The generation of river channel skeletons from binary images using raster thinning algorithms.

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1. Introduction

River channel centrelines are important features for the analysis of river channel parameters and dynamics. Networks of channel centrelines allow the computation of stream orders in braided channels (e.g. Gleyzer et al., 2004) and quantification of bifurcation angles (e.g. EGIS, 2002). Analysis of the change in the location of centrelines through time is central to the measurement of channel migration rates (e.g. Mount and Louis, 2005) and the prediction of channel stability (e.g. EGIS, 2002; Burge, 2006).

Commonly, channel centrelines are quantified manually by digitising an operator's perception of the centre of a channel (e.g. EGIS, 2002) or from the coordinates of digitised section lines (e.g. Mount et al., 2003). However, these methods are time consuming and rely on the interpolation of points to form the channel centreline, losing data in the process. A preferred option would be the automatic extraction of channel centrelines from binary imagery, commonly known as skeletisation. Algorithms for such operations are available in many contemporary GIS. However, they commonly have their roots in algorithms developed for drawing automation or character recognition and are, therefore, seldom optimised to handle the topological complexity and boundary noise that one associates with binary images of river channels. The result is highly irregular skeletons that are poor representations on the channel (Figure 1).

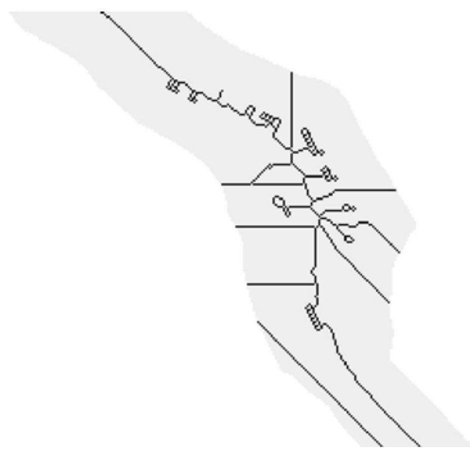


Figure 1. The skeletonisation of a section of the Torrent du Jean Pierre by ArcMap's Thin tool. Spurious limbs and loops are evident.

The skeletisation of binary images is a mature research discipline with several hundred papers published on the subject (c.f. Lam et al., 2002) since the late 1960's. However, virtually no algorithms have been specifically designed and tested on river channels, and those that have (Vincent, 1991) have not been tested in complex multi-channel environments.

This paper outlines a skeletisation algorithm specifically designed for skeletonising complex river channels along with pre and post-processing operations to improve the resulting skeleton. It is based on an amendment to Arcelli et al's (1975) raster thinning algorithm and applied to test data from the Torrent du Jean Pierre in the Ecrins National Park, France. (Figure 2).

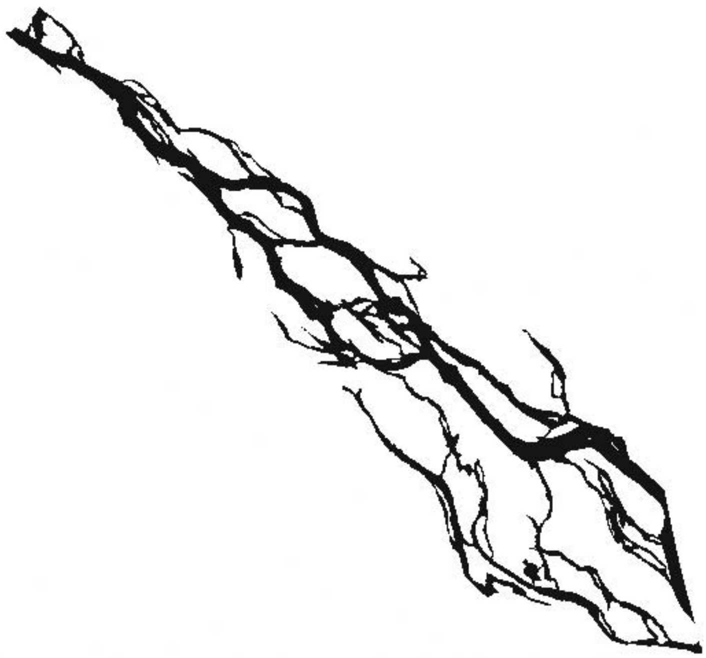


Figure 2: Binary image of the braided Torrent du Jean Pierre, Ecrins National Park, France**.**

2. Using Thinning Algorithms in River Channels

Thinning algorithms reduce binary images to their skeletons via an iterative shrinking process in which each contour pixel is analysed and, if certain removal criteria are satisfied, that pixel is deleted. Many of the published raster thinning algorithms have been designed for applications such as character recognition, in which the data are relatively uniform and possess predictable characteristics. Raster based thinning algorithms for use with river channel data of the complexity of the Torrent du Jean Pierre, must be able to cope with highly irregular, noisy contours, be capable of preserving topology and geometry, and be able to achieve invariance under conditions of rotation.

