Road Detection from Remotely Sensed Images Using Color Features

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***Abstract*—Urban regions are dynamic environments. Especially their road maps change by the expansion of the urban region. Therefore, automatic detection of roads from very high resolution aerial and satellite images is a very important research field. Unfortunately, the solution is not straightforward by using basic image processing and computer vision algorithms. Therefore, advanced methods are needed for road network detection from aerial and satellite images. In this study, we propose a novel method for automatic detection of road segments from very high resolution color aerial and satellite images. Our method depends on choosing a training set from the input image manually. We use color chroma values of pixels as the discriminative features. Since road pixels have similar color characteristics, the distribution of color chroma feature values of the training region have a peak at a certain point in the feature space which shows the road class. Using this information and one-class classification methodology, we label road segments in a given remotely sensed image. Finally, we fit a road network shape on the detected segment. Experimental results on color aerial and Ikonos satellite images show the importance of color features in road detection applications.**

I. Introduction

Automatic detection of roads from very high resolution aerial and satellite images is a very important research field. Although road segments have very simple shapes compared to buildings, detecting roads from remotely sensed images is generally more difficult. The main problem in road detection is the occlusion. Road segments may also have different colors and their widths may change. Besides, junctions of unknown number of roads, roundabouts, and other local road characteristics may increase the difficulty of the road detection problem. Therefore, advanced methods are needed to detect road segments in aerial and satellite images.

In the related literature, some researchers developed semi-automatic techniques to detect roads [15], [2], [4]. They assumed that possible road or urban object segment is previously labeled. Yang and Wang [17], developed a method to detect main roads from satellite images. First, they detected road primitives such as straight lines and homogenous regions. Then, they linked these primitives in order to detect the road network. Unfortunately, their method cannot detect urban roads and occluded road segments. Ma *et al.* [7] detected parallel edges in panchromatic Enhanced Thematic Mapper (ETM) images to detect road segments. They linked discontinuous road segments using perceptual organization rules. Dell'Acqua and Gamba [6] detected road networks and built areas in SAR images. They extracted straight edges and detected built areas with a clustering based approach. They assumed longitudinal gaps as road networks. Rianto *et al.* [11] proposed an approach to detect main roads in SPOT satellite images. For this purpose, the detected Canny edges and classified straight line segments using Hough transform. They assumed straight and parallel line segments as roads. Unfortunately, this approach cannot be sufficient alone to detect curvilinear and complex roads in urban scenes. Some researchers developed algorithms to detect both buildings and roads. Ünsalan and Boyer [16] detected separate buildings and street networks from multispectral satellite images. Their method depends on using vegetation indices, clustering, decomposing binary images, and graph theory. Akçay and Aksoy [1] proposed a novel system for detecting built areas and the road network using unsupervised segmentation in high resolution satellite images. Montesinos and Alquier [8] developed a novel approach to detect thin objects in noisy images. They performed perceptual grouping on edge segments using active contours. They tested the validity of their approach by detecting roads in aerial images and blood vessels in medical images. In a previous study, we proposed an edge detection and spatial voting based system to detect road network from panchromatic Ikonos satellite images [12]. Mayer *et al.* [3], and Ünsalan and Boyer [16] provide excellent surveys on road detection in aerial and satellite images.

Most of the previous methods need very high computation time to extract the road network in large scenes. Besides, most of the previous algorithms are based on edge detection. Unfortunately, edge detection methods are prone to noise in very high resolution aerial and satellite images. Therefore, herein we propose a method for semi-automatic road segment detection from very high resolution color aerial and satellite images. Our method depends on choosing a small training region from the input image manually. Then, color chroma features of the training region and input image are extracted. Since road pixels have similar color characteristics, the distribution of color features of the training region make a peak at a certain point in the feature space which shows the road class. Using this information and one-class classification methodology, we label the road segment in a given remotely sensed image. After detecting the road segment, we fit lines on the boundary of the segment to represent the road network. Next, we introduce one-class classification method to detect road segments.

II. Detecting the Road Pixels

Color may give important information for object detection and segmentation in computer vision applications. In our application, the color information is also valuable. The major difficulty in using the color information in segmentation applications is the variability of the color values in the RGB color space due to illumination changes. Therefore, another color space is needed where the effect of illumination is minimal. Or in other saying we need color invariants for road detection. In a previous study, we benefit from color invariants to detect building rooftops [13]. In this study, we benefit from the CIELab color space as a color invariant space [5]. CIELab color space bands enhance different colors best and minimize color variances. After transforming the RGB image into CIELab color space, we again obtain three bands as L, a, and b [10]. Here L corresponds to intensity of the image pixels. a and b bands contain chroma features of the image. They give information about the color of the pixel independent of illumination. In the literature, researchers used Euclidean distances of L, a, and b bands of images to find similar regions generally for segmentation purposes [18]. We apply a similar methodology to segment out the road pixels from input test images. To have an illumination invariant representation, we discard the L band of the CIELab color space and only use the chroma features a and b.

