

A hierarchical graph matching method to assess accuracy of network extraction from DTM

Thommeret Nathalie

Laboratoire de Géographie Physique - UMR 8591
 Université Paris 1 - CNRS
 Meudon, France
 nathaliethommeret@gmail.com

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Bailly Jean-Stéphane

UMR LISAH - UMR TETIS
 AgroParisTech
 Montpellier, France
 bailly@teledetection.fr

Puech Christian

Maison de la télédétection - UMR TETIS
 Cemagref
 Montpellier, France
 puech@teledetection.fr

Abstract— More and more elevation data and methods are available to automatically map hydrographic or thalweg networks. However, there are few methods to assess the network quality. The most used method to compare an extracted network to a reference network gives global quality information on only geographic criterion. The method proposed in this paper allows a network assessment compared to a reference network whose results can be interpreted more easily and more related to networks morphologies. This method is based on a hierarchical node matching within a graph. Nodes are classified by hierarchical level according to their importance in the tree-structured network. Then, a matching process seeks for nodes pairs between the two networks based on the geographic distance. The hierarchy introduces a priority order in the matching. The relative location of nodes pairs is checked in order to ensure a topological consistency. Finally, similarity statistics based on nodes matching counts are computed. While the usual method only takes into account a geographic criterion, the presented method integrates geographic, geometric and topologic criteria. It is an interactive and object-by-object matching. Moreover, the hierarchical approach helps comparing networks represented at different scales. It provides global statistics but also step-by-step maps that helps characterizing the spatial distribution of network delineation errors.

thalweg networks. Various methods make possible the automatic extraction of such networks from DTMs (O'Callaghan et Mark, 1984; Quinn et al., 1991; Lea, 1992; Tarboton, 1997; Molly and Stepinski, 2007; Thommeret et al., 2010; Pirotti and Tarolli, 2010). Consequently, for a given area, numerous representations of networks can be provided from several elevation data and/or from different extraction methods and sometimes from different softwares (Hengl et al., 2009). Usually, main branches of the different representation are similar but greater differences are pointed out for upstream branches. Each result should be compared to a ground-truth to determine which one is the most representative. In addition, another problem is that ground truth data are not always available with same scale which makes the usual accuracy assessments methods (Heikpe et al., 1997) inappropriate.

To assess the quality of a representation, we need a tool that permits to quantitatively and synthetically compare two networks (at different scales). A network assessment should respond to the following questions: how much of the network is over-detected and how much is under-detected (Heikpe et al., 1997)? But other questions seem to be important like: is the network topology correct? What proportion of errors occurred on the main branches of the network compared to those located upstream?

There is no standard method to assess the quality of an extracted network (Molloy and Stepinski, 2007). The automatic method the most used (known as the buffer method) allows for an estimate of the delineation error based on a geographic overlap of the

INTRODUCTION

The progresses in terrain modeling allow nowadays automatic and systematic mapping of morphological features as drainage or

78 networks (Heipke et al., 1997). It is a global comparison that
79 focuses on the over and under-detection total lengths. It provides
80 valuable first information on the network's geometric accuracy
81 (Heipke et al., 1997). However this method is based on a single
82 criterion of linear geographic proximity while it seems interesting
83 to take into account the networks' morphology and thus integrate
84 a topological criterion. In the other hand, strictly topological
85 comparisons are possible (Ferraro and Godin, 2003) but not
86 adapted to spatially referenced objects.

87 This paper deals with the issue of automatic and quantitative
88 network comparison in order to assess extractions. We propose a
89 method that integrates geometric, geographic and topologic
90 criteria and perform accuracy assessment even when ground truth
91 data are not at the same scale.

92 METHODS

93 The method presented is based on a hierarchical graph node
94 matching when DTM extracted networks are transform in tree
95 graph objects. It aims at seeking pairs of nodes between the
96 extracted network to test (T) and a reference network (R).

97 Firstly, nodes are classified by hierarchical level from
98 downstream to upstream for both networks. Then, an iterative
99 matching is processed: first-classes nodes are matched then
100 second-classes nodes up to the source-nodes. Matching can be
101 based on a simple geographic criterion: the geographic distance
102 of the two networks' nodes.

103 *Node labeling*

104 We chose the method to focus on the nodes rather than the edges
105 of the network due to 1- nodes-edges duality and simple nodes
106 geometry and 2- higher edges sensitivity to noise in geographic
107 positioning: for instance, spatial resolution impacts reaches
108 geometry and extent.

