Comparative Survey of Thinning Algorithms

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Abstract: Thinning or skeletonization is a process for reducing foreground regions in a binary image to a skeletal remnant that largely preserves the extent and connectivity of the original region while throwing away most of the original foreground. Thinning is commonly used in digital image processing, pattern recognition, image analysis and not least, in signature verification. The goal of this paper is to introduce the most common thinning methodologies and propose a method to evaluate their performance, especially in the field of signature recognition. The proposed evaluation method is intended to be objective, therefore it takes into account various properties of a thinned skeleton and compares them to those of an ideal reference image. Fifteen different algorithms have been implemented and rated using this method, the results showed that different kinds of skeletonization techniques have different benefits and drawbacks, however none was found to give perfect results.

Keywords: thinning, skeletonization, signature verification

1 Introduction

The main motivation of this survey was to improve the performance of a signature verification system by surveying the most common thinning algorithms and giving an estimation about their accuracy. A highly modularized framework was available which breaks down the signature analysis process into well delimited steps. The first of these steps is the preprocessing phase in which the input images come through various transformations, including thinning.

The inputs of this application are usually scanned hand-written signatures which can not be processed in their original form by the latter modules of the verification system. The purpose of thinning in the preprocessing phase is cleaning the image of any kind of noise caused by the scanning and to extract a binary, one pixel wide skeleton from the hand-written signature. The discrete skeletons obtained this way can be efficiently interpreted by the other modules of the process.

The aim was to select characteristics of the result skeletons which can be directly examined and compared to those of a reference skeleton. In this way a well defined and objective estimation can be given on the performance of each thinning procedure.

This paper is organized as follows: In Section 2 the most common kinds of algorithms are introduced, then in Section 3 our proposed estimation method is explained in detail. The last section of the paper shows some of the benchmark results

2 Survey of Related Work

The concept of thinning came with the improvement of digital computers and with the need of efficient processing of digitalized images. The widely used methodologies have gone through plenty of changes and improvements in the last decades. The algorithms can be categorized as follows:

2.1 Morphology

The first attempt at extracting skeletons from binary images was using the operators of mathematical morphology (MM) which had been already invented at the time and been used for texture analysis.

The basic idea in binary morphology is to probe an image with a simple, pre-defined shape (called the “probe” or “kernel”), drawing conclusions on how this shape fits or misses the shapes in the image. For thinning, the most important operation of MM is erosion, of which the basic effect is to erode away the boundaries of regions of foreground. Thus areas of foreground pixels shrink in size, and holes within those areas become larger.

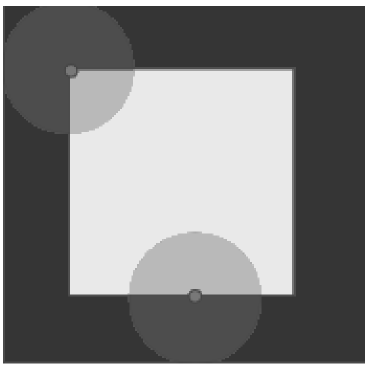


Figure 1
The erosion of the dark-grey square by a disk, resulting in the light-grey square

Erosion in itself does not produce appropriate skeletons, but the approach of this method is clearly noticable in more complex algorithms, especially in windowing.

2.2 Raster Scanning

According to [2], execution of raster scan algorithms usually happens as follows:

1. All the pixels of the binary image are examined in a predetermined order[1]
2. A set of conditions is evaluated for each pixel, either marking it for deletion or retention
3. At the end of the iteration all the pixels marked for deletion are erased from the image and the process jumps back to step 1.

If in an iteration there was no pixel deleted, then the thinning process is done and the remaining black pixels are ought to form the skeleton of the image.

What raster scan algorithms differs from each other is the set of conditions which is evaluated in order to decide wether to delete or retain a pixel. Different condition sets preserve different characteristics of the input image.

2.3 Windowing

A specialized version of the hit-and-miss morphological operator is used in numerous thinning algorithms, and it is usually referred to as windowing or masking.

