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ROAD RECOGNITION FROM REMOTE SENSING IMAGERY USING MACHINE LEARNING

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Abstract - *The advance of remote sensing technology has been capable of providing abundant spatial and contextual information for object or area detection in satellite or aerial imagery, which facilitates subsequent automatic analysis and interpretation of the optical remotes sensing images (RSIs). Most existing object or area detection approaches suffer from two limitations. First, the feature representation used is insufficiently powerful to capture the spatial and structural patterns of objects and the background regions. Second, a large number of training data with manual annotation of object bounding boxes is required in the supervised learning techniques adopted while the annotation process is generally too expensive and sometimes even unreliable. We propose an end-to-end framework for the dense, pixel-wise classification of satellite imagery with convolution neural networks (CNNs). In our framework, CNNs are directly trained to produce classification maps out of the input mages. We first devise a fully convolution architecture and demonstrate its relevance to the dense classification problem. We then address the issue of imperfect training data through a two-step training approach: CNNs are first initialized by using a large amount of possibly inaccurate reference data, and then refined on a small amount of accurately labeled data. To complete our framework, we design this module with the two different stages that alleviates the common trade-off between recognition and precise localization. A series of experiments in MATLAB show that our works consider a large amount of Meta context to provide fine-grained classification maps.*

Keywords: Gaussian filtering, Histogram oriented gradient (HOG) feature extraction, DCNN

1 INTRODUCTION

In Remote sensing systems one of the most important features needed are roads, which require feature extraction to identify them from high-resolution satellite imagery. Nowadays, roads are changing rapidly than ever. In order to keep up with the development trend and adapt to the dynamic road data, updating the road data in real time will contribute to the partition of functional areas around the roads and the assessment of traffic capacity. Road recognition from remote sensing imagery can be divided into two phases: road detection and road classification. The roads are recognized according to the road classification results after detecting and extracting the road networks.

Recognition of roads is critical since they form an important GIS layer in significant civilian and military applications including navigation or location aware systems and emergency planning systems for evacuation and fire response. A number of methods to extract roads from multi-spectral and panchromatic images have been proposed [4]. Roads can be classified using different classification methods. Zhang and Coulorigner proposed a fuzzy logic based classifier to road identification for high resolution multi-spectral imagery [8]

In remote sensing imagery, roads are obviously different from the surrounding backgrounds in color, intensity, and shape. So, we have to extract the features of roads based on the background information of road. [1] Defines extracted road network based on image segmentation, in which the images were segmented by clustering algorithm. They use technique called k-means clustering. It defines "The road extraction involves the two main steps: the detection of road that might have the other non-road parts like buildings and parking lots followed by morphological operations to remove the non-road parts based on their features". Li and Cao [7] used saliency feature extraction model to obtain seed points, and then extracted road network with the active contour model.

The existing machine learning algorithms for road recognition include support vector machine (SVM), neural networks and decision tree, etc. Usually, classification model is obtained by training image samples with learning algorithms, and then to classify

samples, which is called "onetime" learning [2]. For examples, AdaBoost classifier was used to construct the road classification model [12], and Das *et al.* [3] firstly divided remote sensing image into sub blocks, and then selected road and non-road sub blocks as training samples, road was finally recognized by using SVM to train and test samples.

Recently, saliency model has been applied into remote sensing images processing. Existing works show that image recognition based on saliency feature can quickly locate saliency regions from complex background, providing initial region and position reference for target detection, which has lower computing complexity as well as higher recognition rate.

However, traditional saliency model is to compute colour, intensity, and orientation saliency features, which do not include the salient information of roads, such as edges. Obviously, traditional saliency model is not appropriate for urban satellite images with complex background. Hence, we extend the definition of saliency feature to most significant characteristics of roads compared with surrounding background.

