Automatic computation of river channel bifurcation angles

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1. Introduction

Bifurcations are important river channel features that exert a major control over downstream morphological change. The importance of the geometry of a channel bifurcation has become widely recognised (e.g. Pittaluga et al., 2003), with the bifurcation angle determining the division of sediment and water downstream and, hence, the stability of the bifurcation (Bridge, 1993). Bifurcation angles of between 40° and 60° are reported as stable (Burge, 2006), with wider angles indicating instability and a high probability of channel abandonment (Federici and Paola, 2003). See figure: 1 for a schematic diagram of angles of deviation at a bifurcation.

Bifurcation angles can be quantified from remotely sensed imagery (EGIS, 2002; Burge, 2006) across a wide range of river settings and scales and at numerous points in time. Hence, they offer a parameter which can be easily applied in studies attempting to predict river channel stability in varied environments. Indeed, EGIS (2002) developed a predictive tool for the Jamuna River that enables the probability of a bifurcation becoming unstable to be made up to 12 months in advance. However, this model relies on the manual definition of channel centrelines from binary (inundated / not inundated) channel images and the manual measurement of angles of deviation of these centrelines at bifurcations. The result is an enormously time-consuming process that limits the application of the EGIS model to relatively small areas of channel or relatively short periods of time.

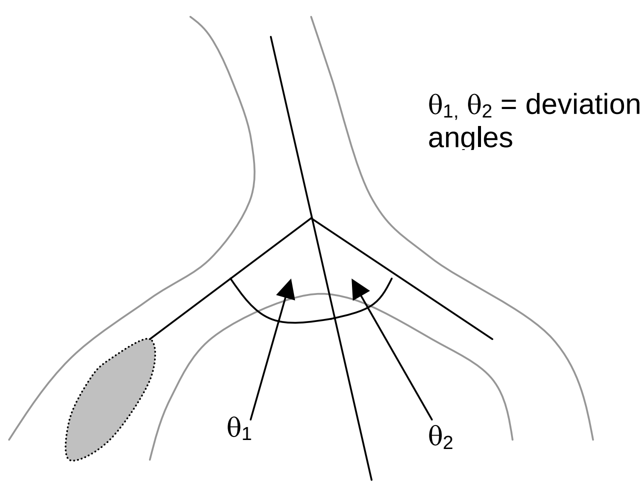

Figure 1. Measurement of angles of deviation at a bifurcating channel

The solution to improving the applicability of the EGIS model lies in the automatic extraction of the channel centreline (through approaches such as raster thinning) and then the automated measurement of bifurcation angles from this skeleton. This paper outlines a new regression-based bifurcation angle measurement algorithm and demonstrates its application to skeletons derived from the highly complex data of the Jamuna River, Bangladesh.

2. Generating the Skeleton

Thinning algorithms reduce binary images to their skeletons via an iterative shrinking process, where contour pixels are analysed and deleted if certain removal criteria are satisfied. To generate the unit thick skeleton (representative of the complete river network's centreline) required for this research, a modification of the well-known, iterative parallel thinning algorithm of Arcelli et al (1975) was used. In this, masks were iteratively applied to the binary river raster and where pixel configurations matched, pixels were deleted. The additional masks of Hilditch (1983) (see figure: 2), were also applied to address the pixel redundancy issues that would otherwise occur (see figure: 2).

0	0	0
	1	
1	1	

	0	
1	1	1
	1	

0	0	0
	1	
	1	1

0	0	
	1	1
	`1	

0		
0	1	1
	1	

Figure: 2 The Masks (with their 90° rotations) used in Hilditch (1983)'s Thinning Algorithm (Hilditch 1983)

Of note is the fact the applied thinning algorithm was selected (from the several hundred papers published on the subject since the late 1960's (Lam et al., 2002)) on the grounds it had the potential to cope with the highly irregular, noisy binary data of the Jamuna, and preserve both channel topology and geometry to an acceptable degree. However like all iterative algorithms the resulting skeletons were subject to artefacts such as noise spurs, loops and necking (see figure: 3). While the former two artefacts may be removed by post-processing, the latter's impact on topology is more difficult to remove.

