

MAN-MADE OBJECTS CLASSIFICATION FROM SATELLITE/AERIAL IMAGERY USING NEURAL NETWORKS

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ABSTRACT:

The classification of man-made objects is a basic step in various mapping and modelling applications. The automation of this task is highly needed as the manual processing is costly and time consuming. Human classification of man-made objects from aerial and satellite images depends mainly on the colors, the textures, and the shapes of the classified regions. These objects attributes are then processed by humans based on past experience and knowledge to decide whether these regions belong to man-made class or not. Man-made objects tend to have regular shapes that have mostly straight lines and uniform texture, while natural objects such as vegetation have irregular shapes and textures. The presented work uses these differences to classify the man-made objects. The proposed approach extracts the regions from the images in vector format based on their colors as a preliminary step. The extracted regions are then analyzed to form a set of descriptors to describe each region. The main harmonics of the boundaries of the extracted regions are transformed to form a reduced rotation-invariant representation that can be used as region descriptors. Also, the uniformity of the region texture are used as region descriptors. The proposed approach, presented in this paper, uses a supervised neural network in which a set of inputs and associated outputs are provided to train the network at the initial stage. The training of the neural network uses the calculated descriptors for man-made objects from previously classified images. After the training phase, the descriptors of the test images objects are fed into the neural network to perform the classification. The results of the proposed approach are presented based on a reference solution for evaluation purposes. Although, images are not a sufficient source for such type of classification, as no elevation profile exists for the regions, causing some classification ambiguities. The presented results for aerial and satellite images classification show the significance of the proposed technique in the classification process.

1. INTRODUCTION

The vast amount of available aerial and high-resolution satellite images has promoted the development of novel automatic features extraction methods to support the various needs of accurate maps. The huge volume of acquired images will exceed the capacity of manual processing to carry out the features extraction duties timely and economically. A lot of segmentation or classification algorithms for man-made objects are evolving at the present time being. These algorithms exhibit different models, features, and classifiers to accomplish the classification task. Different texture features have been used as an input to the man-made object classification stage, such as fractal dimension and coefficient of variation (Solka et al., 1998), Gabor filter (Baik et al., 2004), Non Subsampled Contourlet Transform NSCT (Wei et al., 2010), and Laws texture measures and curvilinear integration based features (Du Buf et al., 1990). (Han et al., 2002; Mokhtarzade et al., 2007) have used the pixel color components directly as the input to the classifier. (Haim et al., 2006; Müller et al., 2005) have utilized both color and texture features to discriminate the desired objects. A wide range of classification algorithms have been employed, such as fuzzy logic (Jalal et al., 2002; Gasteratos et al., 2004; Sheng-hua et al., 2008), Support Vector Machine SVM algorithm (Corina et al., 2008; Inglada, 2007), Neural Networks (Han et al., 2002; Mokhtarzade et al., 2007), and C5.0 algorithm, Naive Bayes classifier (Maloof et al., 2003).

The objective of the proposed approach is to classify the man-made objects in aerial/satellite imagery. The first step of

the presented algorithm is to perform region-based segmentation of the image based on color similarity of the image in vector format. The segmented regions are then described using a combination of shape features (boundary harmonics), color feature (greenness index), and texture feature (coefficient of variation). These descriptors are then fed into an MLP neural network to classify these segmented regions. The neural network is previously trained using the features of extracted segments of a reference image.

The following section illustrates the steps of the proposed approach. Then, experimental results for aerial and satellite images are presented. Finally, the conclusions are provided.

2. METHODOLOGY

2.1 Region Segmentation and Boundary Encoding

The initial step of the proposed approach is to segment the image into separate regions based on color similarity of adjacent pixels of a vector format version of the original image. The boundary pixels of the segmented regions are traversed in clockwise direction to form a sequence of coordinates for each region. Figure 1 depicts a part of an aerial image in vector format. Figure 2 presents the boundaries of the segmented regions of the image in Figure 1.



Figure 1 – A part of an aerial image in vector format.

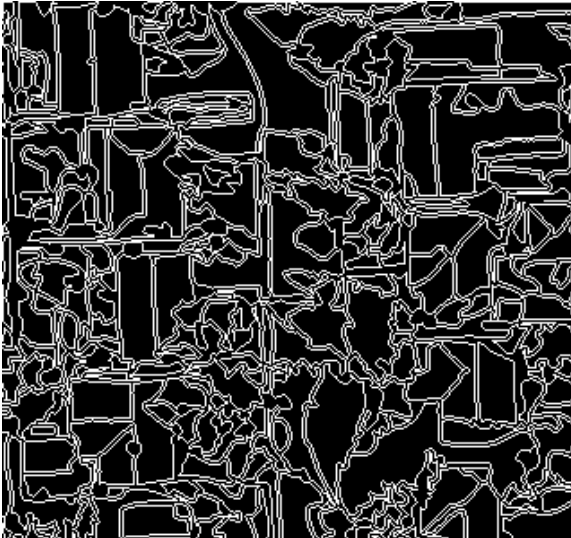


Figure 2 – Boundaries of the segmented regions of the image in figure 1.