With growing number of remote sensing imagery and the constantly changing of the road structure, road recognition from remote sensing imagery is proposed using Machine learning algorithm. Road network is detected from the remote sensing imagery by extracting road features. Machine learning algorithm is employed to recognize the road types. Finally, the recognition rate and computing time are analyzed and compared as the performance indexes of our method.

1.1 LITERATURE SURVEY

R. Maurya, Dr. P.R Gupta, Ajay Shankar Shukla et al. [1] has proposed the road extraction that involves the two main steps: the detection of road that might have the other non-road parts like buildings and parking lots followed by morphological operations to remove the non- road parts based on their features. They used the K-Means clustering to detect the road area and may be some non-road area. Morphological operations are used to remove the non-road area based on the assumptions that road regions are an elongated area that has largest connected component. Clustering is method to group similar objects into one cluster. K-means clustering [11] finds clusters such that objects within each cluster are as close to each other as possible, and as far from objects in other clusters as possible. K-means clustering requires you to specify the number of clusters to be partitioned and a distance metric to specify how close two objects are to each other.

Yoonsung Bae, Won-Hee Lee and Yunjun Choi et al. [2] proposed a novel automatic algorithm for road extraction from remote sensing images. The algorithm includes low- and high-level processing. In the low-level processing, we determine a normalized second derivative map of road profiles of a generalized bar shape, which is width invariant and contrast proportional, and accordingly obtain initial road center pixels. In the high-level processing, using the map and initial center pixels, we initially determine road segments. The segments are then locally refined using their orientation randomness and length-to-width ratio and further refined via global graph-cut optimization. A final road network is thereby extracted in a robust manner. Experimental results demonstrate that the proposed algorithm provides noticeably more robust and higher road extraction performance in various images compared with the existing algorithms.

Jing Zhang, Lu Chen, Li Zhuo, Qi Tian et al. [3] proposed a road recognition method for remote sensing imagery using incremental learning. In principle, our method includes the following steps: 1) the non-road remote sensing imagery is first filtered by using support vector machine; 2) the road network is obtained from the road remote sensing imagery by computing multiple saliency features; 3) the road features are extracted from road network and background environment; and 4) the roads are recognized as three road types according to the classification results of incremental learning algorithm.

Uwe BACHER and Helmut Mayer et al. [4] proposed a road model for areas with different road appearance in IRS satellite image data with a panchromatic resolution of 5 m and 20 m multispectral resolution. We model areas where water makes agriculture possible on one hand, and areas dominated by the desert and dry mountainous areas on the other hand. In agricultural areas, on which they focus in this paper, roads often do not appear as distinct lines. Borders of the fields represented by edges in the image and the knowledge that these borders can be collinearly grouped, possibly together with lines, into longer linear structures are used to construct road sections. To close gaps, pairs of lines or edges are connected by zip lock snakes. To verify these road sections, the paths of the snakes are evaluated using the line strength and the gradient image. The verified road sections are finally globally grouped using the knowledge that roads construct a network between important points. Gaps which have a high impact on the network topology are closed if evidence supporting this is found in the image.

D. Chaudhuri, N. K. Kushwaha, and A. Samal et al. [5] proposed semi-automatic approach for road detection that achieves high accuracy and efficiency. This method exploits the properties of road segments to develop customized operators to accurately derive the road segments. The customized operators include directional morphological enhancement, directional segmentation and thinning. They have systematically evaluated the algorithm on a variety of images from IKONOS, Quick Bird, CARTOSAT-2A satellites and carefully compared it with the techniques presented in literature. The results demonstrate that the algorithm proposed is both accurate and efficient.

Yuan Tian and Yanqing Wang et al. [6] proposed a new approach based on machine learning. First, many features reflecting road characteristics are extracted, which consist of the ratio of bright regions, the direction consistency of edges and local binary patterns. Then these features are input into a learning container, and AdaBoost is adopted to train classifiers and select most effective features. Finally, roads are detected with a sliding window by using the learning results and validated by combining the road connectivity. Experimental results on real Quick bird images demonstrate the effectiveness and robustness of the proposed method.

