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Georeferencing River Networks Using Spatial Reasoning

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ABSTRACT

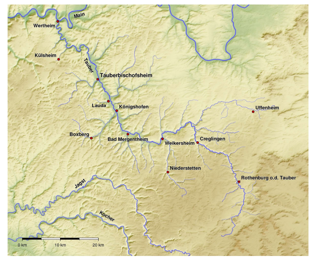
This paper is concerned with automatic georeferencing of river networks from raster images such as aerial photos or maps. Determining reasonable assignments between a given network of rivers derived from a textual description and an image is subject to high combinatorial complexity and uncertainty. We investigate the application of spatial reasoning in automatic georeferencing.

CCS CONCEPTS

• **Information systems** → *Geographic information systems*;

KEYWORDS

georeferencing river networks, spatial reasoning, GIS



…
• Brehmbach (l.), Tauberbischofsheim (18,3km)
• Edelbergshohle (r.), Tauberbischofsheim - Über der Tauberbrücke
• Fahrentalsgraben (r.), Tauberbischofsheim - Über der Tauberbrücke
• Leintalsgraben (l.), Tauberbischofsheim
• Steckenleitegraben (Beilbergsgraben) (r.), Werbach
  • Dockentalgraben (l.)
  • Tannengraben (r.)
    • Unterer Tannengrabe (l.)
• Welzbach (Altbach), (r.), Werbach (15,2km)
  • Bärlesgraben (l.)
…

Figure 1: Tauber river network as presented in Wikipedia (left: relief map; right: excerpt from textual description).

1 PROBLEM STATEMENT

There are search situations where a mapping and linkage of images and text based on a common geospatial context is beneficial, e.g. the labeling of image parts with information derived from texts. In this paper, we focus on structure and hierarchical information. As an example, we map river networks by identifying the river and its named tributaries in the image (s. Fig. 1). We want to know to which extent the task can be automated. Uncertainty in image and network description lead to ambiguous outcomes as discussed below, hence a high degree of automation eases semi-automated approaches. Moreover, in some situations, even an ambiguous result can be sufficient for answering a query at hand.

We assume a *raster image*, e.g. an aerial photo, a relief map (s. Fig. 1, left[1]), a schematic map (e.g. tourism map), or even a historic map, *and* a *textual (river) network description* (s. Fig. 1, right). Network structures must be identified and extracted from the image. For the moment, we use NEFI[2] [2]. Figure 2 gives an example of automated extraction and post-processing by means of joining nearby segments and simplifying the shape. Network extraction poses some challenges for a subsequent assignment step. Errors mainly arise from text labels misclassified as river segments. In general, handling the outcome of automatic identification has to consider that not all river segments are identified and that spurious detections can occur. Moreover, we cannot assume the availability of geographic coordinates, possibly even cardinal direction alignment remains unknown. On the other hand, deriving a network representation from text requires sophisticated information extraction (IE). Designing an IE pipeline (inspired from ontology generation, relation extraction, question answering, etc.) is future work. Here, an already structured textual river network description is used[3]. It may provide various kinds of information: the order of river junctions, the names of tributaries, information on which side a tributary joins, placenames of locations close to the tributaries, elevation information of those places, and length of tributaries. Some information is available on a qualitative level (e.g., left vs. right) and even quantitative information such as river length may not easily be matched against the image if scale remains unknown. Since information varies depending on which sources of information are available, a flexible approach which can handle all aspects of information available, but does not rely on the existence of a specific aspect is most useful. We apply qualitative spatial reasoning (QSR) [1]. It can flexibly handle abstract spatial information. We are particularly interested how spatial background information can be exploited to improve georeferencing.

2 THE QSR APPROACH

We explain how the problem of identifying rivers in a set of map-referenced river segments can be posed as a task of QSR and discuss

[1]Karte des Tauberverlaufs (https://commons.wikimedia.org/wiki/File:Reliefkarte_Tauber.jpg) by BerndH / CC BY-SA 3.0 (last visit: 2.11.17)

[2]Network Extraction From Images: http://nefi.mpi-inf.mpg.de/ (last visit: 2.11.17)

[3]Liste der Fließgewässer im Flusssystem Tauber: https://de.wikipedia.org/wiki/Liste_der_Flie%C3%9Fgew%C3%A4sser_im_Flusssystem_Tauber (last visit: 2.11.17)