109 Labels that will be used to classify and match nodes are attributed
110 to T and R nodes based on geometric and topologic attributes;
111 simple geometric labels: x and y coordinates of the nodes and
112 topologic labels mainly based on Shreve magnitude of each
113 node (Shreve, 1966). We chose the shreve taxonomy rather than
114 Strahler's one for a simple reason: for Shreve's, source-nodes
115 have the same weight along the tree whereas for Strahler's they
116 have not the same impact on the ordering increase. Each node
117 magnitude (S) is normalized by the whole network magnitude
118 (S_T) in order to allow comparison between R and T networks at
119 different scales.

120 *The hierarchical nodes classification*

121 The second step consists in a hierarchical node classification
122 for both networks based on the node importance in the tree. It
123 aims to introduce a priority in the pairs' research.

124 Node importance is determined from the normalized Shreve
125 magnitude that expresses a node relative upstream/downstream
126 position in the tree. The first level of the hierarchy includes the
127 greater junctions of the networks; at the opposite, the last level
128 corresponds to source-nodes. Outlets are matched by definition
129 so they are not taken into account in the classification.

130 The number of classes (N) is directly related to the scale
131 representation of the network: the more the network is detailed
132 (great values of S_T), the more N is high. A theoretical hierarchical
133 level number (N_T) can be obtained by reasoning on a perfect
134 binary tree (Eq. 1). However, studied networks are not perfect
135 binary trees, this number is a maximum. Thus, we introduce an
136 arbitrary correction factor of 2 (related to the two first obvious
137 classes: sources and outlet) in order to obtain a less restricting
138 number of classes given by Eq. 2.

$$139 \quad S_T = 2^{N_T} \quad (1)$$

$$140 \quad N = \text{floor} \left(\frac{\log(S_T)}{\log(2)} \right) - 2 \quad (2)$$

141 At the end of this step, the two set of nodes (extracted and
142 reference) are classified by comparable hierarchical level.

143 *The matching of nodes by class*

144 In the third step, we seek for nodes pairs for the different
145 hierarchical levels. The matching is an iterative process starting
146 with the first class of nodes up to the source class.

147 Geographic proximity rules the matching: a distance matrix is
148 performed from the two node subsets for each hierarchical level.
149 Then each node of the extracted network is related to the closest
150 node of the reference. A distance threshold determines if the pair
151 is acceptable or not. We set the threshold considering the base
152 DTM's resolution, the network extraction accuracy and the
153 length of the shortest distances between nodes in the network.

154 To adjust the matching to other networks or other terrains,
155 more geometric can be easily integrated in the distance matrix
156 calculation.

157 Unmatched nodes are put back into play at the next step. It
158 permits to soften strict class limits.

159 *Topological consistency checking*

160 Once a set of node pairs (T,R) is obtained, we check their
161 topological consistency. Each pair represents the same physical
162 node but in two different trees (T and R): these two
163 representations must have the same topological location
164 (upstream-downstream position) in their respective tree. Else,
165 inconsistent node pairs are rejected. The number of topologically
166 consistent pairs provides a quality criterion of the matching
167 process: if all pairs are topologically correct then the matching
168 completely succeeded. In the algorithm implemented, only the
169 topological consistency with the nearest neighbor was tested.

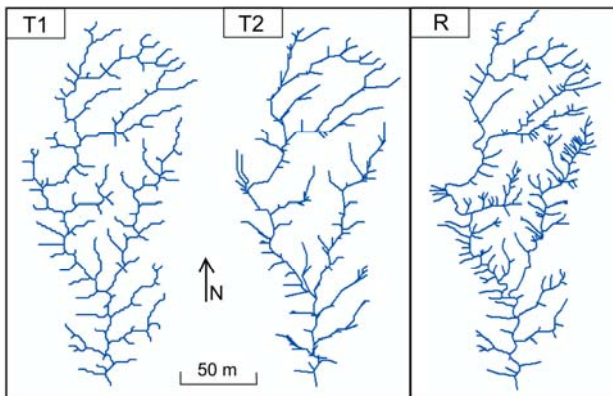
170 *Global similarity statistics*

171 Finally, simple global statistics are computed from the
172 matching. By analogy to Heikpe (1997), we count ratios of
173 matched nodes in T, and ratio of unmatched nodes for both the
174 extracted and the reference networks. In addition to global
175 analysis, these statistics can be computed for each matching step
176 what provide valuable arguments for the networks comparison.

177 RESULTS

178 *Material*

179 The method is applied to compare two extracted networks (T1
180 and T2) to a detailed reference network R (fig. 1) on a test-area of
181 the Draix experimental basins in French Prealps. The study area
182 corresponds to badlands area meaning that terrains are highly
183 dissected. Networks are extracted from a one-meter-resolution
184 airborne LiDAR DTM. The reference is a field-mapped network.