Non-iterative algorithms, which compute channel centrelines on the basis of the contours of the binary data, are highly susceptible to variations under rotation (Lam et al., 1992) and to noisy contours. Hence, they are inappropriate for use in thinning complex river channels. Different challenges face the use of iterative algorithms. Artefacts such as noise spurs and loops are likely but may be removed by post-processing. More problematic is the occurrence of necking (Figure 3) which is a common error resulting from iterative algorithms and has an impact of topology which is difficult to remove. Accepting these outstanding issues, a parallel iterative approach was chosen (parallel algorithms operating on all or a subset of pixels simultaneously), offering advantages in terms of computational efficiency (important for large rasters) and simplicity of code. The risk of necking was believed to be outweighed by the benefits offered by an iterative algorithm.

Figure 3. An example of necking, where the topological relationships of the binary data and skeletonised data have been altered.

The noisy contours associated with binary images of river channel data require filtering to prevent the generation of spurious limbs from small convexities in the contour (Dharmaraj, 2005). A simple, median filter, in which a count of the number of 0s and 1s in a 3x3 window is used to determine the value of the central pixel, was applied to decrease contour noise. Small islands, or holes, in the binary channel raster also require removal to ensure spurious channel nodes, and hence bifurcations, were not identified. To this end, an equivalent of ArcMap’s Region Group tool, in which unique IDs are assigned to the pixels making up each island, was used, and a deletion threshold area, determined manually, was applied to remove small islands. Following these pre-processing steps, the thinning and bifurcation algorithms can then be applied according to the sequence given in figure 4.

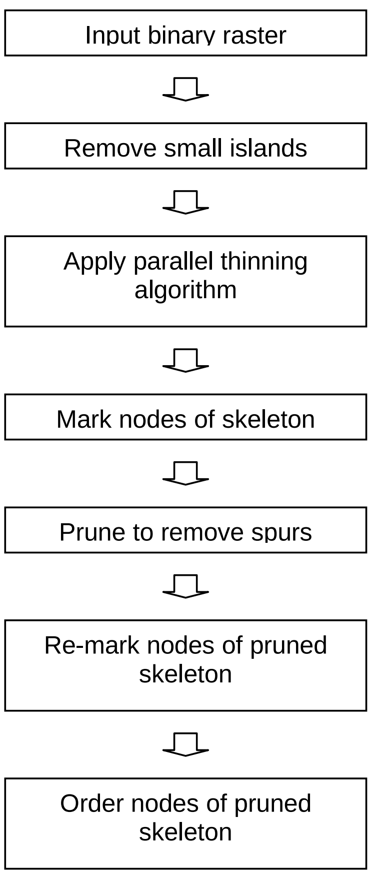


Figure 4. The analytical sequence for generating skeletonised river channels from binary channel images.

3. The application of a thinning algorithm and pruning algorithm to complex river channel data.

Thinning algorithms work via the moving application of a number of masks, of given pixel dimensions (usually a 3 x 3 window), against which the patterns of pixels values in the binary image are assessed. The masks are configured such that, for each iteration, only contour pixels may be deleted based on the presence or absence of given patterns within the contours of the original, binary image. An introduction is given in Ablameyko and Pridmore (2000) with a full review of masks and algorithms in Lam et al., (1992). This study applies a modification of the well-known, parallel thinning algorithm of Arcelli et al (1975), in which additional masks from Hilditch (1983) are applied to address pixel redundancy issues. The algorithm ensures that only a single layer of contour pixels can be removed in each iteration, thereby achieving a more predicitible skeleton with fewer anomalies at the corners.

The modified Arcelli et al., (1975) algorithm results in numerous short, spurious limbs (Figure 5) that require pruning (Dharmaraj, 2005). To achieve this, nodes and end points must be identified so that limbs with short distances between end points and nodes (indicative of a spur) can be identified and deleted. End points may be identified where the number of transitions from 0 to 1 (*T(b)*) that occur when the boundary cells of a 3 x 3 window are traversed cyclically is equal to 1 (Apaphant, 2000). However, in complex river channels, situations in which end points have 2 or 3 neighbouring cells are possible, resulting in up to three transitions. Therefore, the rules for identifying end points can be modified according to figure 6.