Sukhendu Das, T. T. Mirnalinee, and Koshy Varghese et al. [7] propose Dominant Singular Measure. It used to detect locally linear edge segments as potential trajectories for roads. This complimentary information is integrated using an optimization framework to obtain potential targets for roads. This provides decent results in situations only when the roads have few obstacles (trees, large vehicles, and tall buildings). Linking of disjoint segments uses the local gradient functions at the adjacent pair of road endings.

Region part segmentation uses curvature information to remove stray non-road structures. Medial-Axis-Transform-based hypothesis verification eliminates connected non-road structures to improve the accuracy in road detection.

Another approach is Celal Ozturk [7] proposed the Energy Constrained Sensor Networks. While developing and evaluating our privacy-aware routing protocols; we jointly consider issues of location-privacy as well as the amount of energy consumed by the sensor network. Motivated by the observations, we propose a flexible routing strategy, known as phantom routing, which protects the source's location. Source. Our investigations have shown that phantom routing is a powerful technique for protecting the location of the source during sensor transmissions

2. PROPOSED WORK

In order to adapt to continuously updated road samples and overcome the influence of complex background in remote sensing imagery, our road recognition method includes three parts: 1) Preliminary processing: Initially, we perform blocking of images, then the image is converted into gray scale image and then we perform Denoising ; 2) Road feature extraction: the road features are extracted from road network and back-ground environment using Histogram of Oriented Gradient (HOG) feature extraction technique; 3) Machine learning: roads are recognized by using Machine learning algorithm called Deep Convolutional Neural Network (DCNN). The framework of our work is shown in Fig.1.

In machine learning, an artificial neural network is a system of interconnected neurons that pass messages to each other. Neural networks are used to model complex functions and, in particular, as frameworks for classification. Deep Convolutional neural networks (DCNNs) are, therefore, gaining attention, due to their capability to automatically discover relevant contextual features in image categorization problems. DCNNs consist of a stack of learned convolution filters that extract hierarchical contextual image features, and are a popular form of deep learning networks. Our goal is to devise an end-to-end framework to classify satellite imagery with DCNNs. The context of large-scale satellite image classification introduces certain challenges that we must address in order to turn DCNNs into a relevant classification tool.

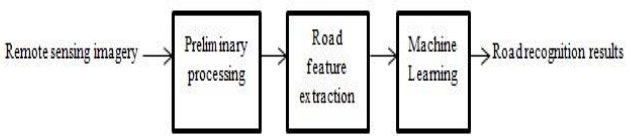

Fig. 1. The framework of our method

Advantages:

- It does not need any separate clustering technique
- Less time consumption
- Accuracy is high
- Used to detect roads from any high resolution images
- Higher road extraction performance

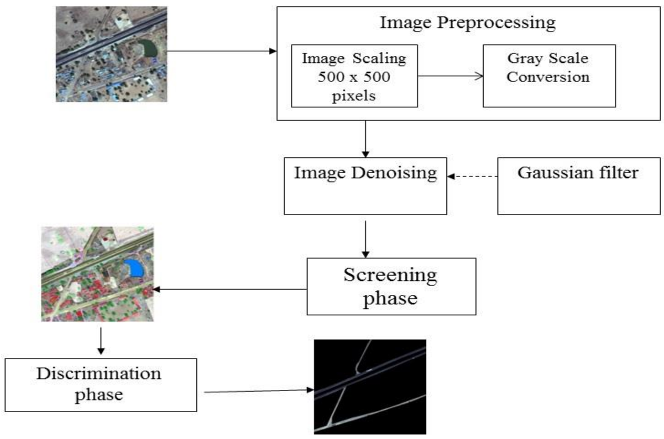

Fig. 2 System Architecture

Fig . 2. Shows the architecture of our model. Initially the image is taken from satellite and then we perform preprocessing steps to the image. The image is scaled into 500 x 500 pixels. Then we have to remove the noise using Gaussian filter. In screening phase, We track the roads and in Discrimination phase the roads are recognized.