In detecting road pixels in our method, we apply a semi-automatic detection method by labeling training road pixels for each image separately. In Fig. 1 (a), we represent the $Ikonos_1$ color satellite image and its selected training region with a red label. First, we obtain the mean values in a and b values for the training samples. In order to classify road pixels of the input test image, we benefit from one class classification method. In classification problems, generally total number of classes and the label for each class is known. However, in remotely sensed images, we have unknown number of classes such as trees, buildings, parking lots, various type of roads, agricultural fields, pool and lakes, etc. If the samples of only one class is known as in our problem, classification cannot be done by a classical two-class or multi-class classifier, since the other all classes are not represented. This is also the case for our road detection problem. Fortunately, a one class classifier can be used to separate this small class from other all classes. The problem in one class classification is to construct a decision boundary to separate interest class. Therefore, the real problem is defining a boundary around the target class.

We obtain the Euclidean distance of each test pixel in the image to the mean values obtained in the training phase. We represent these distances as the matrix $D(x, y)$. Then, we normalize the distances in the $D(x, y)$ matrix between $[0, 1]$. In Fig. 1 (b), we represent the distance matrix $D(x, y)$ for the given test image, where each pixel value represents the normalized distance. In this figure, darker pixels (having very low values) represent test image pixels which have very similar chroma feature values to the training features. As can be seen in this figure, all road network pixels have very low values. In order to classify these pixels, we benefit from Otsu's thresholding method [9]. The threshold calculated by Otsu's method corresponds to the class boundary for our road class (in one class classifier). In Fig. 1 (c), we represent the classification result for the given test image. Here, white pixels represent the detected road pixels. As can be seen in this classification result, all road network pixels are detected successfully.

III. Representing the Road Network

To represent the road network, we fit lies on to the boundary of detected road segment pixels. For this purpose, we first extract the Canny edges of the detected road segment. We discard edges which are shorter than 50 pixels since they might be coming from false detections. After eliminating short edges, we analyze the rest of the edges to fit line segments to them. To do so, our algorithm finds the coordinates of the boundary pixels. The algorithm calculates the maximum deviation from the line that joins two junction or endpoints. If the maximum deviation exceeds the allowable tolerance, then the edge is shortened to the point of maximum deviation and the test is repeated. In this way, the boundary is represented by line segments [14]. In this study, we have chosen tolerance value as five pixels. In Fig. 1 (d), we represent the line fitting results which indicate the detected road network.

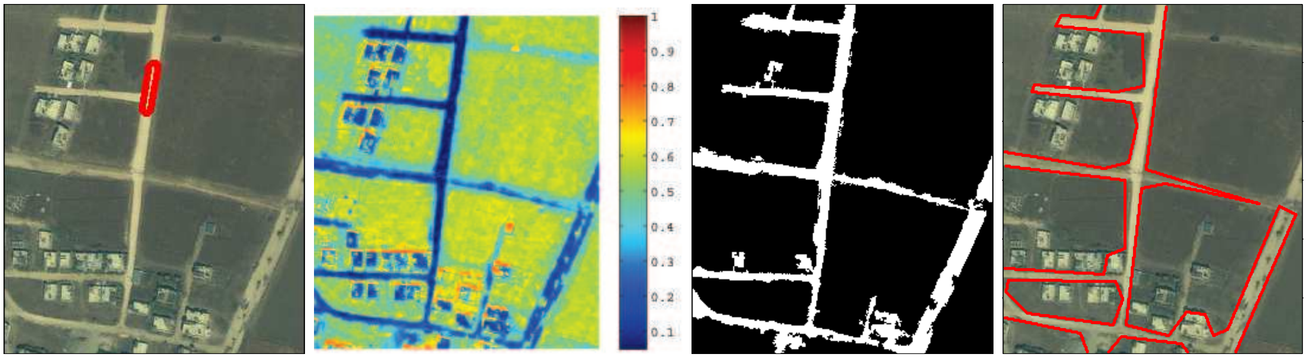
IV. Experiments

In this section, we test the performance of our road detection method using color aerial and panchromatic sharpened satellite images of Istanbul city, having 0.3 and 1 meter spatial resolutions respectively. Before processing aerial images, we applied downsampling with a ratio of 0.5 in order to eliminate redundant details in these very high resolution images.