2.2 Shape Features

Boundaries of man-made objects tend to follow regular patterns that mostly have straight line segments and right angles. These patterns come in different sizes and orientations. For describing such boundary patterns, the harmonics of the coordinate's sequence of the extracted boundaries are used to form a rotational-invariant and scale-invariant features. Figure 3 depicts two objects with the same shape in different scales and orientations. Figure 4 illustrates the derived shape features of the two objects. A very slight difference between the shape features of the two objects is noticeable; this difference is mainly due to the digitization errors of the rotated version representation. Only the first 30 harmonics (X, Y) of the x coordinates sequence, and y coordinates sequence of each boundary are used to form the shape descriptors as follows.

$$S_i = \sqrt{X_i^2 + Y_i^2} \quad (1)$$

Where S_i is the i^{th} shape descriptor, X_i is the i^{th} x harmonic, and Y_i is the i^{th} y harmonic.

These descriptors are then normalized relative to the first descriptor to form the shape features as follows.

$$S_{ni} = S_i/S_1 \quad (2)$$

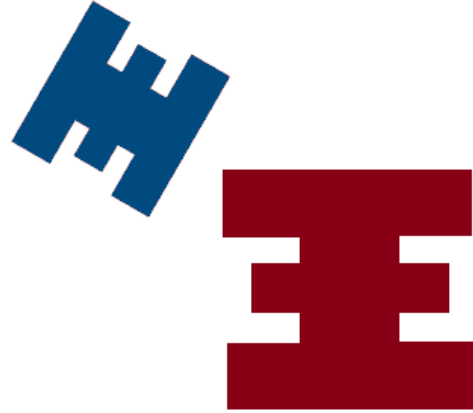


Figure 3 - Two objects with the same shape in different scales and orientations.

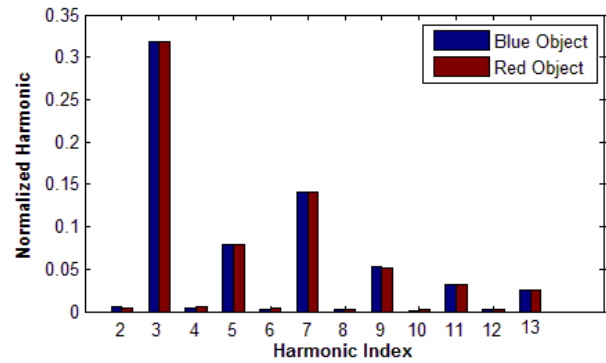


Figure 4 - Shape features of the two objects.

2.3 Color and Texture Features

The color information is a helpful guide in natural objects discrimination. Many natural objects especially in urban areas belong to the green color category. The proposed approach measures the closeness to selected green color samples as a greenness index to serve as a color feature. The distance between the segmented region average color and the sample green colors in Lab color space is calculated to form this color feature. Lab color space is employed to simulate the human perceptual behaviour. Figure 5 shows the greenness index calculated on pixel level of the image presented in figure 1 where bright pixels are far from green color.

Figure 6 shows a sample of the texture of natural objects and man-made objects. The texture uniformity is considerably different between man-made objects and natural objects. The coefficient of variation is calculated for each segmented region as a texture feature. The standard deviation of the distances between region pixels colors and the average region color in Lab color space is divided by the mean distance to form the texture feature for this region.

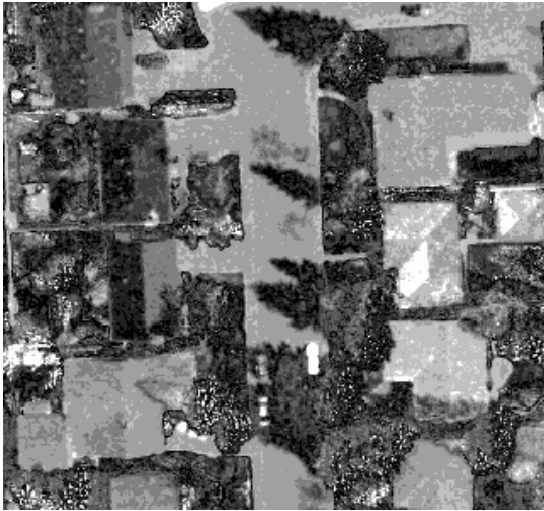


Figure 5 - Greenness index calculated on pixel level of the image presented in figure 1.



Figure 6 - Sample of the texture of (a) natural objects and (b) man-made objects.