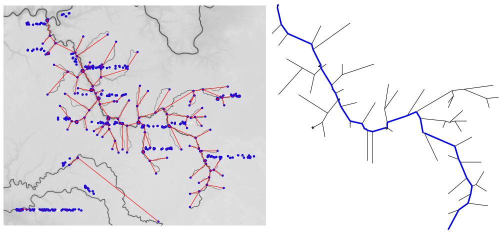


Figure 2: Left: Applying NEFI's default *webs* pipeline to river extraction of the map shown in Fig. 1. Right: Derived structure of main river (longest sequence, blue) and tributaries.

how QSR fosters the efficient computation of reasonable solution candidates. The approach we propose consists of two steps. First, given a raster image of a river system, we identify candidates for rivers and their tributaries. Second, we identify possible assignments of names to tributaries for each of the candidate and rank them. Assignments are required to respect the spatial configuration knowledge extracted from the textual description. Best-ranked solutions form the solution set. Since the assignment task is highly ambiguous if several tributaries have to remain unassigned, background knowledge of relative lengths and locations is crucial to arrive at a reasonably sized set of solution candidates.

Network Extraction: Let a set of potential river segments extracted from the input image be given, for example using NEFI. Already at this stage, background knowledge can contribute to interpret a set of potential segments in terms of a river structure. We characterise reasonable interpretations by two properties:

- rivers and their tributaries form a connected set of directed segments, called dipoles
- rivers are not shorter than any of their tributaries

We proceed as follows. First, we determine the largest connected component of segments and then recursively identify main river and tributaries by searching linear chains of segments which are of maximum length in image space. To accommodate for uncertainty in measured length, sets of tributary candidates are computed, each one represented as a sequence of dipoles. Observe that two different candidates may contain a joint sub-sequence of dipoles. This appears unavoidable if one wants to ensure that any reasonable tributary candidate is considered. During assignment, we thus have to consider that tributaries are matched against disjoint candidates.

Spatial Reasoning for Identifying Tributaries: QSR [1] is a subfield of knowledge representation and reasoning which is involved with relational languages (also called constraint languages) using finite sets of basic relations. The field is particularly considered with techniques for inferring new pieces of information given a set of relational statements. For example, from statements "C is located downstream of B" and "B is located downstream of A", one is able to derive that C is also located downstream of A. A set of such statements is also called a set of *constraints*. If contradicting information can be derived from a set of constraints, it is called inconsistent, for example if A is required to be downstream and upstream of B at the same time. In [5], an approach is presented that employs this form of reasoning to prune off candidates in a matching task which would lead to an inconsistent configuration.

The benefit of applying qualitative reasoning is mainly of computational nature as it allows discarding matching candidates early in the assignment process, but it also fosters flexibility with respect to using different aspects of information. In order to apply this technique, we have to characterise possible matchings using constraints. To this end, we employ two qualitative representations, one capturing the configuration of segments using dipole relations [3] and another order of magnitude comparison $<, =, >$ [4] for relating stream order of joints and relative lengths of tributaries:

(1) Every tributary candidate given as sequence of dipoles is represented as a single dipole by connecting the start point of the spring segment to the end point of the mouth segment. This yields a set of candidate dipoles C. We record whether two candidate dipoles are derived from a shared sequence.
(2) All dipole relations and length comparisons are determined for tributary candidates C based on locations on the map.
(3) For every tributary mentioned in the textual description, we introduce a dipole which constitute a set T.
(4) For every tributary $t \in T$, we establish a constraint stating from which side (left or right) the tributary flows into the river using a dipole relation.
(5) For every pair of tributaries $t_1, t_2 \in T$, we introduce a constraint $t_1 < t_2$ if t_1 is known to join the river upstream of t_2.
(6) For every pair of tributaries $t_1, t_2 \in T$, a disjointness relation is stated to enforce disjointness of associated candidate dipoles.

The task of identifying tributaries in the map can now be posed as task of computing a partial matching of sets C and T such that the constraints imposed on C and T are not contradicting (cp. [5]). Any matching determined thus respects stream ordering, side of the tributary, and the relative length of tributaries. In a last step, we rank solution candidates by the percentage of tributaries and raw segments assigned, maximising the amount of entities matched.

3 OUTLOOK

First experiments indicate the effectiveness of spatial reasoning to prune off unreasonable interpretations. From an average degree of ambiguity per tributary candidate of 9 when aiming to identify the nine longest tributaries in the map depicted, exploitation of stream order reduces ambiguity to 2.44; further consideration of length constraints reduces this even more, immediately below 2.0 (i.e. several tributaries get identified unambiguously). We plan to evaluate and improve the effectiveness of our approach on various datasets (i.e. historic maps, VGI). Furthermore, we want to extend it to other domains such as historic route networks.

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