A CONNECTIVITY SOLUTION FOR EXTRACTION OF THIN OBJECTS

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ABSTRACT

Image processing has frequently to deal with thin structures that hold the information required. In natural images, there is a wide variability of conditions, and the borders of objects are not always well defined. Progressive scan, an algorithm derived from fuzzy-connectedness theory, is described here as a specific case of more general χ–connectedness. Exploiting some analogies to the mechanical world, it allows one to track thin structures and, consequently, is suitable for river, motorway or vessel extraction. In the computation of fuzzy connectedness, a widely used approach is based on an adaptive growing mechanism that follows the best paths starting from a reference seed point. The new algorithm uses three or more seed points in order to better drive that approach along the structure of interest. Results of the algorithm are the best path along an object and a connectivity map. The algorithm can deal with heterogeneous images ranging from medical to remote sensed ones.

1. INTRODUCTION

Extraction of thin structures from natural images is certainly an important requirement in numerous application fields. In GIS applications, localization, measurement and tracking of roads or rivers are useful. In the medical field, angiography can be considered as a typical application. Blood vessels are usually thin and long, have inhomogeneous grey levels and are usually very close to other objects with the same characteristics.

In the same research field as that of this paper, the works by Deschamps [4] and Yim [5] are of great interest for medical applications. The former deals with a front propagation method based on level-set theory. Similarly to our work the latter is focused on strategies for the extraction of the skeletons of blood vessels.

The works by Dell'Acqua [6], who works in GIS and remote-sensing fields, presents an algorithm (based on fuzzy clustering by an unsupervised approach) that is able to extract roads from SAR images. In [7] Katartzis describes a model-based method for automatic extraction of roads and paths from aerial images.

The present paper, starting from the fuzzy techniques presented in [2] and [3], proposes an improvement aimed at obtaining the best results in segmentation of thin and long structures.

Natural images always present the same problems. The borders of objects are never well defined, structures can be twisted, fragmented and, in general, very irregular.

The first aim of the proposed algorithm is to extract the best connectivity path along the object of interest. Then, on the basis of such a result, the next goal is to segment the object.

The presented algorithm goes beyond the state of the art because it is able to extract very thin objects, even also one-pixel wide, from various kinds of images. A semiautomatic method is implemented where the users must select the object of interest by positioning some seed points on it. Then the algorithm extracts the best connectivity path along the object and the final result is the segmented object. Results are very satisfactory as well as time performances: only one fraction of a second is required to process a 512x512 image.

2. FUZZY-CONNECTEDNESS THEORY AND TREE STRUCTURE

The use of fuzzy theory, in particular, the application of *fuzzy connectedness* [1] allows one to develop different formulae ([2],[3]) suitable for the extraction of inhomogeneous structures. In order to clarify this theory, we recall some formulae (taken from [2]) concerning the modified field χ_a and the relative *χ-connectivity*.

If we denote by a the seed point that belongs to the structure we want to extract, we can define a modified field X^a where the seed point has the maximum value and each point of the field can be obtained as follows:

$$X^a(p) = 1 - |\eta(p) - \eta(a)| \qquad \textbf{(1)}$$

where $\eta(p)$ is the fuzzy field derived from the original image.

The connectivity associated with the seed point a is found by applying the classical formula of fuzzy connectedness [2] to X^a:

$$C_{X^a} = c_{X^a}(p) = conn(X^a, a, p) = \max_{P(a,p)} \left[\min_{z \in P(a,p)} X^a(z) \right] \quad \textbf{(2)}$$

Equation 2 defines *"χ-connectivity"* or *"intensity-connectedness"* [2]. It allows one to create a connectivity map where each image element has a grey level dependent on the degree of connectivity with respect to the seed point a.

The growing process of the algorithm is stored in a hierarchical tree, so all the steps are organized into a dynamic structure: the seed point represents the root, and new nodes are added every time a new pixel is computed.

The construction of the tree is based on the concepts of a *generator pixel* and a *candidate* pixel, as defined in [2]. Starting from the seed point, the pixels in the neighbourhood are considered. Such pixels are the seed point's sons: they represent the first level of candidates and are labelled according to Equation 2.

Among the level-1 candidates, the pixels with the maximum degree of connectivity are chosen; they become the level-1 generators, that is, the pixels that propagate the growing tree. In the next step, the pixels in the neighbourhood of the level-1 generators are analysed: these pixels represent the level-2 candidates and the sons of the level-1 generators. In other words, the level-1 generators are the fathers of the level-2 candidates.

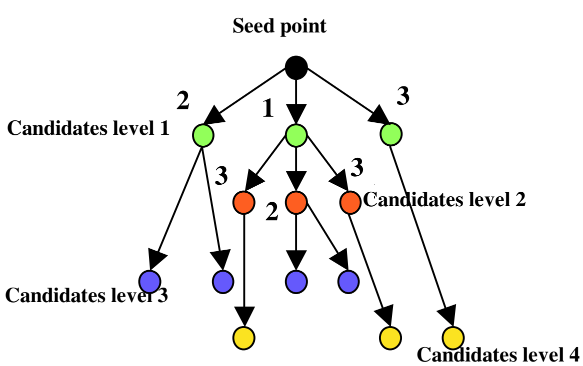

Figure. 1. An example of hierarchical tree. The nodes of the same colour indicate the candidates at a specific processing level. The node numbers denote the generator levels.