2.4 Neural Network

Neural networks have been widely used for classification purposes due its adaptive learning, and complex nonlinear mapping capability. In the proposed approach an Multi Layer perceptron MLP neural network is employed to classify the aerial/satellite images based on the extracted shape, color, and texture features. MLP networks are composed of simple units of processing (nodes) arranged in successive layers where the features are fed into the input layer and the outputs are obtained from the output layer. Back propagation algorithm is used to train the network using a training set in the form of features as input and classes as output derived from reference image. An image of 602 man-made objects and 283 natural regions are used to provide the training set for the neural network. The used neural network has two hidden layers with 50 and 30 nodes respectively between the input layer and the output layer. It has an input layer of 31 nodes to receive the 30 features of each image region (29 shape features + 1 color feature + 1 texture feature) and an output layer of single node that delivers the classification decision.

3. RESULTS

The first test of the proposed approach is carried out using an aerial image of an urban area (Figure 7). The region is selected to exhibit man-made objects (buildings – roads) that overlap

with natural objects. The region contains many shadow areas and buildings with near-green colors. The classification result using the presented approach is shown in Figure 8.

In this test, the usage of different features types assisted the classification process. For example, the three near-green buildings in the top-middle of the image are successfully classified as man-made objects despite having high greenness index as shown in Figure 5. Almost, all the regular man-made regions are correctly classified as the misclassified man-made objects are mainly irregular road segments affected by shadows. Based on manual classification of the image, 94% of the man-made objects are correctly classified, 22% of the natural objects are misclassified, and about 5% of the image is not classified due its very small size.



Figure 7 – Aerial image of an urban area.

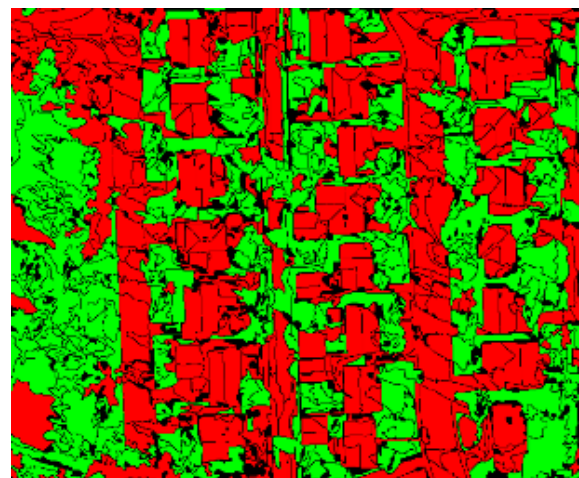


Figure 8 – Classification of the image in Figure 7 using the proposed approach (Red for man-made, Green for natural, Black for unclassified).

The second test of the proposed approach is carried out using a QuickBird satellite image of an urban area (Figure 9). The region contains many shadow areas and many buildings with near-green colors. The classification result using the presented approach is shown in Figure 10.

Most of the regular shaped objects are correctly classified, and the dark shadows areas are misclassified as it exhibits regular shapes, low greenness index, and texture uniformity. Based on manual classification of the image, 82% of the man-made objects are correctly classified, 23% of the natural objects are misclassified, and about 3% of the image is not classified due its very small size.



Figure 9 – QuickBird satellite image of an urban area.

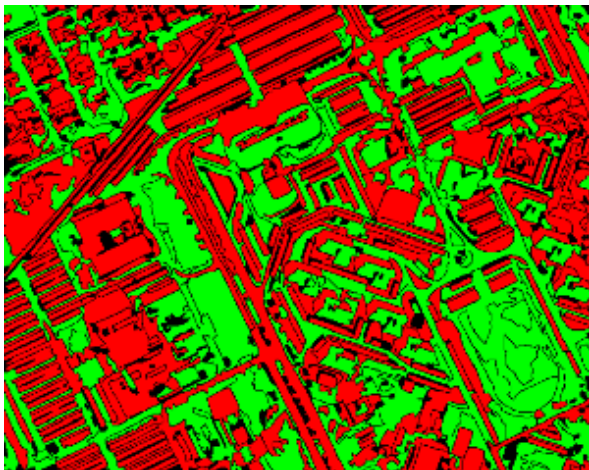


Figure 10 – Classification of the image in Figure 9 using the proposed approach (Red for man-made, Green for natural, Black for unclassified).

4. CONCLUSIONS

The usage of different features that describes the shape, color, and texture of man-made objects appears to assist the classification process. The high correct classification rate of the regular man-made regions shows the effectiveness of the presented shape features in the man-made classification. With the vast amount of available data for this problem, neural networks are good classifier candidate due its ability of learning from similar data sets. The proposed region-based technique allows further context features extraction that can help classify the shadows regions. The presented results for aerial and satellite images classification show the significance of the proposed technique in the classification process.

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