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Verification of road databases using multiple road models

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ABSTRACT

In this paper a new approach for automatic road database verification based on remote sensing images is presented. In contrast to existing methods, the applicability of the new approach is not restricted to specific road types, context areas or geographic regions. This is achieved by combining several state-of-the-art road detection and road verification approaches that work well under different circumstances. Each one serves as an independent module representing a unique road model and a specific processing strategy. All modules provide independent solutions for the verification problem of each road object stored in the database in form of two probability distributions, the first one for the state of a database object (*correct* or *incorrect*), and a second one for the state of the underlying road model (*applicable* or *not applicable*). In accordance with the Dempster-Shafer Theory, both distributions are mapped to a new state space comprising the classes *correct*, *incorrect* and *unknown*. Statistical reasoning is applied to obtain the optimal state of a road object. A comparison with state-of-the-art road detection approaches using benchmark datasets shows that in general the proposed approach provides results with larger completeness. Additional experiments reveal that based on the proposed method a highly reliable semi-automatic approach for road data base verification can be designed.

1. Introduction

1.1. Motivation

Road databases have a large economical relevance, e.g. as the basis for navigation systems, for urban planning and for emergency services. Thus, the providers of road databases spend large efforts to keep them up-to-date. A review of related work shows that, even after decades of research, developing automatic approaches for database update is still a challenging task, while breaking down the problem into two sub-tasks, i.e., the *verification* and the *detection of missing roads*, allows promising simplifications, e.g. (Gerke and Heipke, 2008; Poulain et al., 2010). Both subtasks induce specific strategies that exploit the knowledge given with the original database in different ways. The scope of this paper is *automatic road verification* based on remote sensing data. In the *verification* step one needs to check whether the objects in a database also exist in current imagery and if so, whether they have the required positional accuracy. Thus, in principle, *road verification* corresponds to a well-known problem of object classification, applied to specified image subsets.

Our method fits into a semi-automatic framework similar to (Helmholz et al., 2012), where a human operator checks road objects that the automatic verification component indicates as *incorrect* together with candidates for *missing roads* provided by another method. Helmholz et al. (2012) demonstrated that focusing the human operator on the interesting spots significantly reduces the manual efforts while ensuring the correctness of the updated road database to be high (97%). As road databases mostly have such high quality standards and considering the fact that road databases are typically maintained at a national or even global level, the main difficulty is to develop an automatic component that delivers a high correctness in many different situations. Current methods for road detection are usually tailored to specific circumstances, e.g. rural or urban areas, and typically do not achieve sufficiently high quality standards.

1.2. Contributions

In this paper we present a method for the automated verification of road objects from a database using remote sensing data. The main scientific contributions of the paper can be summarized as follows:

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- By combining up to ten existing road detection techniques (referred to as *verification modules* in this paper), our method is *more general* than existing ones. Whereas each module is based on a specific road model tailored to specific circumstances, our combined solution is able to deal with roads in a very large variety of surroundings, and consequently, it can deliver higher success rates than the state-of-the art in inhomogeneous environments. Nevertheless, our framework is *flexible*, because the actual number of verification modules can be adapted.
- We present a *new consistent framework for decision-level fusion* of the outputs of all verification modules based on the Dempster-Shafer theory (DST). This is the methodological core of our method, and it is the reason why our solution is flexible and why it can be expanded by new modules easily. It also forms the basis for *self-diagnosis* by indicating situations in which none of the individual models is applicable, considered by an additional decision state (*unknown*) in our approach.
- We have developed a *new and unified statistical reasoning framework for modelling the uncertainty* of the output and the *applicability* of each verification module. In this context, we combine the probabilistic output of each module, indicating the uncertainty of the module's decision, with an additional uncertainty measure based on an analysis of the *applicability* of the respective model to a given situation, which is used to control the module's impact on the overall result. This unified framework for describing the *model applicability* is another major methodological contribution.
- For each module we define features that can be derived from the data which indicate whether a model fits to the current situation or not and which are used to derive a conditional probability for its applicability to the current situation. Whereas we do not claim to have developed new modules or significantly improved the existing ones, such a systematic probabilistic analysis of the applicability of the individual techniques has not been carried out so far.

1.3. Structure of this paper

In the next section, the state-of-the-art in road detection and road database verification is reviewed. In Section 3 we describe the general fusion framework. The individual verification modules are presented in Section 4, with a focus on the definition of the respective uncertainty and applicability measures. Section 5 describes an extensive set of experiments with datasets of different geographical regions. Conclusions and recommendations for future work are given in Section 6.

