A NEW ROBUST METHOD FOR BRIDGE DETECTION FROM HIGH RESOLUTION ELECTRO-OPTIC SATELLITE IMAGES

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ABSTRACT:

In this paper, an automatic approach for identifying bridges over water in satellite images is proposed. The proposed algorithm has three main steps. It starts with extracting the water regions in the satellite image by thresholding the NIR and clustering the NDWI images. Next possible river and water canals in the extracted water mask are identified by certain geometric constraints. Finally possible bridge regions are extracted by morphological operations applied to the water and river-canal mask. An optional step for verifying the bridge regions are also proposed in the study. The verification step uses orientation information or road mask for obtaining higher precision values. Tests are conducted using the proposed approach on different satellite images and quantitative and visual results showed that algorithm is successful in identifying different sized bridges over water.

1. INTRODUCTION

Locations of bridges are important for city-region planning and GIS applications to ensure an up to date geographical database. They may be used for monitoring the traffic network in emergency cases such as natural disasters and traffic accidents. Bridges are also critical for military applications since they are highly strategic points. The purpose of this study is to automatically identify bridges over water in high resolution multispectral satellite images.

Bridge extraction from satellite images is not studied extensively in the literature. In the study by Luo et. al., 2007, a knowledge based and supervised approach to extract bridges from IKONOS panchromatic data, using a GMRF-SVM classification method to extract water regions is utilized which is followed by image thinning, removal of fragmented lines, trunk detection using width characteristics, vectorization and feature expression. In a study which focuses on all type of bridges, a supervised approach is proposed which uses neural networks where radiometric, textural and geometrical attributes of each pixel is considered (Triaz-Sans & Lomenic, 2003). There are other works that make use of context knowledge in addition to data extracted from the input image. Using the well known facts about bridges, a rule base is constructed and bridges are extracted according to these rules. In such a study, the image is classified into three classes, water, concrete and background (Chaudhuri & Samal, 2008). Then bridge regions are extracted using this classification results and a knowledge-based approach that exploits the spatial arrangement of bridges. In the study by Gu et. al., 2011, water areas are found using segmentation and possible river mask is extracted from the water regions. Following this step, possible bridge regions are extracted using prior knowledge then verified using geometric constraints. There also exist works in literature which utilize elevation data. For example, in a study, InSAR data is used for feature extraction and visualization of bridges (Soergel et. al., 2008). In this work, the elevation information (DEM) extracted from SAR data is combined with an orthophoto. In the work by Schulz et. al., 2007, the special signature of bridges that emerge in SAR images are utilized for identifying bridge regions. In another study which utilizes elevation information, LIDAR data is used for extracting bridges (Sithole & Vosselman, 2006). This work employs the topological information that exists in the cross-sections to identify seed bridge points. Then these extracted seeds are utilized for detecting individual bridges.

2. METHOD

2.1. Data

In this study, IKONOS satellite images with 1 meter panchromatic and 4 meters multispectral resolution and GEOEYE images with 0.5 panchromatic and 2 meters multispectral resolution are used for automatically extracting bridges over water. The reflectance values for the images are 11 bits. The multispectral bands for the images are Blue, Green, Red and Near Infrared (NIR). Pan-sharpening is applied on the images to fuse the data present at panchromatic and multispectral bands. The tests are conducted using those pan-sharpened images. Example IKONOS and GEOEYE pan-sharpened images are shown at Figure 1.

a) b)

Figure 1 Example Satellite Images a) IKONOS b) GEOEYE

2.2. Proposed Algorithm

This study focuses on identifying bridges over river and water canals. In this study, all the information needed for identifying bridges is extracted from the electro-optic images.

The proposed algorithm starts by identifying the possible water regions in the image. The extracted water mask is then filtered by taking into account the connected components geometric properties to identify the river and water canal regions. Following this step, the bridge regions in the image are extracted using the water mask and river-water canal mask. The verification step could also be added for better precision results. In this step, the identified bridge regions are verified using the geometric constraints of bridges and orientation information. Also, road mask could be used for further verification, since the continuity of road mask on the bridges should be ensured. Flow chart of the proposed algorithm is depicted in Figure 2.Aforementioned steps will be explained in this section.