2.1 PROBLEM FORMULATION

To formulate our problem, first we have convert RGB image into Gray scale image. The remote sensing image is converted to gray scale image, which is calculated by weighted average method of RGB three components

$$I(a, b) = 0.299R(a, b) + 0.587G(a, b) + 0.114B(a, b) \quad (1)$$

Then (1) gamma compression is used to reduce the local changes of shadow and illumination:

$$Y(a, b) = I(a, b)^{gamma} \quad (2)$$

Here, I (a, b) represents the gray value of the original pixel (a, b), and Y (a, b) represents the gray value of the original pixel (a, b) after gamma compression (*gamma* = 0.5).

Then, using (2) the window is divided into several cells. Then, a local 1-D histogram of gradient directions is used to describe gradient information for each cell. For example, the 360° gradient direction of cell is divided into 9 bins, if the gradient direction of pixel lies in 20°−40° , the count of the second bin will add 1. Finally, the gradient directions histogram of cell can be achieved by counting gradient direction of pixels in this cell.

In order to generate more accurate road networks, Total Variation Regularization-based image fusion has been adopted to fuse the input images with noise.

Let u1 (a, b) be the true road network, which is integrated by candidate region feature u2(a, b) and edge feature u3(a, b), the relationship of true image and candidate images.

$u_j(a,b) = \beta_j(a,b)\, u_1(a,b) + \eta_j(a,b)$, j = 1, 2 --> (3)

where β_j (x, y) and η_j (x, y) are the gain and noise respectively. The essence of image fusion is to estimate the true image u_0 from the candidate images u_j .

Algorithm:

Step 1: Convolution

The first layers that receive an input signal are called convolution filters. Convolution is a process where the network tries to label the input signal by referring to what it has learned in the past. If the input signal looks like previous cat images it has seen before, the "cat" reference signal will be mixed into, or convolved with, the input signal. The resulting output signal is then passed on to the next layer.

Step 2: Sub-sampling or Screening

Inputs from the convolution layer can be "smoothened" to reduce the sensitivity of the filters to noise and variations. This smoothing process is called **subsampling**, and can be achieved by taking averages or taking the maximum over a sample of the signal. Examples of subsampling methods (for image signals) include reducing the size of the image, or reducing the color contrast across red, green, blue (RGB) channels.

Step 3: Activation or Discrimination

The activation layer controls how the signal flows from one layer to the next, emulating how neurons are fired in our brain. Output signals which are strongly associated with past references would activate more neurons, enabling signals to be propagated more efficiently for identification. CNN is compatible with a wide variety of complex activation functions to model signal propagation, the most common function being the *Rectified Linear Unit (ReLU)*, which is favored for its faster training speed.

Step 4: Fully Connected

The last layers in the network are fully connected, meaning that neurons of preceding layers are connected to every neuron in subsequent layers. This mimics high level reasoning where all possible pathways from the input to output are considered.

(During Training) Step 5: Loss

When training the neural network, there is additional layer called the *loss layer*. This layer provides feedback to the neural network on whether it identified inputs correctly, and if not, how far off its guesses was. This helps to guide the neural network to reinforce the right concepts as it trains. This is always the last layer during training

2.2 METHODOLOGY

A.PREPROCESSING

1. Blocking

Blocking is the process of dividing the RGB image into four blocks, each 250x250 pixels

2. RGB to Gray

RGB to gray is the process of converting each block RGB image into gray image. Gray scale images are used for measuring the intensity of light at each pixel according to a particular weighted combination of frequencies.

Fig.3(a) RGB image

Fig.3(b) Grayscale image

3. Denoising

The road images taken from satellite are not clear because of noise present in it. So, we have to remove the noise by using Denoising technique called Gaussian filtering. Filtering is a technique for modifying or enhancing an image. For example, you can filter an image to emphasize certain features or remove other features. Filtering includes smoothing, sharpening, and edge enhancement. Gaussian filtering is used to blur images and remove noise in the image.