We provide the pixel wise road detection performance for our aerial image data set in Table I. On our test set, having 10 different scenes, we obtained the true positive (TP) detection performance rate as 81.64% and false alarm (FA) rate as 3.94%. Obtained performances indicate high detection capability of the proposed method on color aerial images.

We also provide the pixel wise road detection performance for our Ikonos image data set in Table II. On our test set, having 10 different scenes, we obtained the true positive (TP) detection performance rate as 66.33% and false alarm (FA) rate as 28.52%. This performance is worse than the one obtained in aerial images. We believe that the resolution of the Ikonos satellite images play a role in this performance.

We provide the detected road segments on seven test images (four aerial and three Ikonos) in Fig. 2. In this figure, the first four images are from our aerial image set as $Aerial_2$, $Aerial_5$, $Aerial_7$, $Aerial_{10}$. The following three images are from our Ikonos image set as $Ikonos_2$, $Ikonos_5$, $Ikonos_6$.



(a) The image and its selected training region

(b) The distance matrix

(c) Road segments after one-class classification

(d) Road segment representation

Fig. 1. Applying the proposed road detection method on the $Ikonos_1$ color satellite test image.

TABLE I
PERFORMANCE OF THE METHOD ON AERIAL TEST IMAGES.

Image	Road Size	TP	FA	TP (%)	FA (%)
$Aerial_1$	4920	4886	59	99.30	1.19
$Aerial_2$	46963	43674	465	92.99	0.99
$Aerial_3$	10600	10593	1199	99.93	11.31
$Aerial_4$	6024	6022	194	99.96	3.22
$Aerial_5$	12941	9252	612	71.49	4.72
$Aerial_6$	5342	3690	310	69.07	5.80
$Aerial_7$	37483	30203	351	80.57	0.93
$Aerial_8$	2400	2267	0	94.45	0.00
$Aerial_9$	106360	81409	6482	76.54	6.09
$Aerial_{10}$	12268	8269	0	67.40	0.00
$TOTAL$	245301	200265	9672	81.64	3.94

TABLE II
PERFORMANCE OF THE METHOD ON IKONOS TEST IMAGES.

Image	Road Size	TP	FA	TP (%)	FA (%)
$Ikonos_1$	8243	6971	0	84.56	0.00
$Ikonos_2$	5246	4724	476	90.04	9.07
$Ikonos_3$	110948	53515	8356	48.23	7.53
$Ikonos_4$	8081	3750	11463	46.40	141.85
$Ikonos_5$	18967	12021	5264	63.37	27.75
$Ikonos_6$	8029	5540	0	68.99	0.00
$Ikonos_7$	13724	11636	8839	84.78	64.40
$Ikonos_8$	12620	6140	6173	48.65	48.91
$Ikonos_9$	100237	82024	40837	81.83	40.74
$Ikonos_{10}$	35917	27297	10444	76.00	29.07
$TOTAL$	322012	213618	91852	66.33	28.52

As can be seen in this figure, our data set is formed from different regions. Therefore, we believe the obtained results indicate the true performance of our road detection method.

Finally, we consider the computational time of the proposed road detection method. The computation time of the method directly depends on the size of the test image. As the number of pixels in the test image increase, the computation time also increases. If we consider the Ikonos satellite image given in Fig. 1, the overall road network detection and representation steps take 4.5 seconds under Matlab (working on an Intel Core2Quad 2.66 GHz PC). This timing shows the high computation speed of the proposed approach.

V. CONCLUSION

In this study, we propose a method to detect road networks in color aerial and satellite images in a semi-automatic and fast manner. Due to the resolution and complexity problems, edge based previous approaches cannot provide good road detection results on complex aerial images. If the color information is available, it can give important cues to detect objects. In the proposed method, we benefit from the color information in terms of chromaticity values. Our experiments indicate the practical usefulness of our approach. Moreover, the proposed approach can also be developed to detect other objects in remotely sensed images. Although our results are encouraging, the proposed method can be improved further by fusing color features with structural ones in future studies.

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Fig. 2. Sample test images and the road detection results. Row wise images: $Aerial_2$, $Aerial_5$, $Aerial_7$, $Aerial_{10}$, $Ikonos_2$, $Ikonos_5$, $Ikonos_6$.