Detection of quasi-circular vegetation patches using GF-2 image with tasseled cap and watershed transformations

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Abstract. It is a key to detect the quasi-circular vegetation patches (QVPs) for studying the establishment and encroachment mechanisms of the QVPs in the Yellow River Delta, China. A variety of spatial resolution remote sensing data have been used to map the QVPs. However, the adhesion between the QVPs with the QVPs or the vegetations of other shape makes the detection accuracy of the QVPs unsatisfactory. This study applied the decision tree classifier to map the QVPs using the brightness and greenness components of the modified intensity-hue-saturation pansharpened Gaofen 2 imagery. Then, the watershed transformation was used to segment the classification result. The final result was obtained using the thresholds of statistical features of the QVPs. It indicated that the method of this work could well detect the QVPs. In the future, more effective image segmentation algorithms should be used to deal with the over-segmentation in order to further improve the detection accuracy.

1. Introduction

Quasi-circular vegetation patches (QVPs) was mapped for the first time in the Yellow River Delta, China in 2011 [1], which have a fast succession rate, and are ideal research objects for studying local vegetation community succession mechanisms, and are of benefit to make an appropriate strategy for the degraded ecosystem restoration [2]. It is a basic and key procedure to detect the QVPs. Remote sensing images have been used to detect the QVPs [1, 3-6]. Because the QVPs have a relatively small patch size, high spatial resolution images (better than 10 m) should be applied in identifying them [7]. Although the area and shape features of the QVPs, characterized by quasi-circular or ellipse-like shape, have been used to distinguish the QVPs from the vegetations of other shape and bare soils, the adhesion between the QVPs with the QVPs or the vegetations of other shape makes the detection accuracy of the QVPs unsatisfactory [3, 5, 6].

The brightness (TCB), greenness (TCG) and wetness (TCW) components of the tasseled cap transformation (TCT) was capable of producing slightly higher classification accuracy of land cover than that of the vegetation indices calculated from any band difference or ratio [8-11]. Compared with the TCG and TCW derived from Landsat ETM + fusion-ready 15 m multispectral image, the TCB was found to be more effective indicator for monitoring the establishment of new QVPs [12]. The watershed transformation is one of the commonly used image segmentation methods [13, 14, 15], which identify “watershed ridge lines” in an image by treating it as a surface, and can segment contiguous regions of interest into distinct objects. In this work, we try to develop an approach for
mapping the QVPs which includes image fusion, the TCT, decision tree (DT), and watershed transformation.

2. Materials and methods

2.1. Data

Gaofen 2 (GF-2) has two multispectral sensors with a panchromatic band with 1 m spatial resolution and four multispectral bands with 4 m spatial resolution (CRESDA, http://www.cresda.com). The fused image with four multispectral bands was more suitable for mapping the QVPs than that of a panchromatic band or four original multispectral bands [16]. One scene of spring GF-2 image was acquired over the study site. To reduce image processing time, the subset of GF-2 image was selected (see Figure 1).

![Figure 1. Subset of the modified intense-hue-saturation pansharpened Gaofen-2 image.](image)

2.2. Methods

The modified intensity-hue-saturation (mIHS) pansharpening method is an updated version of the intensity-hue-saturation transformation, and has been embedded in remote sensing image processing software such as ERDAS imagine V9.2. The mIHS method is one of the commonly used image sharpening methods with preserving the spectral information of images [17, 18]. Thus, the mIHS method is selected to sharpen the GF-2 imagery. The subset of the fused GF-2 imagery was shown in Figure 1.

The coefficients of tasseled cap transformation for the pansharpened GF-2 imagery is shown in Table 1 [19], which was used to calculated the TCB and TCG.

| Tasseled cap transformation component | Band 2   | Band 3   | Band 4   | Band 5   |
|--------------------------------------|---------|---------|---------|---------|
| The brightness                       | 0.4352  | 0.4503  | 0.6041  | 0.4929  |
| The Greenness                        | 0.0483  | -0.2365 | -0.5246 | 0.8164  |

The decision tree (DT) is a simple classifier, and can classify land cover using a flowchart-like procedure based on a set of the splitting thresholds, and has been applied to map the vegetation [20]. In this work, the DT was used to map the QVPs based on several thresholds obtained by many tests.
and visual inspections. The TCB values of the QVPs ranged between 703 and 880, and the TCG values of the QVPs ranged between -90 and -24. The pixels also belonged to the QVPs where the TCB values were more than 880 and the TCG values were more than -70.

