Classification of Buildings and Vehicles in Google Map Satellite Images Using Random Forest Classifier

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Abstract The Google Map provides an additional feature for observing various places of the landscapes as bird's eye view with the help of the satellite images. Google Map satellite images are developed with the help of geographical information systems (GIS) data, aerial images, drone images, and satellite images with the help of image fusion methods to produce a bird's eye view of a landscape. This proposed research work is intended to classify the buildings and vehicles from the Google Map satellite images that are captured at a zoom level of 20 m. This research work carried out to survey an area for various applications which require number of buildings and number of vehicles. The random forest classifier is used for the pixel classification, and this technique is also referred as pixel segmentation. The random forest classifier produces a result of 87% accuracy.

Keywords Google map · Satellite images · Random forest classifier · Building segmentation · Vehicle segmentation

1 Introduction

Segmentation techniques are extensively used in the field of image processing and computer vision for the applications of object detection and identification [1]. A digital image is subdivided into a number of regions referred as segmented region. The segmented region consists of large number of pixels that have similar properties that represents the image. The segmentation of an image is used in several applications. The segmentation approach is used to identify both the buildings and vehicles in a Google Map satellite images that provide the basis for the work. As urbanization is on the increase, the significance of such satellite images is increasing which can be utilized in diverse applications. Such diverse applications include homeland security, effective resource management, emergency responses, and environmental monitoring as well. These Google Map satellite images are normally captured through

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high resolution satellites and have various applications especially in the areas like agriculture, forestry, geology, surveillance, regional planning, and also in education. Having such information helps in rural planning which benefits the residents and the development of various public facilities.

Various approaches have been developed and proposed for applications like extracting road networks [2–8], water regions, green regions, [9] identification of buildings, and vehicles. During the unexpected natural disasters, the loss incurred to assets and people is quite high. If an assessment is prepared in a short time during the disaster period, it provides the technical details of the disaster, quantity of the disaster, area affected by the disaster, etc. Thus, prompt decisions are initiated in short time to control the disaster and start planning for the rescue operation, etc. The significance of the satellite images originates from the fact that it is of high resolution, covers a wide area, and is highly efficient in terms of time. Google Map satellite images are very useful in the context of assessing the damages that are caused in the event of an unexpected disaster. Identifying the impact of the damage is possible to quickly initiate various necessary rescue actions. The field of remote sensing has lot of importance in understanding the extent of land use which helps in understanding the spatial and temporal features. This helps in providing high data availability and computing the data which helps in better understanding the changes. In this research work, classification of buildings and vehicles are carried out and achieved 87% accuracy using random forest classifier algorithm.

2 Related Works

To know about the structure of terrestrial systems, the land cover details are essential. The field of remote sensing generates terrestrial information in a global scale. A methodology is framed for both discrete and continuous land cover that is based on datasets which is time-based and depends on spatial resolution [10]. A method had been proposed that detects eroded and non-forested areas that are tropical. They used image algebra among the colour components that augmented the contrast mainly between green and brown. This helped to differentiate between the areas that are forest and the non-forested parts [11, 12]. Brezonik et al. [13] have specified that images captured from Landsat satellites are useful for estimating various optical characteristics of lakes and various measurements also considered. Prasad et al. [14] have identified that the rapid expansion of urbanization has depleted the water bodies and various infrastructural entities like buildings, roads, parks, and hubs are spreading in a very quick manner. Goswami et al. [15] have specified the importance of recognizing images from satellite images and that it comes under the classification techniques. He proposed artificial neural networks (ANN) for the purpose of object extraction as ANNs are suitable for extracting objects in an automated manner. The data associated with land cover are used extensively in the fields like modelling urban growth, agriculture based on advanced technology, management of coastal regions, and also climate management [16]. Noticed that land cover altered as an effect of natural disasters like landslides, floods, cyclones, and forest fires. Human interventions like urbanization, deforestation activities, and practices followed in agriculture also lead to alteration in the land cover [17].