A thinning mask is an arbitrary-sized but usually small grid, in which each cell denote a custom condition. The mask is fitted onto a region of the tested image, then the conditions of the cells are evaluated for the pixel which is under the given cell. We say that the mask fits onto the region of the image, if every pixel under the mask satisfies the corresponding condition.

This technique is used in raster scan algorithms, where the conditions evaluated for each pixel are given in form of a thinning mask [3].

A	A	A
0	P	0
B	B	B

Figure 2

Example of a commonly used thinning mask

1 In some cases only the borders of connected objects are examined (contour following).

In Figure 2 an example of thinning masks can be seen, where the meaning of the mask cells are the follows:

- Pixels marked with 0 have to belong to the background (white)
- Pixel marked with P is the center point, it is the point where the mask is fitted onto an image
- Each group of pixels marked with A or B must have at least one foreground (black) pixel

The mask is used to preserve connected components of an image, because if it (or any of its 90° rotation) fits onto a pixel, it means that erasing it would break apart a connected component into two distinct parts.

2.4 Complex Methods

There are numerous other algorithms which do not fit into the above categories. Usually they are based on a unique idea with which the skeleton of an image can be extracted.

One example is the Sparse Pixel Vectorization method in which a ray is casted and traced inside the foreground of the image components and then the medial points of the rays are connected [4]. An other example is the line following algorithm proposed by Peng in [5], which attempts not to iteratively erode contour pixels, but extract the skeleton by following the two sides of the in the input image (this method is stated as a natural approach, considering that the human eye identifies lines in the same way).

These algorithms are usually more complex to implement and can be quite vulnerable to various attributes of the input skeletons, thus careful configuration of them might be needed in each environment, depending on the line width and other properties of the input shapes. In return they can perform considerably well in certain areas and usually have low computational cost, since they do not have to examine every pixel, nor to iterate recursively.

3 Proposed Method

The goal of the proposed method is to objectively evaluate the performance of the different thinning algorithms. The process uses reference images provided by the database of the signature verification project. Imitated signatures have been created from one pixel wide reference skeletons, then the signatures have been thinned with the skeletonization algorithms. At last the thinned result of each algorithm is compared to the ideal reference skeleton.

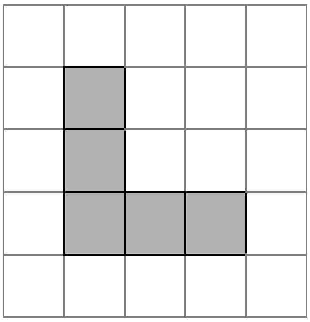
3.1 Pratt Evaluation

The starting point of the comparing technique is the evaluation algorithm introduced by Pratt in [6]:

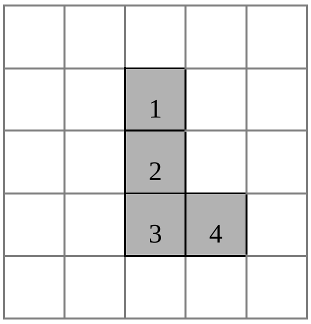
Let N_R and N_A be the number of foreground (black) points in the reference skeleton and the actual thinned result, respectively. The distance between the i-th pixel of the result skeleton and the pixel of the reference skeleton nearest to it is notated by d_i. The Pratt evaluation score is defined by

$$PES = \frac{1}{N_M}\sum_{i=1}^{N_A}\frac{1}{1+a\cdot d_i^2}$$

where $N_M = \max\{N_R, N_A\}$ and a is a scaling constant, adjusting the level of penalization for distances.



Reference skeleton



Actual result

Figure 3
Example of a Pratt evaluation rating

In the above example the evaluation score is calculated as follows:

$N_R = 5, N_A = 4$

$$d_1 = 1, d_2 = 1, d_3 = 0, d_4 = 0$$

$$PFS = \frac{1}{5}\left(\frac{1}{1 + a_p \cdot 1^2} + \frac{1}{1 + a_p \cdot 1^2} + 1 + 1\right) = 0.76$$

if a_p is chosen to be 1/9 (which is a typically used value [6]).