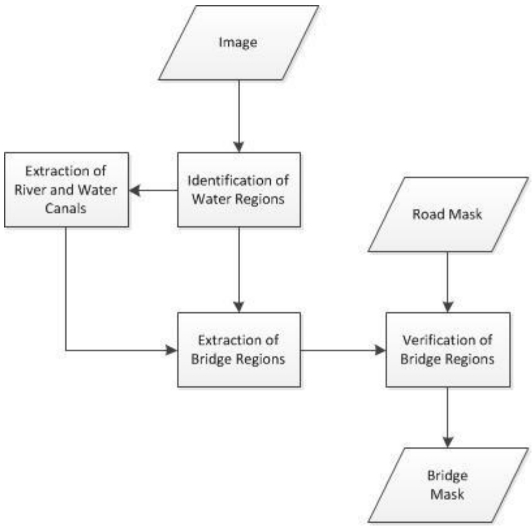

Figure 2 Flow Chart of the Proposed Approach

2.2.1. Identification of Water Regions: Even though identification of water regions in satellite images is an extensively studied subject, the different spectral characteristics of satellites and atmospheric differences at satellite images makes finding a sweeping solution difficult. However, it is known that the NIR reflection values of water regions are generally smaller than the other band reflection values as it stated in previous works in the literature (Zhao et. al., 2009). Utilizing this knowledge, input image is filtered using the NIR band to find the water regions. The tests which are conducted using high number of satellite images showed that, in 11 bit GEOEYE and IKONOS images, water regions have reflection values smaller than 250 in the NIR band. This value, which is obtained experimentally, is used in the proposed method. Using a threshold value smaller than this resulted in such an outcome where the actual water regions are classified as non-water. Similarly, using a threshold value higher than the obtained value resulted in classifications where many regions that are not water being classified as water regions. However, shadows and some man-made objects have similar reflectance characteristics to water. To achieve better classification, Normalized Difference Water Index (NDWI) is used. Computation of NDWI is shown at Equation 1.

$$\mathrm{NDWI} = \frac{\mathrm{Green(G)} - \mathrm{Near\ Infrared(NIR)}}{\mathrm{Green(G)} + \mathrm{Near\ Infrared(NIR)}} \quad (1)$$

Since the water regions have higher reflection values in green band than near infrared band, NDWI values of such regions will be higher than the rest. After the image is filtered such that only the pixels with NIR reflectance value smaller than 250, NDWI values of the filtered image is computed. Then the NDWI values of the filtered image are clustered into two using the k-means clustering algorithm. The members of the cluster with the higher valued centroid are chosen as the water regions. Although it is not always possible to distinguish water from shadows using this approach, it still gave better results than simple thresholding. Visual outputs of this approach are given at Figure 3.

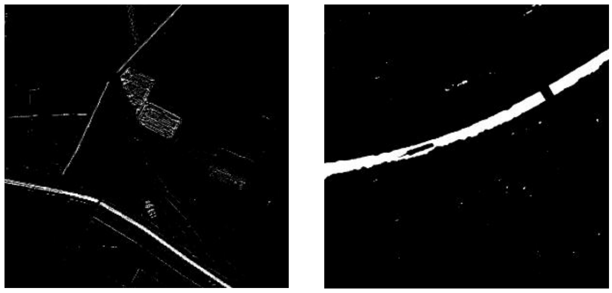

Figure 3 Water Region Outputs

2.2.2. Extraction of River and Water Canals: After finding the water regions at the image, connected components which depict characteristics of river and water canals are extracted using the binary mask obtained in the former step. It is known that rivers and canals are thin, long and continuous structures. For this purpose, every connected component at the water mask is checked to see if they satisfy some geometric constraints. These geometric constraints are having a major axis larger than 300 pixels (meters) and satisfying the inequality shown in Equation 2. The threshold value 300 is found experimentally. A higher threshold for major axis resulted in classifying regions which are not actually river and water canals as such. Similarly, actual river and water canal regions are not found as such if a smaller threshold is used. The inequality depicted in Equation 2 makes sure that the resulting connected components are long and thin. A broader explanation of this inequality and its members are present at the literature (Karaman et. al., 2012).

$$\frac{\left(\mathrm{Major\ Axis} * (2 - \mathrm{Extent})\right)^2}{\mathrm{Area}} > 15 \quad (2)$$

Using the mentioned constraints, long and thin connected components are identified and included in the river and canal mask. Outputs of this step are shown at Figure 4.