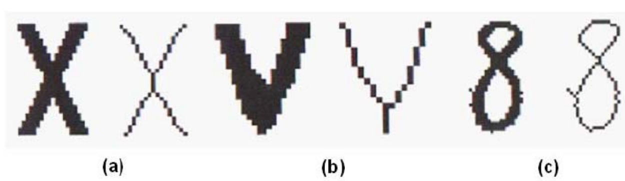

Figure: 3 Classic Thinning Artefacts: a) Necking b) Tailing c) Spurious Projection (Parker 1997)

3. Automating Bifurcation Angle Measurement

Bifurcation angles are measured relative to the upstream channel orientation and accordingly, which of the three skeletal segments at a node, represents it, must be identified. Although the actual node can be easily identified according to both the number of black pixels (N(b)) and transitions from white pixels (0) to black (1) (T(b)) in a cyclical traversal of *N(p)* (see figure: 4), the identification of the upstream segment is problematic where no flow direction/elevation data is available. To solve this problem a node ordering routine was developed that tracked along all skeletal segments (i.e. examine *N(p)* for each cell, find the next cell in the segment and step into it), established which node was upstream of which, and marked the nodes with hierarchical values.

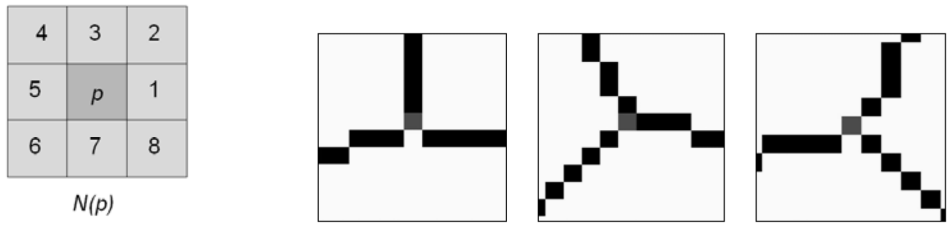

Figure 4 Possible *N(p)* Node Configurations - N(b) > 2 AND T(b) > 2)

Starting from the most upstream node (e.g. marked 1) all stream segments were tracked along in turn until a new node was reached. Where this new node was ‘downstream’ in terms of a user defined bearing and distance, it was then labelled with the next hierarchical order (e.g. 2). For each node, the order and coordinates were stored in an array, and after its three segments were analysed, the process was repeated for the next stored node. Where segments were tracked along in both directions (starting from either end node), the initial assigned value was retained. Ideally the algorithm would result in all nodes upstream of another, being assigned a lower value (enabling the upstream segment to be automatically identified) (see figure: 5).

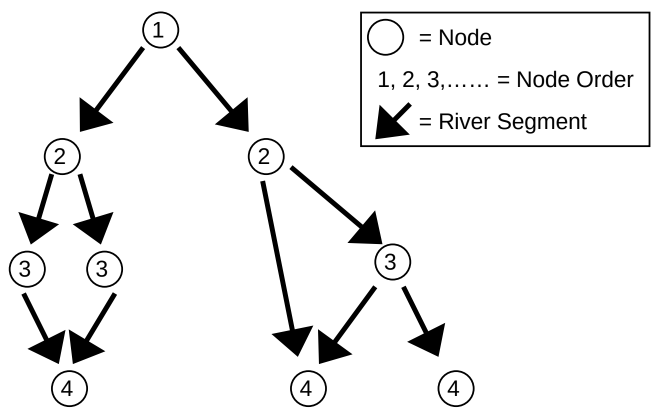

Figure: 5 Schematic Diagram of the Node Ordering Hierarchy

Bifurcation angles were then calculated directly from the node ordered skeleton. The node values enabled bifurcations to be automatically identified as nodes with one upstream, and two downstream, segments. For each bifurcation identified, all river segments were again tracked along and for a specified length; each one had its row/column coordinates stored in an array. These coordinates were then used to generate a regression line (coming closest to passing through all coordinates and having the minimum sum of distance^2 to them) that approximated each channel centreline and as such reduced the influence of noise on the data.

