UDC 628.336

NOISE REDUCTION METHOD FOR SKELETONIZED IMAGES

Yuan Liu, Master student

Belarusian state university of informatics and radioelectronics

г. Minsk, Republic of Belarus

S. B. Salomatin

Annotation. Thinning framework that based on the scale space technique to automatically extract skeletons from images without manual-tuning. The proposed framework can increase the robustness of the thinning algorithm, it not only can suppress the boundary noise, but also can alleviate the inner noise. These two types of noise generally cause the appearance of the abundant of the unwanted branches in the outcome of the thinning algorithm, which arise the difficulties of the later recognition or matching process in skeleton.

Keywords. Skeleton. Robustness. inner noise. boundary noise.

Skeletons, that extracted by the thinning algorithms, preserve the topology and connectivity of the original objects, hence they are compact and useful image descriptors that can used in many various fields of pattern recognition [1]. However, one of the challenges of the applying of the skeleton is that almost all the thinning algorithms fail to well suppress the effect of the noise, which may cause much unwanted branches in skeletons.

The noise can divided into two classes, which are border noise and inner noise. Border noise is the noise that along the boundary of the foreground pixels and background pixels. They may cause the appearance of many extra branches. Whereas inner noise is the noise that appear in the inner of the objects and far from the boundary, they may cause the appearance of the false hole. Both of these noise may dramatically influence the resulting skeletons.

Pruning methods [2] are proposed in the past decade for removing the redundant branches. These methods can dramatically improve the thinning algorithm robustness against to the border noise. These methods are generally applied directly on the skeleton that extracted by the thinning procedure from the original pattern. However, one of the limitations of these methods is that it fails to suppress the inner noise.

Another type of methods for promoting the performance of the robustness of the thinning algorithms are the methods that based on scale-space filter. When there is a suitable smooth parameter, these methods can not only deal with the border noise but also offset the effects that caused by the inner noise. However, it is a tough task to find a suitable smooth parameter. As we know, a large smooth parameter may deform the original pattern and a small smooth parameter may not be able to suppress all the types of noise.

A scale-space method for thinning both grayscale and binary images has proposed by Hoffman and Wong[3]. This method first produces filtered versions of an input image and then extracts skeleton by searching some special pixels from it, which includes peak, ridge and saddle pixels. These pixels are named as the most prominent ridge line pixels (MPRL) by authors and they are used to form the skeleton. In the image scale space pyramid, each MPRL pixel is a pixel such that all ridge-line pixels have greater second derivatives in sub-pyramid. The robustness of the skeleton against to the noise strongly depends on a parameter, which requires manual tuning.

Cai has proposed a robust filtering-based thinning algorithm [] for pattern recognition in 2012 to offset the effects of the contour noise caused by pen perturbations and image scanning in the field of handwriting and fingerprints by introducing Oriented Gaussian Filters. The Oriented Gaussian Filters are used to divide the pixels into edges, valleys and ridges, which presents information for the trimming. The skeleton extracted by this method does not have any redundant branch. However, their method can only be applied on the field of handwriting and fingerprints, and the Oriented Gaussian Filters should predetermine in advance.

Houssem Chatbri and Keisuke Kameyama proposed a framework to make thinning algorithms robust against noise in sketch image. By using sensitive measure to evaluate skeletons extracted from different grayscale images which filtered by different scales, they can automatically obtain the skeleton that has the lowest value on sensitive measure. Their sensitive measure focus on the skeleton variation, which counts the numbers of the connected points and fake skeletal points (which exist in the skeleton, but not in the original pattern) in skeleton. Therefore, their methods prefer to selecting the concise skeleton rather than a complex one. However, the connectivity and topology of the skeleton produced by their methods may change.

In this paper, an improved thinning framework based on Houssem's method is presented. The framework uses different scales to blur the original image so that internal and boundary noise can be filtered out. Then, we pass the blurred image to the binarization procedure, the skeletonization procedure and the evaluation procedure in turn to obtain an ideal skeleton. The whole framework is described as follows.

Input: Original grayscale image I, maximum scale σ_{max}, increase step st.