Figure 4 River and Water Canal Outputs

2.2.3. Extraction of Bridge Regions: It is known that bridges divide rivers and canals into two different components by passing over them. Also fluidic regions like river and water canals are expected to connect to another water region. Using these pieces of knowledge about bridges, the water and river canal mask obtained in the previous steps are analyzed together. The main idea of that analysis is to connect the connected components at the river and water canal mask to the closest water regions to their extrema points. Extrema points could be briefly defined as the corner points of any convex shape. For example, Figure 5b shows the extrema points of the river-canal mask which is shown at Figure 5a. For finding extrema points of a component, the method which is used commonly in the literature is used (Haralick & Shapiro, 1992). For any extrema point, a circular search region is created with the extrema point at the center of this region. Inside this search region, if any water region exists, edge pixels of this water region are extracted. The edge pixels which are inside the search region and have the lowest distance to the extrema pixel of the river-water canal component are matched. Finally, matched pixels are connected with a line and the area between those lines is filled. Resulting new filled area corresponds to the possible bridge regions.

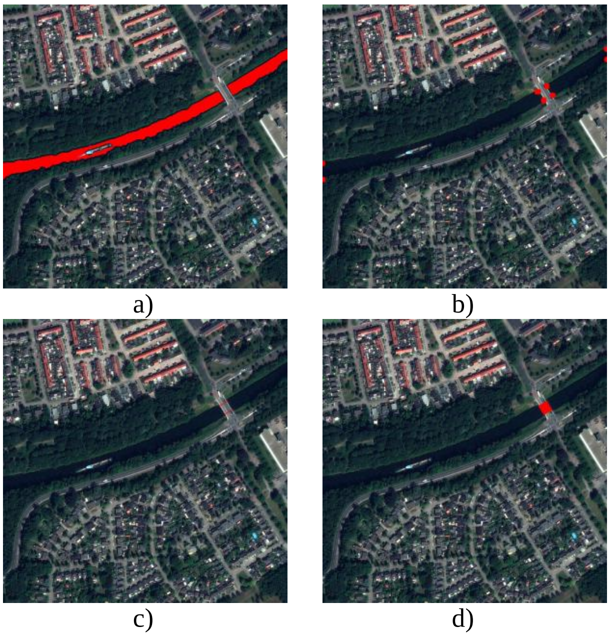

Figure 5 Extraction of bridges a) River and Water Canal mask b) Extrema Points c)Connection of extrema points and matching pixels d) Bridge regions

2.2.4. Verification of Bridge Regions: Regions found by connecting river-water canals and water regions are not guaranteed to be rivers. Especially when dealing with images that include complex features, it would be needed to verify the bridge regions using supplementary modules. In this study, two different methods for verification of bridges are proposed. Those two approaches respectively rely on the geometric characteristic of bridges and continuity of roads over bridges.

2.2.4.1 Verification using Orientation Information: One of the most important characteristics of bridges over water regions are perpendicularly cutting of the water structures they are over. To analyze the orientation differences between the bridge regions and river-canal structures, the input satellite image is segmented using Mean-Shift Segmentation method which is extensively studied in the literature (Comanicu & Meer, 2002; Christoudias et. al., 2002). Then, every segment that forms the bridge region is found and their orientation is computed. Those segments orientation then compared with the connected component in the river-canal mask which created the bridge region in the former step. For the real bridge regions, it is expected that orientation difference between the bridge segments and the river-water canal component to be higher than 70 degrees. Segments that do not satisfy this orientation difference are excluded from the bridge mask. Figure 6 shows a simple run of the proposed verification step. The segments in Figure 6a are verified using the orientation difference and resulting mask is given at Figure 6b.

a) b)

Figure 6 Verification using orientation information a)Bridge Mask b) Orientation-Verified Bridge Mask

2.2.4.2 Verification using Road Mask: It is known that bridges must ensure the continuity of roads and bridge regions should also be included in the road mask. To check the validity of the bridge regions, a road mask which is extracted from the image using the method explained in the work of Karaman et. al., 2012, is used. The regions which are identified as bridges should also be present at the road mask. Therefore any segment which is included in the bridge region but not present at the road mask is excluded from the final bridge mask

a) b) c)