Each tree level is represented by pixels labelled in the same processing step, so the pixels that are at the *i-th* tree level are called i-level candidates, whereas the generators at the *i*–1 level are the fathers of the *i*-level candidates (Fig. 1).

3. THE PROGRESSIVE SCAN METHOD

The progressive scan method exploits all backgrounds of the *χ-connectivity* implementation, thus realizing a multi-seed algorithm aimed at dealing with thin and long structures. Progressive scan is a supervised segmentation algorithm and requires the user' selection of the object of interest. The segmentation is performed by placing some seed points on the object. There are three categories of seed point:

- Start point;
- Intermediate points;
- End point;

The first ("Start point") and the last ("End point") categories are made up of only one seed point. The "Start point" localizes the beginning point of the algorithm, whereas the "End point" is the stop condition of the segmentation. The "Intermediate points" are composed of one or more seed points and are the leaders of the algorithm, i.e.,each of them leads the algorithm in a given direction, thus realizing a **driven ordered region-growing algorithm**.

Therefore, the first step is the selection of the N points of the set S of seed points, $s_i=(s_1,s_2,s_3)\in Z^3$; the points must be at least three. s_0 is the starting seed point, s_N the ending point, and s_1 … s_{N-1} are the intermediate ones. The scanning algorithm can start.

The algorithm, called *progressive scan* is based on the mentioned above connectivity measure and exploits some concepts derived directly from mechanical physics. The connectivity measure is the kinetic energy of the algorithm at every step p and is denoted by E_k^p, every seed point has a potential energy $E_p^{seed} = 255 = E_{pot}^{max}$. When the processing starts, the first seed point gives the algorithm energy. This potential energy, transformed in to kinetic energy, allows the algorithm to begin the growing process. By analogy to the mechanical world, the algorithm energy decreases during the process, and the algorithm stops when the energy goes to zero.

The energetic law that describes the above phenomena at every step p is fully derived from eq. 2 as follows:

$$E_k^p = conn(X^a, a, p) = \max_{P(a,p)} \left[\min_{z \in P(a,p)} X^a(z) \right] \quad \textbf{(3)}$$

When the algorithm reaches an intermediate seed point, it receives again the maximum energy. Note that intermediate seed points hold the maximum energy (255), but can give the algorithm only the portion of energy the algorithm needs to get the maximum energy:

$$E_{pot}^{yielded} \leq 255 - E_k^p \quad \textbf{(4)}$$

The pixel at step p that has received the energy is the point of the algorithm that holds the maximum energy. So it is the point that continues the scanning process.

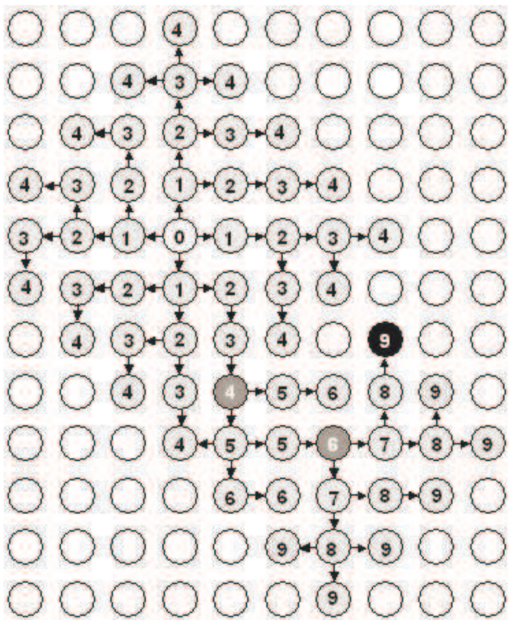

Figure. 2. Example of scanning mechanism. The number inside a circle is the step number.

Figure 2 depicts some steps of the algorithm scanning mechanism. The number inside a circle denotes the step number of the growing process. Each circle corresponds to a pixel. The first seed point is the number zero and is the starting point of the scanning process. The middle gray circles are the intermediate points, and the black one is the last seed point, which corresponds to the end point.
Starting from the first seed point, the algorithm scans the pixels until it reaches an intermediate seed point (step 4). This gives algorithm its energy; the algorithm holds at in this point the maximum energy (255). Therefore, the growth continues from this new seed point because it holds the maximum energy. This phase goes on until all the intermediate seed points are visited. Finally, the stopping condition is the reaching of the ending point.
Once progressive scan is completed, the following step is the extraction of the related path. For this purpose the growing tree is exploited and, by using a simple backtracking algorithm, the extraction of the best connectivity path between the starting and ending points (going through the intermediate seed points) is easily performed. Finally, the last task to be performed consists in a thresholding phase that provides the segmentation of the object of interest.