If the two compared skeletons are identical to each other, then the result is 1.0 and lower values mean lower level of similarity.

3.2 Proposed Improvement

The main problem of the above method is that it does not take into consideration the number, position and direction of end points in the input images, however, they would be important characteristics of skeletons in the field of signature analysis.

The improved algorithm firstly executes the Pratt evaluation described above, let the result score be denoted by P_0. Then the two images are scanned to obtain all their endpoints. Then the position of the result end points are compared to the reference end points, using the the Pratt evaluation method again, but in this case only the end points are given as input. Let the result of the second evaluation be denoted by $P_{EP.}$

Finally, the directions of the endpoints are analyzed. In this case, a black point is considered to be an end point if it has exactly one black neighbor pixel. Thus there are eigth possible end point directions depending on the position of the one black neighbor.

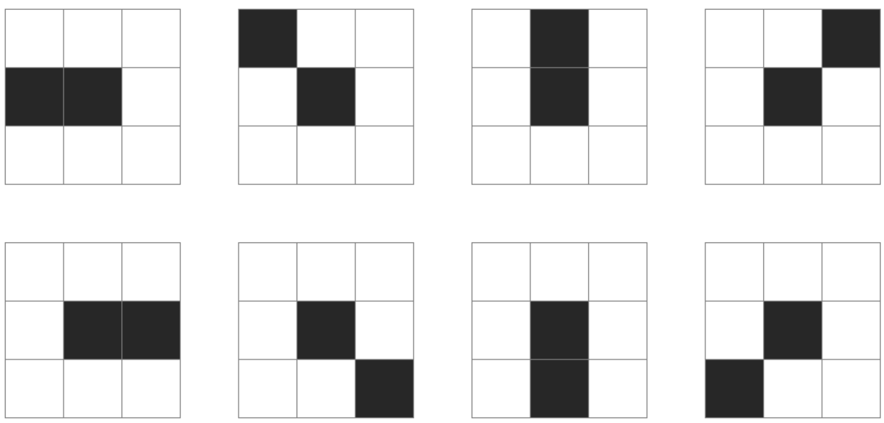
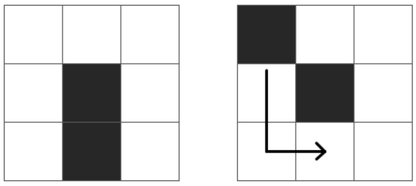


Figure 4
Different possible end point directions

In order to compare the end points of the reference and the result, a new metric has to be defined: the difference of end point directions. The difference between the directions of two end points is the number of 45° rotations needed to transform the one end point into the other (rotation means shifting the black neighbor one step along the neighborhood of the end point).



End point A End point B

Figure 5

Example of calculating difference between end point directions

In Figure 5 two end points can be seen, where the difference between their directions is 3, because it would take 3 rotations to transform one to be identical to the other. We denote this difference by *EPD(A, B).*

The values obtained this way are summarized in the same manner the Pratt evaluation method sums the minimum distances. Let N_{EPR} and N_{EPA} be the count of end points in the reference and in the actual result skeleton, respectively. Therefore

$$P_{EPD} = \frac{1}{N_{EPA}} \sum_{i=1}^{N_{EPA}} \frac{1}{1 + a_{EPD} \cdot EPD(ea_i, er_i^*)}$$

is the evaluation score of the end point directions, where ea_i is the i-th end point of the actual result skeleton and er_i^* is the nearest end point to it in the reference skeleton.

To sum up, we have three metrics about the precision of the skeleton: P_0 rates its shape in general, P_{EP} the position and number of end points and P_{EPD} the direction of end points. The avarege of these three values gives a general evaluation about the similarity of two skeletons thus the performance of different thinning algorithms can be rated by comparing the result of each one to a reference skeleton.

