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An automated mathematical morphology driven algorithm for water body extraction from remotely sensed images

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ABSTRACT

The detection and extraction of water bodies from satellite imagery is very important and useful for several planning and developmental activities such as shoreline identification, mapping riverbank erosion, watershed extraction and water resource management. Popular techniques for water body extraction like those based on the normalized difference water index (NDWI) require reflectance information in the green and near-infrared (NIR) bands of the light spectrum. Moreover, some commonly used approaches may perform differently according to the spatial resolution of the images. In this regard, mathematical morphological (MM) techniques for image processing have been employed for spatial feature extraction as they preserve edges and shapes. This study proposes a flexible MM driven approach which is very effective for the extraction of water bodies from several satellite images with different spatial resolution. MM provides effective tools for processing image objects based on size and shape and is particularly adapted for water bodies that have typically specific spatial characteristics. In greater details, the proposed extraction algorithm preserves the actual size and shape of the water bodies since it is based on morphological operators based on geodesic reconstruction. Moreover, the choice of the filter size (called structural element (SE) in MM) in the proposed algorithm is done dynamically allowing one to retain the most precise results from different set of inputs images of different spatial resolution and swath. The availability of more than one spectral band of satellite imagery is not necessary for the proposed algorithm as it utilizes only a single band for its computation. This makes it convenient to apply in single band imageries obtained from satellites such as Cartosat thereby making the proposed approach effective over commonly used methods. The accuracy assessment was carried out and compared with the maximum likelihood (ML) classifier and methods based on spectral indices. In all the five test datasets, extraction accuracy of the proposed MM approach was significantly higher than that of spectral indices and ML methods. The results drawn from visual and qualitative assessments indicated its capability and efficiency in water body extraction from different satellite images.

1. Introduction

Water is one of the most common and dynamic natural resource for the environment, which plays a vital role in social development, human life and climatic variation. Fast and accurate identification of water bodies from satellite images is of great importance due to its utility in several applications such as water resources development, land use planning, wetland protection, lake change detection, flood prediction and evaluation. Precise extraction and automatic identification of water bodies are of great importance in present times. Remote sensing data have been extensively used for automatic extraction of features over the recent years (de Castro and Centeno, 2010; Rishikeshan and Ramesh, 2017a). With the rapid increase of remote sensing data with a pace of gigabytes on a daily basis, the need for robust and automated tools for retrieval, management and processing of data for effective exploitation has also increased (Aptoula, 2014; Moser et al., 2018). However, the manual investigations of large geographical areas require to process numerous images which turn to be an expensive and time-consuming operation (Munyati, 2000). Automated feature extraction can significantly reduce the time and cost involved in data processing and can update databases effectively with a minimal turnaround time (Rishikeshan and Ramesh, 2017b; Momm and Easson, 2010). This is especially significant in remote sensing (RS) applications due to varying attributes like sensor fluctuations, changes in spectral and spatial resolutions, alteration of atmospheric conditions between images, and different targeted features of interest. The increased availability and

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accessibility of RS images free of charge with varying spatial and temporal resolutions and worldwide coverage gives the prospective of monitoring lake water locations at broader spatial coverage and wider timescales (Song et al., 2014).

Most of the remote sensing water body extraction strategies proposed in the literature are based on geography, satellite imagery used or the category of the feature to be extracted, rather than a general approach. Existing approaches may underperform for coarser resolution imagery and may require reflectance information in specific spectral bands such as NIR or green of the satellite imagery. In the traditional classification techniques (except object-based classifications), only the digital numbers of pixels are considered; but with MM strategies, one can additionally consider shape, neighborhood, size and other features of an object within the image. According to the latest available literature, a very limited number of MM based methods provide an option to feed structural element (SE) size dynamically (Tickle et al., 2013; Bartovský et al., 2014; Bartovský et al., 2015; Dalloo and Garcia-Ortiz, 2016). Such methods based on adaptive SE size provide a flexibility to work with different resolution images. Especially for water body extraction none of the state-of-the-art methods present this feature. The present study attempts to develop an MM based algorithm on a single spectral band image. This algorithm uses core MM concepts and provides flexibility to work with different resolution imageries by reconstruction-based operations to preserve the actual size and shape of the objects in the extracted output.

The rest of this paper is organized as follows. In Section 2, related works are briefly presented and discussed. Section 3 presents basic notations, definitions of MM operations that are necessary to undertake the analysis. Section 4 is devoted to the description of important datasets used and methodology for the present study. This section also explains the methodological flowchart and algorithmic steps of the present study. Experimental results obtained from the proposed MM algorithm and that of existing methods in the literature such as ML classifier and spectral indices are discussed in Section 5. Finally, Section 6 contains the concluding remarks of the paper.