Figure 7 Verification using road mask a) Bridge Mask b) Road Mask c) Verified Bridge Mask

Figure 7 shows a sample run of the verification step. It could be seen that by verification, width characteristics of the bridge is corrected, the region now only covers the real parts of the bridge. Some parts, that are not actually present in the

3. EXPERIMENTS AND DISCUSSION

The proposed approach was tested on 10 GEOEYE and 10 IKONOS satellite images. GEOEYE images have 9 and IKONOS images 8 bridges on them, 17 bridges in total. Our algorithm, without any verification attempt, found all of the bridges at GEOEYE images and 5 out of 8 at IKONOS images. Unidentified bridges at those tests are mostly due to missing water areas in the water mask. Also, 1 region in the GEOEYE and 2 regions in the IKONOS images are mistakenly identified as bridges in those tests. This is again due to ill formed water mask. In some cases, shadow regions are still mistaken for water regions. If the misclassified shadow region is structurally similar to the river and water canals with long and thin geometry, the gaps between them could be misclassified as bridges. The orientation verification step marked those 3 misclassified bridges as false bridges and eliminated them, but in the process some real bridges are also eliminated (3 in IKONOS and 1 in GEOEYE images). Similar to the orientation verification, verification using road mask was successful at eliminating the false positives. But it also excluded three actual bridge regions,. This is caused by reason that the extracted road mask does not always provide true information. The real bridges marked as false ones in the verification step are mostly small sized bridges which do not show specific orientation characteristic in segment analysis. Quantitative precision and recall values are given at Table 1. No similar works that show quantitative results are found in the literature so we cannot compare our results. The thinning method proposed in the literature (Luo et al., 2007) is also implemented and tested on these example satellite images. Quantitative results were the same when the proper width is supplied to the thinning method. However, the outcome of the thinning method does not readily provide the features of the bridges such as the width of the bridge. The proposed method is clearly more successful at finding such characteristics of the bridges. Example visual results are given at Figure 8.

Table 1 Quantitative Results

Precision	Recall
14/16	14/17

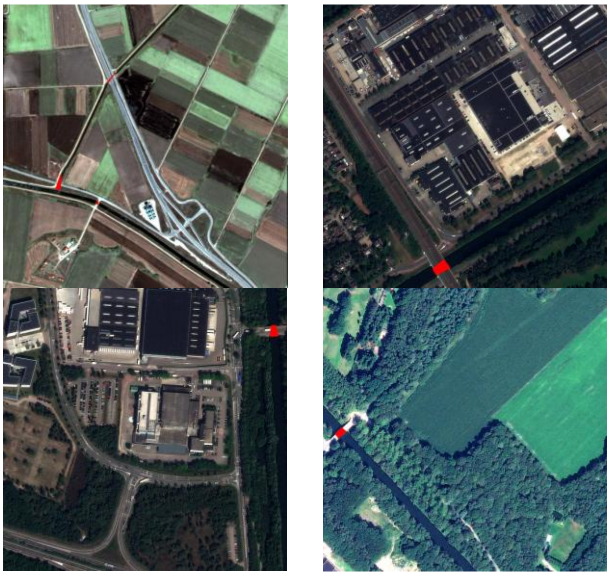

Figure 8 Bridge Outputs

4. CONCLUSIONS AND FUTURE WORK

In this study, an automatic approach for detecting bridges over water using high resolution multispectral satellite images is proposed. The proposed algorithm starts with identifying water regions in the image and extracts the river and water canal mask. Using the water mask and river-water canal mask, the approach identifies the possible bridge regions in the image. A verification step is also proposed for eliminating false bridges. Obtained results showed that the proposed algorithm is highly scalable and successful at finding bridges of different sizes. Possible false identification of bridges is generally caused by the false regions of water mask, which are usually due to the presence of shadows or roads with low NIR reflectance. It is expected that results will be more satisfactory with the usage of a more reliable water mask. Presently, the algorithm is dependent on the water mask and it is not possible to find bridges over dry rivers and water canals. An added module that can extract dry rivers and canals would alleviate this problem. Proposed approach should also be tested on more and different types of satellite images. In this way, a more robust algorithm could be obtained.

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