4 Experimental Results

The following fifteen algorithms have been implemented and tested with the above evaluation method: raster scan by Rutovitz, 1966 [3], raster scan by Yokoi, 1973 [2], window matching by Beun, 1973 [2], contour scan by Arcelli, 1978 [2], window matching by Pavlidis, 1981 [2], raster scan by Holt, Stewart, Clint and Perrott, 1987 [3], window matching by Chin, Wan, Stover and Iverson, 1987 [3], raster scan by Zhang and Wang, 1988 [3], raster scan by Eckhardt and Maderlechner, 1993 [3], window matching by Wu and Tsai, 1992 [3], raster scan by Guo and Hall, 1992 [3], window matching by Jang and Chin, 1992 [2], raster scan by Hilditch, [2], and the Sparse Pixel Vectorization method by Dov Dori and Wenyin Liu, 1999 [4].

Firstly, all algorithms have been tested with 4 simple shapes shown in Figure 6. Some examples of the different results can be seen in Figure 7. The average ratings calculated with the proposed evaluation methods are shown in Figure 8.

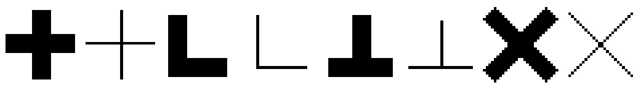


Figure 7
Test input shapes and their corresponding reference skeletons

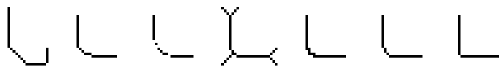


Figure 8
Examples of the results given by different algorithms to the L shape as input

Algorithm	**Pratt rating**	**End point rating**	**End point direction rating**	**Average**
YokoiRasterScan	0,84007894	0,62790482	0,913682432	0,79388873
RutovitzRasterScan	0,83132284	0,55486695	0,91097561	0,7657218
SPVThinning	0,84003723	0,48583145	0,941112378	0,75566035
JangChinWindowMatching	0,81077425	0,54068627	0,9	0,75048684
BeunWindowMatching	0,76381305	0,56066017	0,904560811	0,74301135
HilditchRasterScan	0,78832559	0,54068627	0,9	0,74300396
ZWRasterScan	0,78758747	0,54068627	0,9	0,74275791
HSCPRasterScan	0,78758747	0,54068627	0,9	0,74275791
GuoHallARasterScan	0,80575579	0,4745098	0,911946903	0,7307375
PavlidisWindowMatching	0,8709161	0,30735294	0,955736253	0,7113351
EckhardtMRasterScan	0,87035159	0,30735294	0,955736253	0,71114693
GuoHallBRasterScan	0,73783886	0,33284314	0,935516944	0,66873298

WTWindowMatching	0,65657694	0,35487153	0,924324324	0,6452576
CWSIWindowMatching	0,70237822	0,29221814	0,940488968	0,64502844
ArcelliCountourScan	0,48369098	0,36068405	0,929268293	0,59121444

Figure 9
Performance of the different algorithms with the simple shapes as inputs

Note that some of the algorithms obtained identical ratings, which is because to these simple shapes they have given perfectly identical results.

The next step was to evaluate the performance using more complex input shapes, which were chosen to be human signatures in this case. The database of the Signature Verification Competition 2004 [7] with 40 different signature types was used to render the one pixel wide skeletons of real signatures, captured with digitalizer tablets. From these skeletons imitated signatures have been created which served as the input of the thinning algorithms. Finally, the results were compared to the reference skeletons.