2. Related works

A brief review of remote sensing methods used for lake feature extraction has been published by Jawak et al. (2015). The authors pointed out that misclassification of dark pixels in feature extraction accounts for most of the inaccuracies in lake identification. This is observed particularly in rough terrains (where shadows are cast), where dark pixels occur. Similarly, Song et al. (2014) discussed the factors leading to inaccuracies when detecting lakes such as water-level variations from multisource satellite imagery and studied the uncertainties in mapping the characteristics of glacial lakes by means of RS strategies. A texture analysis based water extraction method without using spectral characteristics of water was proposed by Wang et al. (2008). This algorithm works well with high-resolution panchromatic imagery, but changes in spatial resolution affect its performances. Li et al. (2011) proposed a more complicated oscillatory network-based algorithm for water body extraction. This oscillation network could bind an object based on similar property. NDWI is used to encode the binding of pixels of water bodies. Similarly, Luo et al. (2010) used Landsat TM images and presented an approach consisting of classification, global-scale and local-scale segmentation for water extraction, which yielded better results.

McFeeters (1996) suggested an NDWI assisted approach (Eq. (1)) for surface water extraction using raw DN (digital Number) of Landsat imagery by imposing a threshold value of zero, where all negative NDWI values were categorized as non-water and all positive values as water. However, Xu (2006) later on suggested that the NDWI is affected by radiations from built-up surfaces and a threshold of zero on the NDWI does not allow to discriminating water pixels from built-up surfaces. Therefore, the author modified the approach of McFeeters (1996) based on the NDWI and replaced the NIR band (0.77–0.90 μm) by MIR band (1.55 to 1.75 μm) of Landsat imagery while keeping the green band (0.52–0.60 μm) unchanged, and named this as Modified NDWI (MNDWI) (Eq. (2)).

$$\mathrm{NDWI} = \frac{\mathrm{Green}-\mathrm{NIR}}{\mathrm{Green}+\mathrm{NIR}} \tag{1}$$

$$\mathrm{MNDWI} = \frac{\mathrm{Green}-\mathrm{MIR}}{\mathrm{Green}+\mathrm{MIR}} \tag{2}$$

The use of the NDWI approach maximizes the reflectance properties of water by minimizing the low reflectance of the NIR band and maximizing the reflectance in the green band (McFeeters, 1996; Xu, 2006). Several studies indicate that this method yields better results for deeper parts and worse results for shallower parts of the water bodies. Among the existing methods, MNDWI is one of the most broadly used water indices for diverse applications.

A novel Automated Water Extraction Index (AWEI) was proposed by Feyisa et al. (2014) to refine the accuracy of classification containing dark and shadow regions in images where existing classification strategies fail to correctly discriminate among different land covers. Performance of the classifier was matched with that of the MNDWI and Maximum Likelihood (ML) classifiers. Duong (2012) showed that the spectral pattern examination of red, green, shortwave infrared (SWIR) and NIR bands are very useful for water body extraction. Supervised classification presents more accurate and reliable output than unsupervised methods but differs with higher resolution data. Nevertheless, supervised techniques require sufficiently large spectral training data sets that are not fully automated and do not account for the spatial features of the objects (Mishra and Prasad, 2015).

Object-based methods for water body extraction were discussed by several researchers (Yue et al., 2010; He et al., 2016; Kaplan and Avdan, 2017). A detailed study on object-based image analysis for remote sensing datasets was conducted by Blaschke (2010). In contrast, numerous studies were carried out using object-oriented segmentation and classification methods for automated delineation of lakes (Selmes et al., 2011; Sundal et al., 2009; Johansson and Brown, 2013). Several studies have shown the advantages of object-based classification over pixel-based classification, while devoting lesser attention to their potential limitations (KampourakiWood and Brewer (2008); Hay and Castilla, 2008; Blaschke, 2010). The advantages and limitations of an object-based approach for remote sensing image classification relative to a pixel-based approach were assessed in Desheng and Fan (2010). Hay and Castilla (2006) discussed the limitations of object-based methods, there still exists a limited understanding of spatial scale and hierarchical relations among objects derived at different resolutions and hence there is a lack of consensus and research on the conceptual foundations of an object-based image analysis (OBIA) paradigm. Two categories of errors often found in image segmentation are over-segmentation and under-segmentation (Möller et al., 2007; KampourakiWood and Brewer (2008)). Segmentation accuracy and the overall effect of object-based classification are both dependent on the scale of image segmentation (Addink et al., 2007; Benz et al., 2004; Kim et al., 2009). This is one of the typical limitations of object-based methods.

MM techniques are popular in remote sensing because of their capacity to process, denoise and segment objects of different textures and complete edges, which is very useful for extracting features (Kowalczyk et al., 2008). Several image processing algorithms used for the extraction of image shape features by employing various shape-structuring elements are based on the theory of mathematical morphology (Shih et al., 1995, Kupidura, 2013). These processing techniques have proven to be useful for numerous computer-vision tasks in binary and grey scale images, such as noise suppression, edge detection, skeletonization, image enhancement and pattern recognition (Ortiz et al., 2002).

The morphological profile (Ghamisi et al., 2015) is a powerful tool