Contour segmentation of the transversal section of photonic fibers in SEM images using mathematical morphology

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1. Introduction

Microstructured optical fibers, or photonic crystal fibers (PCFs) [1], are fibers that present an array of holes in their transversal section running axially along the whole extent of the fiber (Figure 1). The diameter of the holes of the microstructure, as well as the mean distance between them, is within the order of magnitude of the light wavelength, and therefore the arrangement of these holes may have a strong influence in the optical characteristics of the fiber, allowing the execution of fundamental and technological studies not accessible with traditional optical fibers.

In order to predict the optical properties of a photonic fiber, its transversal section must be known with nanometric precision. This information is used in softwares that solve numerically Maxwell's equations [2]. Presently, the transversal section of the fibers is estimated through manual segmentation of the contours in scanning electron microscopy (SEM) images, which is a slow, tedious and subjective procedure. The automation or semi-automation of the segmentation would speed up this procedure, as well as make it more objective.

To perform the segmentation of the PCF images, we developed a semi-automated tool, based on mathematical morphology (MM) operations. For this purpose we used the MM toolbox [3] developed for the python software (http://www.python.org). Python is a high-level programming language, similar to Matlab, but with free and open source code.

(a)   (b)
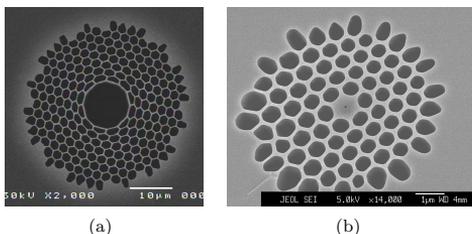
Figure 1. Examples of photonic fibers SEM images.

2. Contour segmentation

Essentially, the contours segmentation is achieved through the following steps:

(1) Segmentation of the observed fiber holes in the image through thresholding.

(2) Use of MM operations to eliminate residues and imperfections resulting from thresholding, and to smooth the segmented image. These operations consisted basically of opening, area opening and closing, labeling, closing, and union.

(3) Verification of the segmentation – if any hole was not properly segmented, it will be necessary to indicate subroutines in order to correct its segmentation.

(4) Extraction of the segmented holes contours and computation of a pixels coordinates list for each contour, which will be the input for the numerical analysis software. This step will be further explained in Section 2.2.

As can be seen in Figure 1, the size and disposition of the holes, as well as the gray intensity and contrast of the images, may vary substantially from fiber to fiber. This brings difficulties to our task since our aim is to generate a unique routine capable of segmenting the majority of the images with minimal user intervention, and in the case where this is essential, the intervention should not demand image processing knowledge of the user.

To attain this objective, we attempted to get automatically both the mean gray level and the mean area of the holes, which are used as parameters in the thresholding and morphological operations. It is important to point out that this is an ongoing work, and that it is being developed in parallel with the images acquisition. Therefore in the future other parameters may be defined beyond those aforementioned, according to necessity.

2.1 Extracting image information

The aim here is to determine a group of parameters that could, in principle, be used to segment the highest possible number of images.

All the fiber images possess a common characteristic: the holes areas consist of a significant fraction of the total area of the image, and therefore it may be expected that the gray level associated to the holes will produce a peak in the image histogram. This characteristic was confirmed in practice and it is illustrated in Figure 2(a).

It remains then to find out which is the peak of interest, and for this purpose a routine was written which computes the histogram, finds the peaks and uses the gray level of each peak as parameter for the thresholding. The program first uses the peak with lowest gray level, performs the thresholding and shows the image to the user asking whether the result is good and if the user wants to try the next peak, and so on.

Another desirable information is the mean area (number of pixels) of the holes, which as seen varies considerably from fiber to fiber. For this purpose, the connected structures of the binary image resulting from thresholding are found and labelled, and their respective areas computed. With these values an area histogram is generated, where the peak corresponds to the mean area of the holes. This is used as a parameter for the morphological transformations applied in step (2) listed above.

(a)   (b)
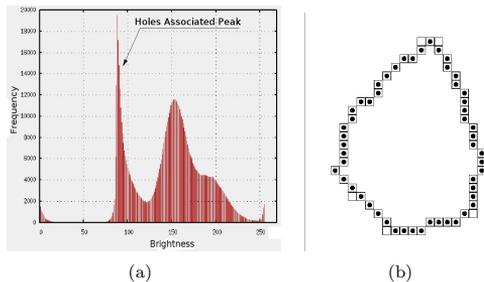
Figure 2. (a) Gray level histogram. (b) IFT algorithm illustration: The empty squares represent a contour obtained with the segmentation. The marked squares represent the result of the IFT over the original contour.

2.2 Contour coordinates

Due to limitations imposed by the fibers numerical analysis program, it is necessary to ensure that the contour line is only one-pixel thick. For this we wrote an algorithm that uses the Image Foresting Transform (IFT) [4] to eliminate the extra pixels, based on [5].

The IFT has as input parameters the binary image with the contours, an image with seeds (in this case, a pixel from each contour), an adjacency relation (we used 8-neighborhood) and a cost function (we used the geodesic distance). These informations are used to calculate the minimum-cost paths for each pixel in the image, starting from the seeds. The output parameters are the labelled image, a cost image and a graph indicating the predecessor of each pixel in its minimum-cost path. In this context we used the predecessors graph generated by the transform to ob-

tain the minimum-cost path to close a given contour, starting from its root and returning to it. The result is that unnecessary pixels are excluded, as it may be seen in Figure 2(b).

3. Results

Figure 3 shows the results of the segmentation of the fibers shown in Figure 1.

(a)   (b)
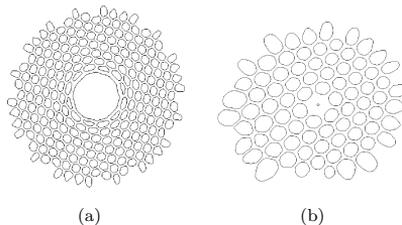
Figure 3. Examples of segmented contours, relative to the images shown in (a) Fig. 1(a), and (b) Fig. 1(b).

4. Conclusions

The results obtained with the MM transformations for the fiber SEM images tested so far have been satisfactory. MM showed to be a flexible and efficient technique, justifying its use for this application. The next step in the program development is to segment the scale bar shown in the images, which will be used to transform the contour coordinates from number of pixels to distance units.

Acknowledgements

References

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