Figure 10
Example of a reference skeleton and the imitated signature created from it

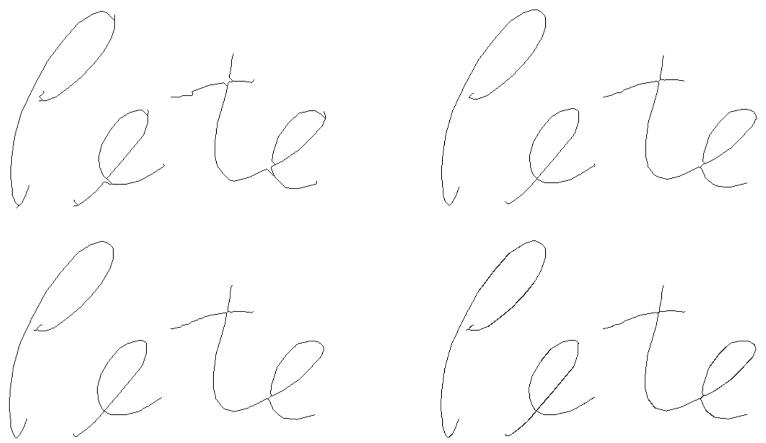
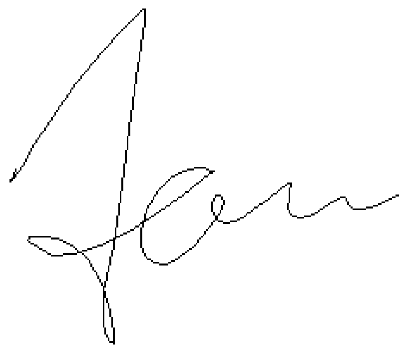


Figure 11
Some examples of the thinning results

Algorithm	**Pratt rating**	**End point rating**	**End point direction rating**	**Average**
WTWindowMatching	0,86660286	0,39190531	0,961306128	0,7399381
RutovitzRasterScan	0,91900608	0,32707126	0,953919253	0,7333322
JangChinWindowMatching	0,87670026	0,36526506	0,952012679	0,731326
HSCPRasterScan	0,91310922	0,32348931	0,954824039	0,73047419
YokoiRasterScan	0,8600851	0,36853022	0,951306458	0,72664059
ZWRasterScan	0,90867065	0,31057388	0,954478371	0,7245743
HilditchRasterScan	0,84330167	0,33539488	0,949071549	0,70925603
BeunWindowMatching	0,83639705	0,31214975	0,948800185	0,69911566
GuoHallARasterScan	0,91052146	0,1166814	0,968222951	0,66514194
EckhardtMRasterScan	0,82071934	0,25649282	0,874822298	0,65067815
PavlidisWindowMatching	0,81775327	0,22797358	0,874648506	0,64012512
GuoHallBRasterScan	0,87088713	0,06135171	0,973832554	0,63535713
SPVThinning	0,76789649	0,13460885	0,966371038	0,62295879
ArcelliCountourScan	0,57647139	0,2877483	0,960008535	0,60807608
CWSIWindowMatching	0,5558805	0,01957329	0,972337455	0,51593042

Figure 12
The average ratings, tested with 40 signatures

In the benchmark test the raster scan algorithm by Guo and Hall obtained fairly high score by the Pratt evaluator, (it had the third best rating) while it performed rather poorly in the end point rating.



Reference skeleton

Imitated signature

Raster scan by Guo and Hall

Figure 13

In Figure 13, a skeleton produced by the above mentioned algorithm can be seen. The result contains several small gaps, especially in the diagonal lines (it does not preserve connectedness, which is an important aspect of every skeletonization method). This is not desirable, since some of the latter phases of the signature verification process would work with upstrokes, which are falsely recognized by this algorithm.

However, the Pratt evaluator does not penalize this kind of error (in fact, the lack of black points can even increase the rating). On the other hand, the score given by our improved evaluation method is significantly lower, because the "broken" line segments represent many false end points, which is well reflected by the the poor end point rating, and therefore low average value.

Conclusions

Each of the fifteen algorithms yielded slightly different skeletons, however, all provided acceptable result. The raster scan and the window matching algorithms had similar performance in this survey, while the only complex algorithm tested (Sparse Pixel Vectorization) performed rather poorly. It was shown, that our proposed distance measures can detect and characterise some of the special aspects of skeletons and thereby provide significant improvements to Pratt rating algorithm in the field of signature verification.

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