Postprint: Land Cover Extraction in Qingtu Lake Based on Texture Features and LSSVM

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Abstract

Texture features, as a form of non-spectral information, can enhance the discriminative characteristics between land cover types, which holds significant importance for feature extraction from high-resolution remote sensing imagery. This study selects Qingtu Lake as the research area and Worldview-2 imagery as the data source, determines the optimal window scale by introducing a weighting factor to define a joint probability function, extracts texture features at the optimal window scale using the Gray Level Co-occurrence Matrix (GLCM), fuses them with the original remote sensing imagery, and employs Least Squares Support Vector Machine (LSSVM) for land cover extraction. The extraction results are comparatively analyzed against those from Support Vector Machine (SVM) using spectral information alone and SVM supplemented with texture features. The results indicate that the proposed method can more rapidly and accurately extract land cover features in Qingtu Lake, achieving an accuracy of 85.86%, which outperforms the 65.13% accuracy of SVM using only spectral information and the 73.45% accuracy of SVM with texture features, thereby providing a valuable reference for land cover extraction from high-resolution remote sensing imagery in arid regions with fragmented land cover.

Full Text

1. Study Area and Data

The study area, Qingtu Lake, is located in Minqin County, Gansu Province, China, between 39°04 ∼39°09 N and 103°36 ∼103°39 E, with an elevation of 1292–1310 m. The region has an average annual temperature of 7.8°C and accumulated temperature >10°C of 3289.1°C · d. Annual precipitation is 2640 mm, concentrated in July–September. The lake surface features and surrounding vegetation show distinct spectral and textural characteristics in remote sensing imagery.

A WorldView-2 image acquired on July 19, 2015 was used as the primary data source. The image has a spatial resolution of 0.5 m with 8 spectral bands and dimensions of 7319$×6917*pixels.Toenhancethespectralinformation,texturefeatureswereextractedusingtheGr*
occurrenceMatrix(GLCM)method.Thekeytoeffectivetexturefeatureextractionliesinselectingtheoptimalwi
pixels. The extracted texture features were then synthesized with the original spectral information to create a multi-dimensional feature set for classification.

2. Methods and Results

Texture features were extracted using GLCM based on the method of Haralick et al. [?]. The GLCM calculates the spatial co-occurrence relationships of pixel pairs at specific displacement vectors $\delta = (\Delta x, \Delta y)$ within a given window. For an image region of size M × N with gray levels Ng, the element (i, j) in the GLCM represents the frequency of pixel pairs with gray values i and j separated by displacement δ. Fourteen Haralick texture features were computed from the GLCM for each window size.

The classification was performed using Least Squares Support Vector Machine (LSSVM), which provides an efficient solution to the robustness, sparsity, and large-scale computing problems associated with conventional SVM [?]. The classification results were compared with two alternative approaches: (1) SVM using only spectral information, and (2) SVM combined with texture features.

The sample distribution for training and validation is shown in [TABLE:N]. A total of 240 samples were collected, including 87 for training and 290 for validation across four land-cover types: water body, saline-alkali land, vegetation, and bare land.

The classification accuracy assessment (Table 5) demonstrates that the LSSVM method achieved an overall precision of 85.86% and a Kappa coefficient of 0.8225. This performance significantly exceeded that of SVM using only spectral information (65.13% overall precision, Kappa = 0.5829) and SVM with texture features (73.45% overall precision). The LSSVM approach improved overall accuracy by 12.41 percentage points compared to SVM with texture features, with a Kappa increase of 0.1484.

The optimal window size was determined to be 5$×$5 pixels based on the weighting factor method, which balanced the trade-off between capturing local texture details and maintaining computational efficiency. The LSSVM classifier effectively integrated the spectral and textural information, demonstrating particular advantages in extracting fragmented objects in arid regions from high-resolution remote sensing imagery.

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Note: Figure translations are in progress. See original paper for figures.