	1
	32.94	32.90	32.96	32.61	32.64	32.62	0.81	34.9	0.81	1	1	1

	32.90	32.85	32.92	32.96	32.91	32.95	0.68	37.3	0.74	1	1	1
	32.98	32.96	33.00	32.98	32.97	32.96	0.81	38.3	0.85	1	1	1
	32.96	32.94	32.95	32.98	32.80	32.82	0.79	32.1	0.82	1	1	1
	33.07	33.04	33.08	32.83	33.00	33.02	0.76	39.5	0.77	1	1	1
	32.90	32.86	32.92	33.19	32.94	32.96	0.79	38.1	0.80	1	1	1
	32.90	32.89	32.92	32.95	32.94	32.97	0.74	39.6	0.71	1	1	1
	32.90	32.90	32.92	32.95	32.82	32.83	0.83	36.6	0.81	1	1	1
	32.90	32.90	32.92	32.84	32.89	32.89	0.76	33.2	0.80	1	1	1
	33.09	33.08	33.10	32.90	33.58	33.58	0.78	31.9	0.80	1	1	1
	33.10	33.08	32.10	33.59	32.93	32.94	0.76	41.2	0.83	1	1	1
	33.79	33.79	33.80	32.97	33.01	33.04	0.84	33.7	0.74	1	1	1
	32.80	32.79	32.82	33.05	32.81	32.82	0.84	38.7	0.91	1	1	1
	32.91	32.87	32.90	32.83	32.93	32.93	0.76	37.0	0.75	1	1	1
	32.93	32.92	32.94	32.88	32.87	32.87	0.80	35.5	0.79	1	1	1
	32.94	32.96	32.98	32.90	32.89	32.89	0.78	38.7	0.75	1	1	1
	32.92	32.90	32.92	32.94	32.92	32.93	0.66	32.33	0.88	1	1	1
	32.84	32.82	32.85	32.85	32.83	32.85	0.67	40.17	0.74	1	1	1
	32.87	32.85	32.89	32.96	32.95	32.95	0.71	40.16	0.76	1	1	1
	32.87	32.85	32.90	32.79	32.78	32.80	0.70	37.93	0.73	1	1	1

	32.88	32.84	32.87	33.01	32.98	33.00	0.77	36.07	0.77	1	1	1
	32.91	32.90	32.93	32.89	32.83	32.85	0.76	30.48	0.82	1	1	1
	33.03	33.03	33.04	32.78	32.76	32.77	0.69	28.67	0.83	1	1	1
	32.95	32.92	32.97	32.92	32.90	32.91	0.69	27.57	0.69	1	1	1
	32.86	32.86	32.87	32.97	32.94	32.95	0.70	31.29	0.74	1	1	1
	32.86	32.84	32.90	32.78	32.77	32.78	0.71	33.02	0.74	1	1	1
	32.90	32.91	32.92	32.92	32.89	32.90	0.68	33.18	0.72	1	1	1
	32.85	32.84	32.85	32.87	32.84	32.85	0.68	30.93	0.77	1	1	1
	33.12	33.10	33.15	32.85	32.82	32.84	0.71	25.50	0.72	1	1	1
	33.03	33.01	33.05	32.80	32.78	32.79	0.69	32.77	0.76	1	1	1
	32.96	32.94	32.98	32.78	32.75	32.76	0.72	29.92	0.71	1	1	1
	32.95	32.96	32.97	32.89	32.87	32.88	0.70	33.35	0.76	1	1	1
	32.90	32.89	32.92	32.90	32.85	32.88	0.74	34.78	0.75	2	2	2
	32.97	32.96	33.00	32.77	32.75	32.76	0.68	32.07	0.78	2	2	2
	32.94	32.92	32.96	32.90	32.86	32.88	0.69	28.84	0.72	2	2	2
	32.94	32.93	32.93	32.85	32.82	32.84	0.68	38.47	0.72	2	2	2
	32.98	32.97	33.00	32.95	32.91	32.92	0.74	25.06	0.72	2	2	2
	32.87	32.85	32.89	32.88	32.78	32.78	0.74	32.00	0.78	2	2	2

From the above results, we can conclude that Zhang and Suen algorithm and Zhang and Suen modified is better than Guo and Hall algorithm in terms of connectivity, mean square error, peak signal to noise ratio and execution time.

8. Conclusion and Future Scope

Huge number of skeletonization algorithms has been proposed by different authors till now but due to some complicated nature of skeletonization sometimes it is difficult to understand that how these different approaches are related to one another in terms of the algorithms processing quality and execution time. So far we have discussed Zhang and Suen, ZS modified and Guo and Hall algorithm in terms of connectivity, PSNR, MSE and execution time and concluded from the above results that ZS modified is better in terms of PSNR and execution time than GH algorithm.

The present work relates to the comparative analysis of two skeletonization algorithms i.e. Zhang and Suen algorithm and Guo and Hall algorithm. Future work will be related to review the applications of neural networks in image processing and skeletonization too. Future work will be related to the proposal of new algorithm for skeletonization using neural networks and improving one or more parameter over the existing algorithms. Other conditions like noise robustness can be tested and results can be tested on various other datasets.

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