B.FEATURE EXTRACTION

HOG Feature Extraction:

Histogram of Oriented Gradient (HOG) is widely applied in the field of computer vision and image processing which is extracted by calculating the gradient histogram of local region of the image.

The **histogram of oriented gradients (HOG)** is a feature descriptor used for object detection. The technique counts occurrences of gradient orientation in localized portions of an image. This method is similar to that of shape contexts, but differs in that it is computed on a dense grid of uniformly spaced cells and uses overlapping local contrast normalization for improved accuracy.

The image is divided into small connected regions called cells, and for the pixels within each cell, a histogram of gradient directions is compiled. For improved accuracy, the local histograms can be contrast-normalized by calculating a measure of the intensity across a larger region of the image, called a block, and then using this value to normalize all cells within the block.

Since HOG is a kind of local feature, if extracting HOG feature for a whole image, different images may produce similar features, which is difficult to achieve a satisfied result. Remote sensing imagery is relatively large and usually contains a huge number of complex background information.

The HOG feature is obtained by combing the features of all blocks. In the process of extracting the HOG feature, a whole image is divided into sub blocks of 32 × 32 pixels and the 360° gradient direction of cell is separated into 9 bins, which is different from the standard HOG extracting.

Therefore, block processing is necessary before extracting HOG feature. However, if the size of sub-block is too large, the dimension of HOG feature will increase; otherwise, it will lead to incomplete information of the road in the sub-block. Therefore, we cut the whole remote sensing imagery into sub blocks, and then to extract HOG feature from every sub-block.

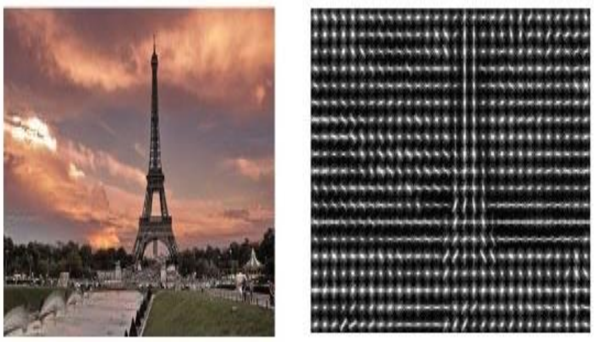

Fig. 4. Histogram Analysis

HOG feature extraction algorithm:

Step 1: The color image is converted to gray scale

Step 2: The luminance gradient is calculated at each pixel

Step 3: To create a histogram of gradient orientations for each cell.

Step 4: Normalization and Descriptor Blocks

C. FILTERING OF ROADS

Road information detection in remote sensing imagery is a typical binary classification problem. DCNN is the one type of supervised classification technique used in our method to determine road information and to filter road area from non-road area in the satellite images. DCNN is one of the forms of deep learning method in machine learning. It consists of a stack of learned convolution filters that extract hierarchical contextual image features.

3. EXPERIMENTAL RESULT

A set of experiments carried out for recognizing the road. The screenshots of various phases of Road Detection are as follows.

