ISPRS Journal of Photogrammetry and Remote Sensing 97 (2014) 204–218

Contents lists available at ScienceDirect

ISPRS Journal of Photogrammetry and Remote Sensing

journal homepage: www.elsevier.com/locate/isprsjprs

Semi-automatic verification of cropland and grassland using very high resolution mono-temporal satellite images

Petra Helmholz [a,*], Franz Rottensteiner [b], Christian Heipke [b]

[a] Department of Spatial Sciences, Curtin University of Technology, GPO Box U1987, Perth, WA 6845, Australia
[b] IPI – Institute of Photogrammetry and GeoInformation, Leibniz Universität Hannover, Nienburger Str. 1, 30167 Hannover, Germany

ARTICLE INFO

Article history:
Received 8 May 2014
Received in revised form 6 August 2014
Accepted 12 September 2014
Available online 8 October 2014

Keywords:
Automation
GIS
Quality control
Verification
Mono-temporal
Satellite images

ABSTRACT

Many public and private decisions rely on geospatial information stored in a GIS database. For good decision making this information has to be complete, consistent, accurate and up-to-date. In this paper we introduce a new approach for the semi-automatic verification of a specific part of the, possibly outdated GIS database, namely cropland and grassland objects, using mono-temporal very high resolution (VHR) multispectral satellite images. The approach consists of two steps: first, a supervised pixel-based classification based on a Markov Random Field is employed to extract image regions which contain agricultural areas (without distinction between cropland and grassland), and these regions are intersected with boundaries of the agricultural objects from the GIS database. Subsequently, GIS objects labelled as cropland or grassland in the database and showing agricultural areas in the image are subdivided into different homogeneous regions by means of image segmentation, followed by a classification of these segments into either cropland or grassland using a Support Vector Machine. The classification result of all segments belonging to one GIS object are finally merged and compared with the GIS database label. The developed approach was tested on a number of images. The evaluation shows that errors in the GIS database can be significantly reduced while also speeding up the whole verification task when compared to a manual process.

1. Introduction

Many public and private decisions rely on geospatial information. Today, geospatial data are stored and managed in Geospatial Information Systems (GIS). The smallest semantic unit of a GIS database is an *object*, typically belonging to exactly one object class. The definition of these classes is given in the GIS object catalogue. In order for a GIS to be generally accepted, the underlying data need to be of high quality. As a consequence, quality control of GIS data has become increasingly important. In practical use quality control of GIS databases is still often performed manually (Krickel, 2010).

According to the ISO standard *quality* is defined as the "degree to which a set of inherent characteristics fulfils the requirements" (ISO 9000, 2005, page 18). There are five important measures for quality of GIS data: *logical consistency*, *completeness*, *positional accuracy*, *temporal accuracy* and *thematic accuracy* (ISO 19113, 1999). Only the logical consistency can be checked without a comparison of the GIS data with the *real world* as it is represented for instance in aerial or satellite images. We call the step of comparing the GIS database content with the *real world* (as represented in these images) and highlighting differences the *verification* of the GIS database (see Gerke and Heipke, 2008 for a detailed discussion of the related terminology). Our work focuses on *thematic accuracy* (sometimes also called *semantic accuracy*) which indicates the percentage of objects in a GIS database with a correct class label. While checking the *thematic accuracy* the *temporal accuracy* is simultaneously checked, too. The *temporal accuracy* indicates whether the class label of the GIS objects are correct at a specific point in time. We do not deal with *completeness* in our work, and we assume that the *positional accuracy* of the database is good enough for our purposes.

In this paper, we describe a novel method for the semi-automatic verification of cropland and grassland GIS objects using ortho-rectified *mono-temporal* very high resolution (VHR) multispectral satellite images with a ground sample distance (GSD) of approximately 1 m. The verification is based on image classification and a subsequent comparison of the classification results with the GIS database

* Corresponding author.
E-mail addresses: petra.helmholz@curtin.edu.au (P. Helmholz), rottensteiner@ipi.uni-hannover.de (F. Rottensteiner), heipke@ipi.uni-hannover.de (C. Heipke).

http://dx.doi.org/10.1016/j.isprsjprs.2014.09.008
0924-2716/

information. Our main goal is to significantly reduce the percentage of incorrectly labelled objects in the GIS database. At the same time the manual effort required for the quality assessment should be reduced to a minimum.

The classes cropland and grassland are of special interest for society at large, as they contribute to the food supply of the population. The verification of cropland and grassland is a complex problem. Firstly, cropland can have very different appearance throughout the year (e.g. covered by bare soil or by different growth stages of vegetation). Secondly, GIS objects as defined in the object catalogue can contain several fields, which need to be analysed individually during the verification process. The GIS object catalogue also defines the smallest object which should be contained in the GIS data, the so called minimum mapping unit (MMA). Applying the MMA leads to a certain generalisation of the GIS data: objects smaller than the MMA are merged with neighbouring objects. This generalisation effect introduces differences between the GIS data and the image content, which has to be taken into account during verification, and which is considered by our method.