Output: The best skeleton I_{mth}

Step 1: Initialize the scale of the Gaussian filter σ_0 with 0;

Step 2: use Gaussian filter with a scale of σ to blur the image I and obtain a grayscale image I_g;

Step 3: Binarize I_g to generate a binary image I_b;

Step 4: Extract the skeleton I_{th} from I_b using the FPSA thinning algorithm;

Step 5: Calculate the sensitivity measure S_σ of the skeleton I_{th} and record it in the memory;

Step 6: If the sum of σ and the st is less than σ_{max}, increase σ with a given step st and go to the step 2; Otherwise, go to step 7;

Step 7: Find the smallest S_m and then obtain corresponding skeleton I_{mth}

The input and output of the proposed frameworks are the original grayscale image I and the best skeleton S_m respectively. The framework iteratively generates the various skeletons that are extracted from the grayscale image that is blurred by gaussian filters with different scale parameters which is gradually increased from 0 (denote we do not conduct the filter operation) to a given number. In each iteration, the original image should be processed by the four procedures, which are gaussian filter procedure, binarization procedure, thinning procedure and evaluation procedure.

The input of this procedure is the grayscale image and outputs the blurred grayscale image I_G. The Gaussian filter is defined by the following formula.

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{(x+y)^2}{2\sigma^2}}$$

where σ is the smoothing parameter that controls the scale, and x and y are the pixel coordinates.

The input of this procedure is the blurred image that is obtained from the previous procedure. The output is the binary image. Here we adopt an adaptive binarization, using the average of non-white grayscale intensities as the threshold for binarization th:

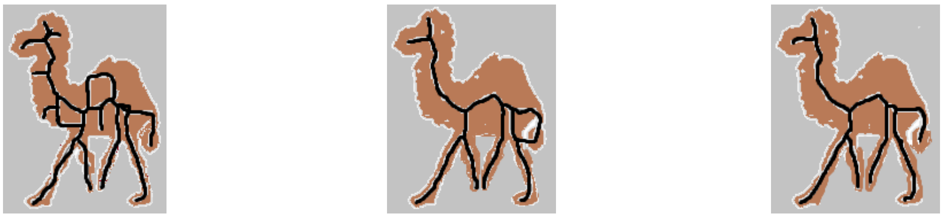
$$th = \frac{1}{N_b} \sum_{i=0}^{N} \sum_{j=0}^{M} f(i, j)$$

Here N_b is the number of foreground pixels in the image, M and N are the dimensions of image I, and function f is defined as follows:

$$f(i,j) = \begin{cases} 0, & \text{if} \quad I_{G(i)}(i,j) = 255, \\ I_{G(i)}(i,j), & \text{otherwise.} \end{cases}$$

Experiments and results

It is clear that in the following figure, the skeleton extracted by FPSA has many skeleton rings caused by internal noise. And both Houssem's method and the proposed method can eliminate these rings very well. But Houssem's method fails to maintain the original topology because there is a ring at the tail of the skeleton. The proposed method in this paper can basically obtain a good skeleton.



a b c

Conclusion

It is experimentally demonstrated that the proposed method in this paper can suppress internal noise and boundary noise and has better performance than the existing Houssem framework in terms of topology preservation and connection preservation.

References:

1. M. Fons, F. Fons and E. Cantó, "Fingerprint Image Processing Acceleration Through Run-Time Reconfigurable Hardware," in IEEE Transactions on Circuits and Systems II: Express Briefs, vol. 57, no. 12, pp. 991-995, Dec. 2010, doi: 10.1109/TCSII.2010.2087970.

2. X. Bai, L. J. Latecki and W. Liu, "Skeleton Pruning by Contour Partitioning with Discrete Curve Evolution," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 29, no. 3, pp. 449-462, March 2007, doi: 10.1109/TPAMI.2007.59.

3. *M. E. Hoffman and E. K. Wong, "Scale-space approach to image thinning using the most prominent ridge-line in the image pyramid data structure.", in: Photonics West'98 Electronic Imaging, International Society for Optics and Photonicss, 1998.*