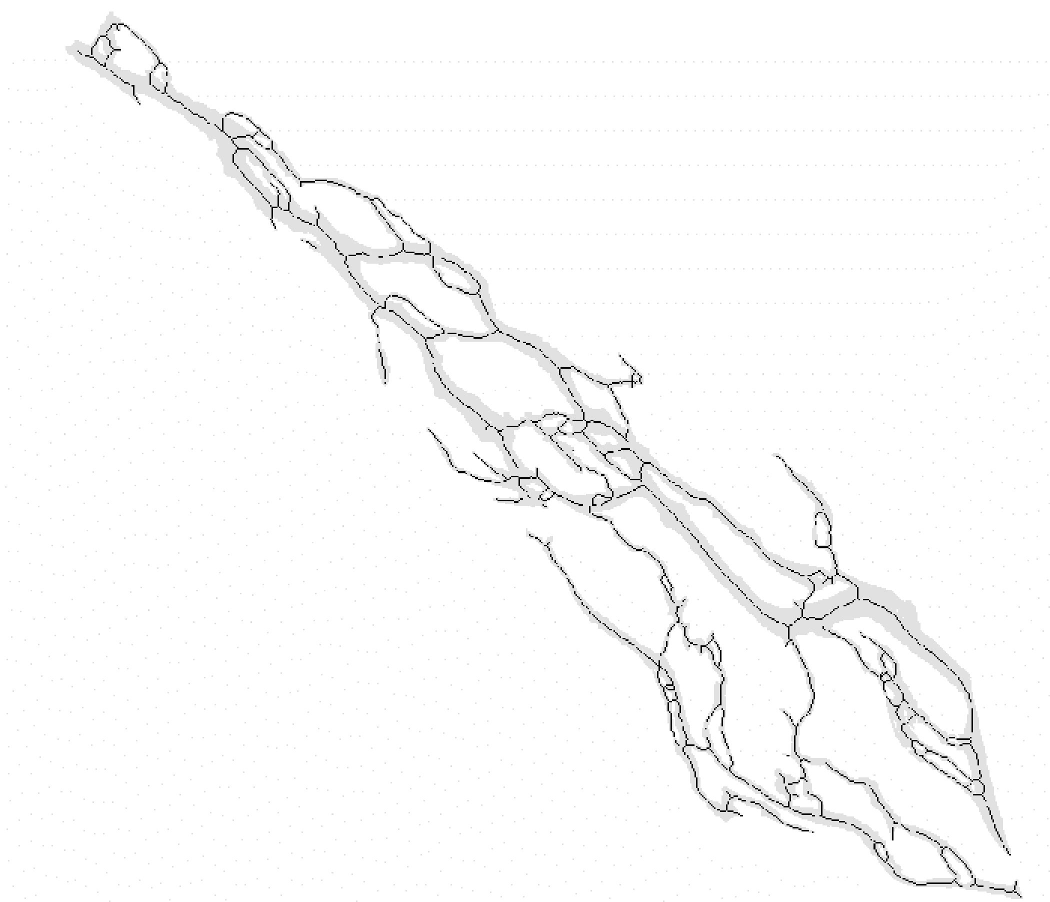


Figure 5: Spurious limbs prior to pruning.

End Point with 2 Neighbours (N)	End Point with 3 Neighbours (N)
***N(b)* < 3 and N2 = 1 and N3 = 1**	***N(b)* < 4 and N2 = 1 and N3 = 1 and N4 = 1**
***N(b)* < 3 and N3 = 1 and N4 = 1**	***N(b)* < 4 and N4 = 1 and N5 = 1 and N6 = 1**
***N(b)* < 3 and N4 = 1 and N5 = 1**	***N(b)* < 4 and N6 = 1 and N7 = 1 and N8 = 1**
***N(b)* < 3 and N5 = 1 and N6 = 1**	***N(b)* < 4 and N2 = 1 And N1 = 1 And N8 = 1**
***N(b)* < 3 and N6 = 1 and N7 = 1**	
***N(b)* < 3 and N7 = 1 and N8 = 1**	
***N(b)* < 3 and N2 = 1 and N1 = 1**	
***N(b)* < 3 and N1 = 1 and N8 = 1**	

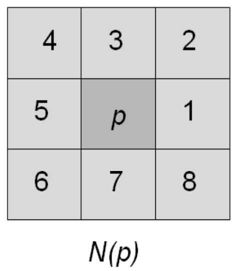


Figure 6. Rules for identifying end points in complex, skeletonised river channels. *N(b)* is the number of black pixels (pixel value = 1) existing in a 3 x 3 window, where N_n is the number of the neighbouring pixel (*N(p)*) according to the numbering scheme shown.