To ensure that each regression line was representative of its equivalent channel centreline, the length of the sampled segment (starting from the node) was adjusted in accordance to the scale and character of the Jamuna data. For sections unaffected by thinning artefacts (and over 1 km), the first 1/3 of the segment was proven to be representative of the channel centreline in the majority of cases. From the regression line, slope (as a function of X) could be calculated and converted to a bearing (in degrees) using $\tan^{-1}$. From the three bearings (one for each segment) relative angles were then calculated and the bifurcation angle derived.

4. Algorithm Application

In applying the algorithm to a data set as complex as the Jamuna river, some examples of failure were expected, and indeed this was the case. However, from a mathematical perspective the algorithm successfully calculated bifurcation angles based on the information it collected (i.e. the sampled coordinates for each line segment). Furthermore in general the generated skeleton proved suitable for the purpose of calculating angles of deviation, with good results being achieved (see figure: 6(a)). In validating the results through comparison with 45 manually derived results, errors ranged from 0.13 to 50.4°, with an average of 12.80°. Where larger inaccuracies were experienced, this was a result of the regression line generated being unrepresentative of the river channel and there were two major causes for this:

i) The skeleton contained thinning artefacts that resulted in sections of arbitrary centreline (mainly at intersections), and as such some derived measurements were meaningless.

ii) The length of segment from which samples (coordinates) were taken was un-representative of the channel centreline. This was a particular problem where the sampled section was acute and the generated line was essentially an averaged misrepresentation (see figure: 6(a)).

Another issue was the fact that the node ordering procedure did not always succeed. Failures occurred in situations where thinning artefacts produced additional arbitrary nodes at skeletal junctions (disrupting the node ordering process) or where flow direction was highly ambiguous. This resulted in the incorrect identification of the upstream segment and therefore the bifurcation also. Accordingly angles calculated in these circumstances were again un-representative.

(a) (b)

Figure: 6 Raster lines (black) illustrating a) Successfully calculated line orientations at two nodes b) A failure at an acute section of channel

5. Discussion

The aim of this research was to develop an algorithm that could measure bifurcation angles with the highest level of automation possible. Although full automation was not achieved, the algorithm worked well, and the average error of 12.80° was in fact low when considering the approximate nature of manual centreline extraction (calculations being based on channel shape only, with no consideration of water depth or the location of dominant flow), as well as the limitations of an average value. The research also succeeded in clearly identifying the issues that at present prevent full automation being achieved.

In the case of thinning artefacts; such errors were inevitable as a result of the local focus and simplicity of the thinning algorithm used, and considering this, and the complexity of the Jamuna River data, results were better than expected. Further, in some cases it was possible to skip over unrepresentative sections and still extract meaningful results. However the main problem was that artefacts prevented the algorithm from being robust and as such human intervention/checking remained a requirement (a major barrier to automation).

The issues resulting from measuring accurate, but un-representative, sections of centreline resulted from the use of parameters (i.e. specifying the proportion of segment to be sampled). Although parameters were applied to prevent this problem, their relative rigidity in contrast to the irregularity of the Jamuna data, meant that they were not suitable in all situations. Conversely a parameter based approach provided the algorithm with the flexibility to be applied to braided river data sets of all scales.

Finally the problems arising from the failures of the node ordering algorithm were expected, as it was a rather basic attempt to achieve a greater level of automation, in the absence of flow direction information. To a certain extent it achieved its purpose and when applied to simple or localised data examples it worked well. However, again skeletal artefacts and complex channel configurations degraded the results.

6. Conclusion

This novel research successfully outlines a new regression-based bifurcation angle measurement algorithm and demonstrates its successes and failures when applied to skeletons derived from the highly complex data of the Jamuna River. Although the issues identified may be difficult (if not impossible) to overcome, there remains much scope for improvement. Indeed it is hoped that the study has laid down good foundations and will stimulate further research to see full automation achieved.

Future research should focus on i) the development of thinning algorithms with the capability to better preserve river channel centrelines/junctions, ii) investigation into the potential of more complex/numerous (e.g. rule based) parameters to ensure that the algorithm is more robust, iii) further development of the node ordering algorithm to attempt to overcome the current causes of failure.

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