Because the classification results from the DT included some small vegetation patches and the holes within the QVPs, post classification processes such as sieve (thirty-six pixels) and majority (5×5 pixels) function were used to remove small vegetation patches and noises, and fill the holes. The DT classification result were converted to the JPG image format which was used as the input image of watershed transformation performed in MATLAB software.

After image segmentation, the centroid, area, and perimeter of every object in image were calculated, and the boundaries of every object was measured. Then, the distance of each point to the centroid was calculated for every object. On this basis, the maximum distance, minimum distance, mode of the distance, and the difference between the maximum and minimum distance were calculated. The circular-like QVPs were determined using the thresholds where the difference between the maximum and minimum distance was less than 14, and the maximum distance was less than 40, the minimum distance was more than 5. The ellipse-like QVPs were detected using the thresholds where the ratio of the area to the product of the maximum, the minimum and the pi ranged between 0.85 and 1.37, and the mode of the distance was more than twenty-six, and the maximum distance was less than 40, the minimum distance was more than 5.

In this work, the image fusion was performed in ERDAS imagine V9.2, and the calculation of the TCB, TCG components, the DT, and post classification processing were carried out in ENVI v5.5 software, and the watershed transformation and the detection of the QVPs base on the shape were done in MATLAB software.

3. Result and discussion

Figure 2 presents the classification result of the QVPs from the decision tree with post classification using the TCB and TCG of GF-2 fused multispectral image. There were two types of the adhesion in the image. One was the adhesion between two or more QVPs, and anther was the adhesion between the QVPs and the surrounding vegetation stripes. The common classifiers such as the K-means, the DT, and random forest, was difficult to identify them even if the area, area/perimeter, or other shape indices were applied, generally the detection accuracy of the QVPs was lower (overall accuracy was less than 76%, and F measure was less than 60%) [5, 6].

![Figure 2](image_url)
The segmentation result from watershed transformation was shown in Figure 3. The contiguous QVPs were well segmented. The over-segmentation happened, especially for the vegetation stripes in the image, which needed to be study in the future. Figure 4 was the final detection result of the QVPs in the study site using the thresholds of the maximum distance minimum distance, mode of the distance, the difference between the maximum and minimum distance, and the ratio of the area to the product of the maximum, the minimum and the pi.

![Figure 3. The segmentation result of the QVPs by watershed transformation.](image)

![Figure 4. The QVPs detected by the method proposed by this work.](image)

There were about one hundred and ninety-eight QVPs from visual interpretation in the image. The number of the detected and correctly detected circle-like QVPs were one hundred and ninety-one, and
one hundred and forty, respectively, and the number of the detected and correctly detected ellipse-like QVPs was thirty-four, and ten, respectively. The precision rate of the circle-like QVPs was 73.3%, and that of the ellipse-like QVPs was 29.4%, which was attributed to small difference of shape features between the ellipse-like QVPs and the vegetations of other shapes because the shape of QVPs are irregular. Overall, the precision rate, recall rate, and the F measure of the detection of the QVPs were 66.7%, 75.8%, and 70.9%, respectively.

Compared with the previous studies [6, 16], the detection accuracy of the QPVs was improved by the method in this work. It indicated that the detection accuracy of the QVPs could be improved by the segmentation of the contiguous QVPs using watershed transformation with the appropriate thresholds of the features of the QVPs. In the future, more effective image segmentation algorithms should be used to deal with the over-segmentation in order to further improve the detection accuracy of the QVPs.

4. Conclusion

It is a key to detect the QVPs. Although the area and shape features of the QVPs, characterized by quasi-circular or ellipse-like shape, can be used to identify the QVPs from the vegetations of other shape and bare soils, the adhesion between the QVPs with the QVPs or the vegetations of other shape makes the detection accuracy of the QVPs unsatisfactory. In this work, the decision tree was established based on the TCB and TCG components derived from the mIHS pansharpened GF-2 imagery, and the DT classification result were segmented by the watershed transformation, the final detection accuracy of the QVPs were improved. It indicated the method in this work was effective for detecting the QVPs in the YRD, China. However, there was a problem of over-segmentation. In the future, more effective image segmentation algorithms should be used to deal with the over-segmentation in order to further improve the detection accuracy of the QVPs.

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