In a similar way to endpoints, nodes can be identified according to the number of black pixels (*N(b)*) and the number of transitions from white pixels (0) to black (1) (*T(b)*) in a cyclical traversal of *Np*. Apaphant (2000) used the rule *N(b)* > 2 AND *T*(*b*) = 2 to identify nodes, but this fails to identify nodes where the configurations shown in Figure 7 occur**.** Therefore, the rule was modified to *N(b)* > 2 AND *T(b*) > 2.

From any end point a limb can be tracked via examination of *N(p)* for each cell, finding the next cell in the segment and stepping into it. Where there are two potential cells in *N(p)*, immediate neighbours are tracked preferentially to prevent nodes being missed (Figure 8). By counting the number of cells traversed between an end point and the first-encountered node, the length of a limb can be calculated and, where this length is shorter than a defined threshold, the limb is deleted. By applying these steps to all end points in a skeletonised image, limbs are pruned. A comparison of a pruned and unpruned channel skeleton is given in figure 9.

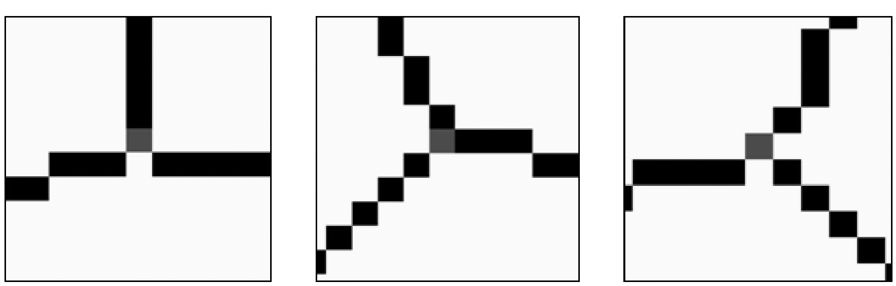


Figure 7. Node configurations in which *N(b)* > 2 AND *T*(*b*) = 2 fails.

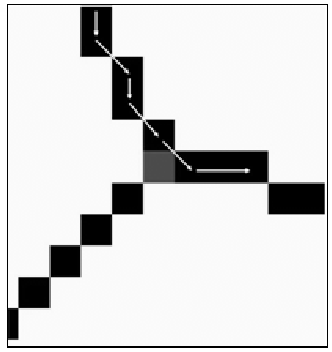
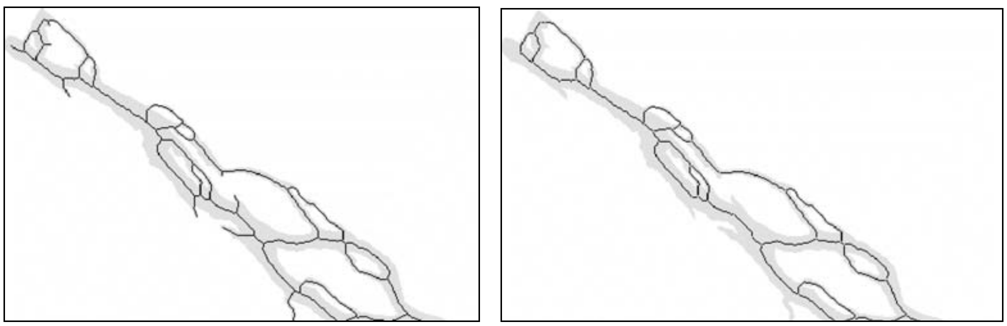


Figure 8. Example node configuration in which a node could be missed without the application of a preference for immediate neighbours.



(a) **(b)**

Figure 9. (a) Skeletonised channel prior to pruning and, (b) skeletonised channel after pruning.

4. Conclusions

The parallel, iterative algorithm presented here, whilst based upon Arcelli et al's established thinning method, contains a number of specific modifications that ensure it is applicable to the skeletonisation of complex river channels. Initial median filtering, to reduce contour noise reduces the frequency of spurious limbs in the thinned skeleton. Moreover, the application of additional masks from Hilditch (1983) ensure that only a single layer of contour pixels are removed in each iteration, resulting in a skeleton with fewer anomalies. Finally, the modification of the end point and node identification rules of Apaphant (2000) ensure improved pruning of any spurious limbs that exist in the thinned skeleton. The result is a set of tools which enable the successful skeletonisation of complex river channels which can then form inputs for further analyses.

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Biographies

Jonathan Hasthorpe is a 2006 Graduate of the University of Nottingham's MSc in GIS programme. He developed this work as a part of his MSc dissertation investigating the automation of channel bifurcation angle measurement for complex river channels in Bangladesh. Nick Mount is a lecturer in GIS at the University of Nottingham with a particular interest in the spatio-temporal analysis of dynamic river systems.