185
186 Figure 1. Comparing extracted networks (T1 and T2) to the ground-truth
187 network (R)

188 The extracted networks result from different extraction
189 method: T1 was extracted using Thommeret et al. (2010) method
190 that combines a morphological index and a drainage algorithm

191 (CI based network); T2 was obtained using the classical D8
192 algorithm (O'Callaghan et Mark, 1984).

193 *Hierarchical matching results*

194 In this particular case study, the distance threshold chosen is 2
195 m, considering that twice the resolution of the base DTM
196 approaches the data's planimetric noise. The extracted networks
197 have the same number of classes. Every node pairs of both
198 networks are topologically consistent.

199 The matching progression for CI based network and reference
200 is shown figure 2. We can distinguish for each step of the
201 matching the extracted nodes that find a reasonable pair (in red)
202 and those that are not matched (in green).

203 The hierarchical matching process provides step-by-step
204 results. Thus the results are sharper than with the global buffer
205 approach. Step-by-step results for the two extracted networks
206 show different extraction quality (fig. 2). For the CI based
207 network, unmatched nodes are localized in specific areas where
208 the DTM is less accurate. While unmatched nodes of the D8
209 network are dispersed in the space.

210 Global ratios coming from the matching are presented TABLE
211 1. For the CI based network, the matched nodes represent 87% of
212 the total number of nodes. For the D8 network, they represent
213 76%. Thus, the D8 network shows more over-detected nodes
214 than the other network.

215 TABLE I. QUANTITATIVE MATCHING RESULTS

| Networks | Total node number | Pairs | Unmatched nodes | |
|----------|-------------------|-------|-----------------|-----------|
| | | | Extracted | Reference |
| T1 | 200 | 174 | 26 | 170 |
| T2 | 238 | 181 | 56 | 162 |

216 DISCUSSION AND CONCLUSION

217 In this paper, we propose an interactive method to
218 quantitatively and automatically compare two networks of a same
219 area. The method aims to help assessing networks extracted from
220 DTM to a reference since more and more elevation data and
221 methods are available to automatically extract thalweg networks.

222 This method relies on hierarchical node matching. It is based
223 on an object-by-object approach which provides more controlled
224 results. The hierarchical approach helps comparing networks
225 represented at different scales. It helps distinguishing extraction
226 artifacts from unmatched nodes resulting from a scale difference
227 between the networks.

228 Results are satisfying and compliant to visual comparison.
229 This method provides results with clear significations that can be

230 directly interpreted: while the buffer method provides global
 231 results based on the network overlap, the proposed method
 232 supplies more significant and detailed results. Step-by-step
 233 matching maps observation helps qualifying the spatial
 234 distribution of extraction errors. The matching progression
 235 through the steps can be used to better characterize the networks
 236 adequacy along the network hierarchy. It provides another key to
 237 the assessment and the interpretation of the differences between
 238 the networks.

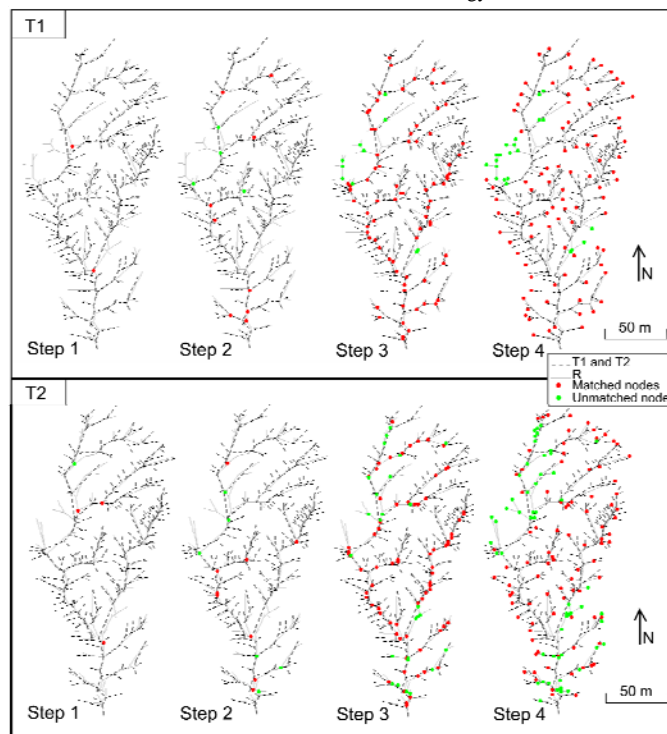
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 279 Figure 2. Matching progression through the different steps for the two extracted networks (T1 and T2)