The paper is structured as follows. In Section 2 we discuss approaches dealing with the classification and quality control of cropland and grassland objects, including a brief introduction of the algorithms and features used for this task. In Section 3, our new approach for the verification of cropland and grassland objects is described. A detailed evaluation follows in Section 4. The paper concludes with a discussion and an outlook in Section 5.

2. Related work

2.1. Classification of agricultural areas

As mentioned above, verification is based on classification. In this section we therefore give a short overview of image classification approaches, in particular those used for agricultural areas. We restrict the discussion to mono-temporal VHR images.

The vast majority of papers dealing with the classification of agricultural areas are based on supervised classification algorithms such as *Maximum-Likelihood* (e.g. Warner and Steinmaus, 2005), *Decision Tree algorithms*, especially the C5-approach (e.g. Ruiz et al., 2007), *Random Forest* (e.g. Toscani et al., 2013), *rule-based* approaches (e.g. Schlager et al., 2013), *Markov Random Fields* (e.g. Busch et al., 2004), and *Conditional Random Fields* (e.g. Hoberg et al., 2012).

Support vector machines (SVM; Vapnik, 1998) have been used for a wide range of classification tasks (Nemmour and Chibani, 2006; Fujimura et al., 2008; Büschenfeld, 2013), but not yet for the classification of the agricultural classes cropland and grassland. One of the main advantages of SVM classification is that the SVM can handle spatially separated clusters of one and the same class in feature space. This makes SVM particularly well-suited for the classification of cropland which comes in different appearances, because different crops grow at different times during the year.

One way to categorise classification methods is to differentiate between object-based and pixel-based classification (Blascke, 2010), where the term *object* (in particular in the literature concerning the so called geographic object based image analysis – Geobia) is often used for the results of a segmentation step. In this paper we call such results *segments*, the classification of segments is consequently referred to as *segment-based classification* – while the term *object* is exclusively used for the smallest unit of the GIS database – a GIS object.

For the classification of agricultural areas Trias-Sanz (2006) and Ruiz et al. (2007) used segment-based approaches, while pixel-based methods were employed e.g. by Wassenaar et al. (2002), Warner and Steinmaus (2005) and Hoberg et al. (2012). There are two main advantages of a segment-based classification. Firstly, features describe the whole segment and not only a single pixel and its immediate neighbourhood. Therefore, segment-based classification represents an integral approach, typically resulting in more robust features. Secondly, some features can only be calculated for a segment, e.g. features describing the segment size, form or structures within a segment. On the other hand, because the features describe the whole segment in an integral way, segment borders and therefore possible segmentation errors have a direct influence on the classification. In contrast, pixel-based classification is (obviously) not influenced by segmentation errors.

Different types of features are typically used for the classification of agricultural areas, namely spectral, textural, structural and geometric features. *Spectral features* alone do not have too much value for mono-temporal image classification of agricultural areas due to the ever-changing vegetation (e.g. Pakzad et al., 2001); however, they can be used in combination with other features, see e.g. Ruiz et al. (2007). *Textural features* are used e.g. by Rengers and Prinz (2009), who classified different classes including cropland and grassland using features derived from the *Normalised Gray-Tone Difference Matrix* (NGTDM; Amadasun and King, 1989). Although colour images were available, spectral features were not used. Furthermore, the authors only used a simple chess-board-segmentation to consider the possibility of different fields in cropland objects. The borders of these segments did not correspond to the actual field boundaries, which can lead to additional problems.

Compared to approaches using only spectral or only textural features, those using only *structural features* for the analysis of agricultural areas can be found more frequently in the literature. Structural features describe explicit structure elements like lines. Trias-Sanz (2006) used structural features for the classification of tilled and untilled cropland as well as objects belonging to other classes of a field boundary cadastre. The classes were differentiated by the number of main tilling directions and the distances between the tilling tracks which were calculated using a semi-variogram. The author achieved an overall accuracy of 95%. The approach is suitable for the classification of the separate classes cropland and grassland, as long as those classes themselves are homogeneous. Problems occur with heterogeneous regions, e.g. if the distances between the tilling directions vary. In addition, a field boundary cadastre is often not given. Warner and Steinmaus (2005) use autocorrelation to identify orchards and vineyards in IKONOS panchromatic images. This method achieved an overall accuracy of 95.5%. However, it assumes the image structure to be regular (e.g. rows of plants should have an equal spacing), which is not always the case for cropland.

Most frequently a *combination of different types of features*, incl. also *geometric features* such as size, compactness or elongation, is used for the classification of agricultural areas. The combination of spectral and textural features has been shown to yield superior results compared to only using spectral features for multispectral imagery with a GSD of 2 m (Gong et al., 2003). A combination of spectral and geometric features was used in (Peled and Gilichinsky, 2010) for the classification of agricultural areas, forest and water. The authors achieved an overall accuracy of 83.6%, however, only 62.0% of the agricultural areas could be classified correctly.

The most promising approach is a combination of features from more than two groups. Such approaches were used for the segment-based classification of different classes such as cropland, shrub, forest and citric plantations of a field boundary cadastre (e.g. Ruiz et al., 2007). The authors used multispectral images with a GSD of 0.5 m and achieved an overall accuracy of at least 90%. Since a segment-based approach was pursued, the results are prone to segmentation errors.