2. Related work

The objective of this work is road verification, which requires the detection of roads in the imagery in the first place. Hence, the first part of this review is about road detection approaches. Existing work on *road database verification* is dealt with in the second part.

2.1. Road detection

Automatic road detection is a well-studied problem (Mena, 2003; Mayer, 2008). Existing road detection approaches can be characterised by their underlying *road models*. A significant group of approaches models roads as *lines* of more or less constant brightness and width (Steger, 1998). Introducing thresholds for curvature and width allows the detection of different road types (Wiedemann and Ebner, 2000). Line models usually focus on imagery with a ground sampling distance (GSD) of about 1–2 m, either using panchromatic images (Wiedemann and Ebner, 2000), nDSM[1] images (Hinz and Baumgartner, 2003), NDVI[2] images (Gerke and Busch, 2005), or Synthetic Aperture Radar (SAR) data (Tupin et al., 1998). The algorithms applied in this context include the Steger line detector (Steger, 1998), the wavelet (Gruen and Li, 1995), Radon (Zhang and Couloigner, 2006) and Hough transforms (Hu et al., 2004), active contours (Peng et al., 2010) and statistical sampling (Chai et al., 2013). Higher resolution imagery (GSD $\leqslant$ 0.5 m) allows the use of more sophisticated models. For instance, roads can be modelled by *pairs of parallel edges* of known distance (Heipke et al., 1995; Ruskoné and Airault, 1997). Road models tailored for an urban context have been proposed on the basis of *colour* (Zhang and Couloigner, 2006), *texture* (Haverkamp, 2002) and *edge alignment* (Youn et al., 2008). *Colour-based models* have been used by methods based on maximum likelihood estimation (Doucette et al., 2001), expectation maximization (Poullis and You, 2010), support vector machines (SVM) (Fujimura et al., 2008) and k-means clustering (Zhang and Couloigner, 2006). Another information source is tapped by *context models* for roads, based on the relations of roads and *context objects* such as *buildings* (Poulain et al., 2010), *trees* (Gerke and Heipke, 2008), *low vegetation* (Zhang, 2004), *road markings* (Hinz and Baumgartner, 2003) and *cars* (Grote et al., 2012). Finally, roads have been modelled as parts of larger *road networks*, which implies that roads never appear as isolated parts (Zhang and Couloigner, 2006) or connect places at relatively short distances (Baumgartner et al., 1999), or that roads form a graph with a certain connectivity (Chai et al., 2013).

Some models are based on statistics whereas others rely on heuristics or expert knowledge. Statistical definitions are better suited for models that rely on more specific (image and scene-dependent) properties of roads, such as *colour* (Fujimura et al., 2008) or *texture* (Mena and Malpica, 2005), whereas heuristics are preferred when dealing with general road properties, e.g. constant road width (Steger, 1998), the parallelism of the road borders (Heipke et al., 1995) or the fact that the road surface is situated on the terrain (Zhang, 2004). Context models have been defined on a statistical basis in the form of Bayesian inference (Gerke and Heipke, 2008), neural networks (Mnih and Hinton, 2010), conditional random fields (Montoya et al., 2015) and point processes (Chai et al., 2013), or based on heuristics in form of semantic nets (Zhang, 2004) and fuzzy rule sets (Grote et al., 2012; Hinz and Baumgartner, 2003).

For each basic model numerous strategies have been developed and tested. Despite the differences between implementations, the applicability of a method is mainly restricted by its basic model. For example, Mayer et al. (2006) showed that *line models* are only applicable in rural areas with homogeneous background, whereas *colour models* may also work in an urban context if the colour of roads and building roofs are sufficiently different.

Many authors combine several of the basic models described previously. This can be achieved by aggregating the respective features spaces, e.g. integrating *colour*, *texture* and *context* properties, which is a straight-forward extension for statistical approaches (Mnih and Hinton, 2010; Zhang and Couloigner, 2006). However, this may lead to a higher computational complexity, and it may require an increased amount of training data. An alternative is to combine different more or less independent road detection methods. An example for such an approach that integrates statistical and heuristic methods is (Bacher and Mayer, 2005), where the results of a very restrictive heuristic method provide the training

[1] Normalised Digital Surface Models (nDSM) contains the height above the ground.
[2] The Normalised Difference Vegetation Index (NDVI) is frequently used to represent the vitality of the vegetation. It is based on the different reflections in the red and the infrared channel of a multispectral image.