4. RESULTS

The algorithm was tested on images coming from different application fields, from remote-sensing application to biomedical ones. The structures considered were usually very thin, and sometimes were made up of only one or two pixels. In the following, a most significant example concerning the remote-sensing field is presented.
Figure 3 is a 256x256-pixel portion of an xsar quick look. It shows the mouth of a river and is very intricate because of the various branches. The structure of interest is the branch indicated by the arrows.
The proposed algorithm result (Figure 7) is compared with the one obtained by the older χ_a-connectivity algorithm (Figure 5). As can be seen, the older algorithm is unable to provide a good segmentation.
Figure 4 shows the placed seed points, and in Figure 6 the extracted path is depicted. Then, in Figure 7, the branch of interest is well segmented.

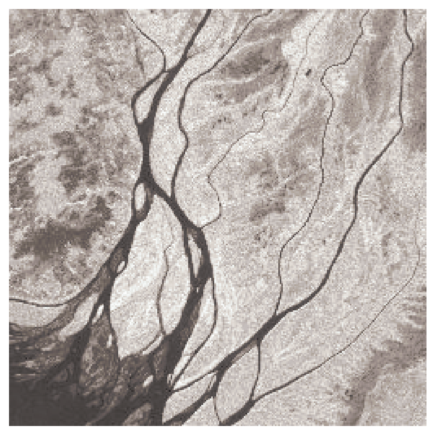

Figure 3 Xsar image of an intricate river mouth.

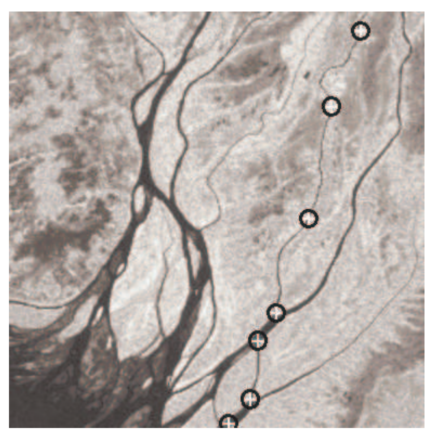

Figure 4 Xsar image with the seed points placed on the branch of interest (circled crosses)

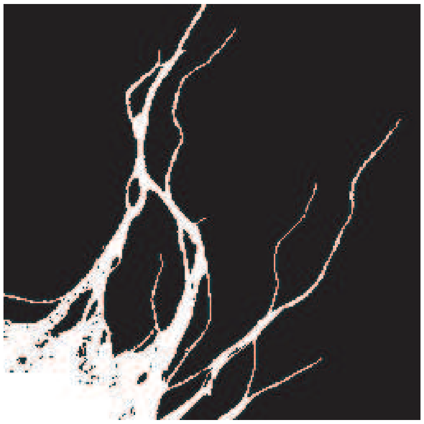

Figure 5 Result obtained by thr χ_a-connectivity algorithm

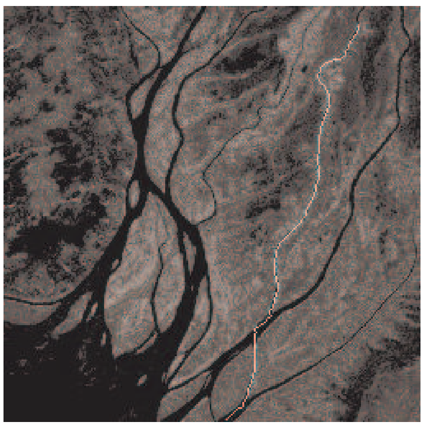

Figure 6 The path extracted by the progressive scan algorithm (note that the image pixels have been rescaled to improve the visualization)

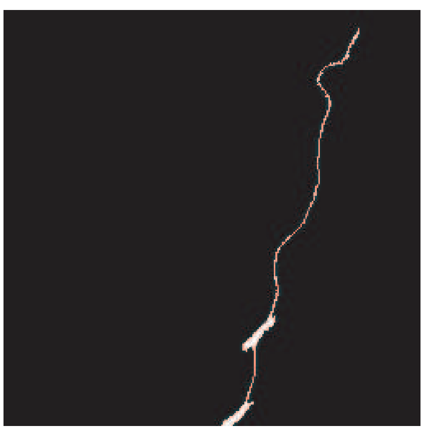

Figure 7 Result obtained by progressive scan: the branch of interest is carefully segmented

The classical χ_a-connectivity algorithm fails to segment the branch and results is an incomplete or an over-segmentation. However, Figure 5 shows a good segmentation of the all water in the image, but the water is not the object of interest.

Progressive scan provides a segmentation of the branch of interest even in a very intricate river mouth, like the one considered in the above example. The segmentation obtained is complete and accurate for the entire branch.

5. CONCLUSIONS

The example given above demonstrates the validity of proposed method for thin or very thin structures. The extraction of the path is correct and accurate. Moreover, it should be stressed that, if a bad path occurs, the problem can be solved by using more or better placed seed points.

The proposed algorithm, based on the *χ-connectivity* computation, is able to better extract thin structures, and shows satisfactory results on very long structures. The path extracted is very near the skeleton of the structure considered and the computation time is very short. Future work will aim to exploit this technique on wider and three-dimensional structures.

6. REFERENCES

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