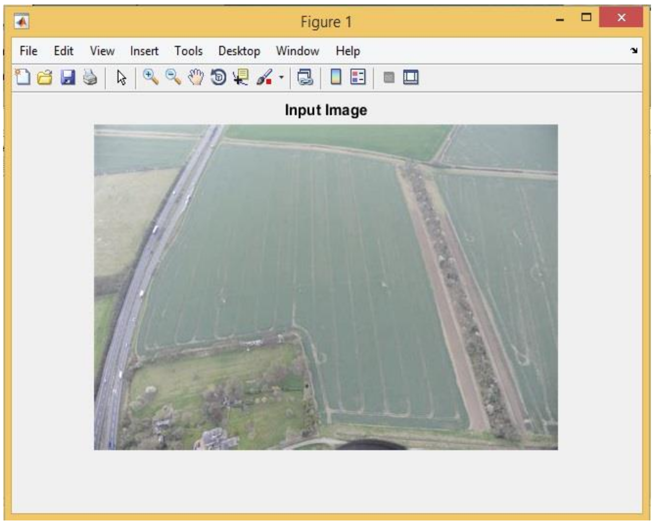

FIG-5 REPRESENT THE INPUT SATELLITE IMAGE

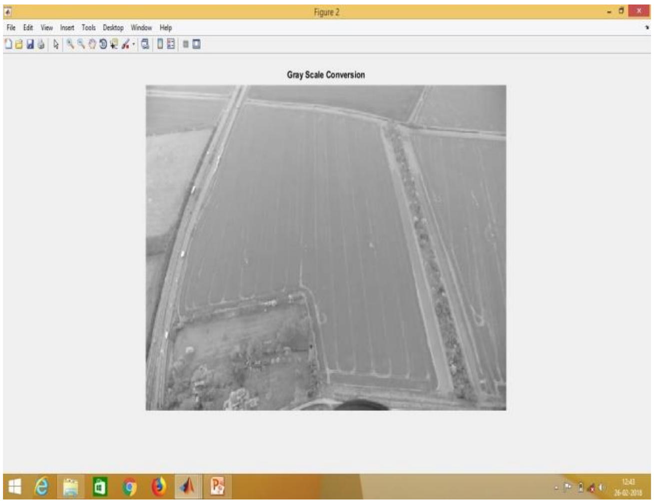

FIG-6 REPRESENT THE GRAY SCALE CONVERSION

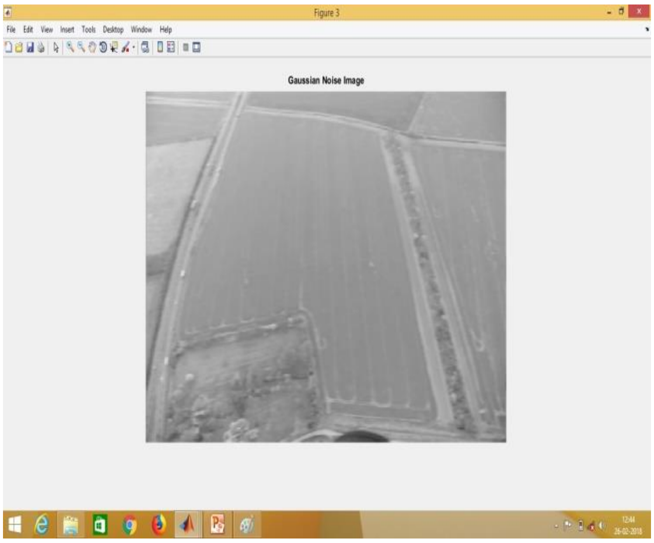

FIG-7 REPRESENT THE GAUSSIAN NOISE IMAGE

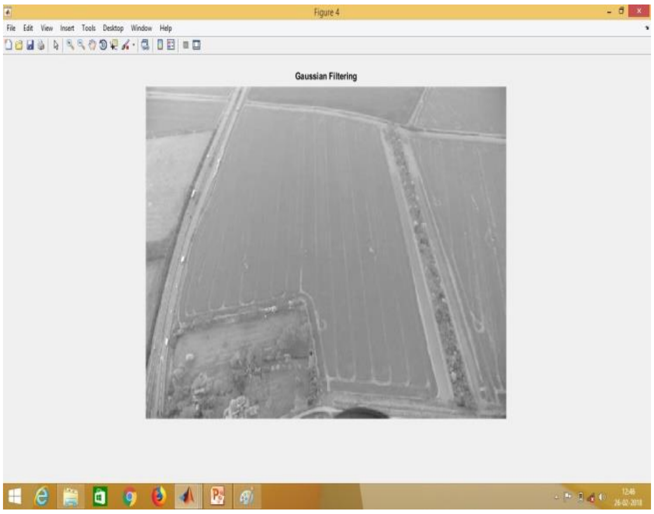

FIG-8 REPRESENT THE GAUSSIAN FILTERING

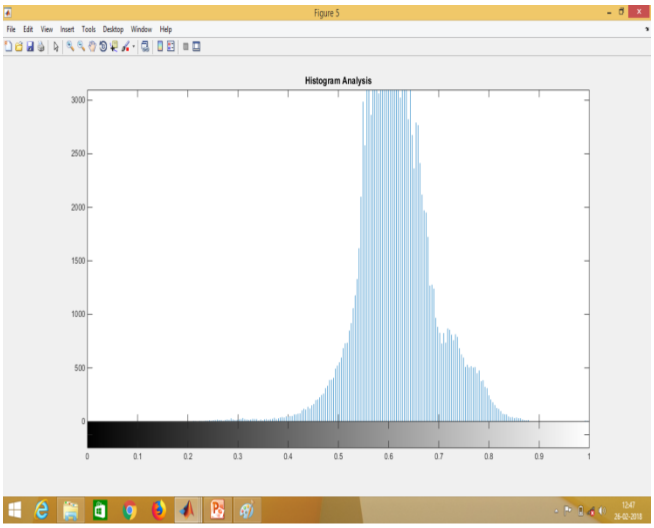

FIG-9 REPRESENT THE HISTOGRAM ANALYSIS

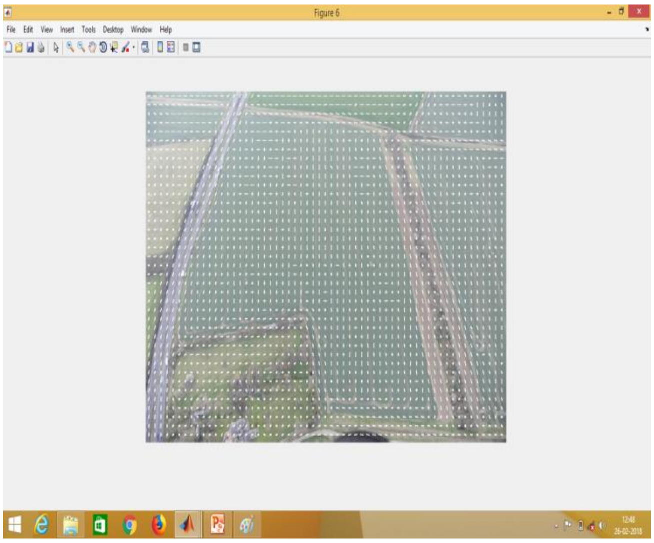

FIG-10 REPRESENT THE FEATURE EXTRACTION

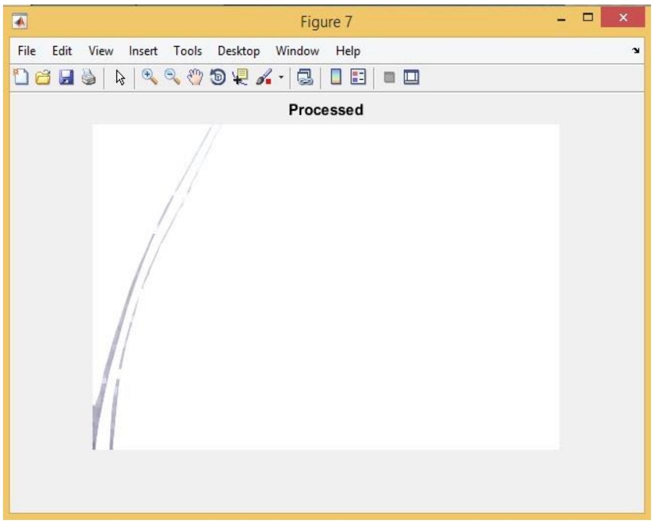

FIG-11 REPRESENT THE PROCESSED IMAGE

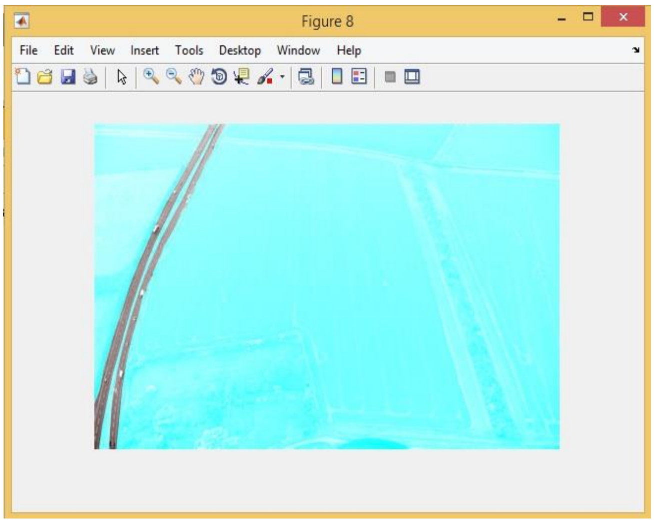

FIG-12 REPRESENT THE RECOGNIZED ROAD

4. CONCLUSION

A method of road recognition from remote sensing imagery is proposed by using Machine learning in this paper. First, the preliminary processing is utilized to perform Scaling the image and convert RGB to Gray and then perform Denoising. Second, extract the road features using HOG feature extraction. Finally, Machine learning algorithm called DCNN is used to filter roads from non-road areas. The experimental results show that our method has higher road recognition rate as well as less recognition time than the other popular algorithms

5. FUTURE ENHANCEMENT

In the future work, we will exploit some very similar objects, such as rivers and buildings and also some moving objects like vehicles, human beings etc. Then we will add topological features and texture features to the road network detection

REFERENCES

[1] R. Maurya, P. R. Gupta, and A. S. Shukla, “Road extraction using K-means clustering and morphological operations,” in Proc. Int. Conf. Image Inf. Process. (ICIIP), Shimla, India, Nov. 2011, pp. 1–6.

[2] Y. Bae, W. H. Lee, Y. W. Jeon, J. B. Ra, and Y. J. Choi, “Automatic road extraction from remote sensing images based on a normalized second derivative map,” IEEE Geosci. Remote Sens. Lett., vol. 12, no. 9, pp. 1858–1862, Sep. 2015.

[3] Jing Zhang, Member, IEEE, Lu Chen, Chao Wang, Li Zhuo, Qi Tian, Fellow, IEEE, “Road recognition from remote sensing imagery using incremental learning,” IEEE Remote Sens. Dec. 2016.

[4] U. Bacher and H. Mayer, “Automatic road extraction from IRS satellite images in agricultural and desert areas,” Int. Arch. Photogramm., Remote Sens. Spatial Inf. Sci., vol. 35, pp. 1055–1060, Jul. 2004.

[5] D. Chaudhuri, N. K. Kushwaha, and A. Samal, “Semi-automated road detection from high resolution satellite images by directional morphological enhancement and segmentation techniques,” IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens., vol. 5, no. 5, pp. 1538–1544, Oct. 2012.

[6] Y. Q. Wang, Y. Tian, and X. Q. Tai, “Extraction of main urban roads from high resolution satellite images by machine learning,” in Computer Vision (Lecture Notes in Computer Science). Berlin, Germany: Springer, Jan. 2006, pp. 236–245.

[7] S. Das, T. T. Mirnalinee, and K. Varghese, “Use of salient features for the design of a multistage framework to extract roads from high resolution multispectral satellite images,” IEEE Trans. Geosci. Remote Sens., vol. 49, no. 10, pp. 3906–3931, Oct. 2011.

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