The changes that happen in the ecological and physical systems due to human activities, understanding the land cover, help to understand both the ecosystem and the climate models [18]. The conservation of natural resources and its management and to formulate polices for urban and environmental development is essential. Poullis and You [19] proposed a road detection method and classified the method into three categories that are namely region-based, pixel-based, and knowledge-based. Line detectors [20], [21] and ridge detectors [22], [23] are employed for the identification and classification of road points. These interconnected road points are producing road segments that are provided as input to the further processing level stages. The techniques used in deep learning like convolutional neural networks (CNNs) are showing better performance than ANNs as they overcome the pitfalls and they produce better results when compared with machine learning techniques like support vector machines and random forest [24]. Studies have shown that spectral values are supplied in a vector format in one-dimensional format to the CNNs that is used for classification of land cover, but this approach fails to avail full advantage of CNNs that extracts spatial characteristics from images that are in two-dimensional form [25].

3 Methodology

Three hundred Google Map satellite images are collected by cropping various locations. Two hundred images are selected for training, and one hundred images are reserved for testing. The 200 images are marked with red colour for building and green colour for vehicle. These marked images are trained using the random classifier model. Fiji is used for pre-processing the images. The random classifier algorithm is used for training and testing. The Weka has developed the model for classification of building and vehicle. Further, the 100 images are tested using the model.

In a Google Map satellite image, segmentation techniques are used to identify both buildings and vehicles. The image processing tools used for this segmentation are Fiji and Weka. Random forest classifier is used for classification purpose of the above-mentioned images. The classifier is being built with around 200 images in the training set. The classifier is then loaded, and the results are created with a test set of 100 images.

The practice of subdividing an image into various objects or primary parts is the main purpose of segmentation. Once this is accomplished, the extracted regions are applied to different feature extraction algorithms used in both image processing and computer vision applications. This process depends on the application and grouping of pixels based on the intensity values is helpful for separating the required and other objects as well as other parts of the original image. Segmentation is useful for various areas like detection of vehicles, recognition of faces, in the field of medical diagnosis, and in various other fields as well. It has immense applications in pre-processing steps for image compression techniques and identification of object boundaries. Segmentation algorithms are classified into thresholding, clustering methods, region growing methods, and histogram-based methods. Partitioning an image into different regions that is similar and alike satisfies the similarity property while partitioning an image into several regions that is based on changes in intensity values satisfies the discontinuity property.

In the field of data science, different classification algorithms are available such as random forest, support vector machine, decision trees, logistic regression, Naive Bayes classifier, and few others. One of the frequently used classifiers in this hierarchy is the random forest classifier. The basic idea is the formulation of decision trees, and they are combined together to construct a typical random forest. Any random forest representations are built up using decision trees. Decision trees use features that help to split the data, and the resultant groups formed will be different in various respects.

An open source package for image processing that is based on Java named Fiji is used for this research work. The purpose of Fiji is to provide Java-based plugins that are bundled. Users are provided with a detailed menu supported with broad documentation with tutorials and are robust thereby avoiding installation of different components from various components. Developers use Fiji with version control systems, numerous development channels, infrastructure for prototyping and support numerous scripting languages.

The plugin initiates with two classes and hence producing the binary pixel classification. With the various tools for identifying the region of interest (ROI), users have the freedom to add traces to these classes.

The training set consists of 200 images that are captured from the Google Map satellite images taken at a resolution of 20 m zoom level. The random forest classifier is trained based on this training set, and the classifier is made accordingly. The images that are used for the training purposes are illustrated as follows. The following two images displayed in Figs. 1 and 2 are also employed in the training process.

The two classes that are developed here are namely buildings and vehicles, respectively. The ROI tools are used to indicate the regions present in both the classes from the training images. The pixels that belong to the buildings are marked with red colour, and the pixels corresponding to vehicles are marked with green colour. These boundaries are marked for each class for each and every training image that is being stacked from the training set in the Weka. The resultant classifier images are as follows Figs. 3 and 4.

After the boundaries for each class are being marked for all the images in the training set, as shown in the below images Figs. 5 and 6, the images are trained in Weka. It is noted that the training time depends on the total number of pixels present in each class. Once the training process is completed, the classifier model is saved for testing other images.

Fig. 1 Google Map satellite image 1

Fig. 2 Google Map satellite image 2

4 Results and Discussion

After the classifier is build and then trained, the next step is to perform the testing operations on the classifier developed. A sample test dataset of 100 images is considered for testing, and the results are replicated on these dataset. The classifier is loaded, which was built previously and then click on the generate results option. The results obtained are as shown above.

As mentioned earlier, buildings are mapped with red pixels, and the vehicles are mapped with green pixels. The probability map is shown below where it represents the probability of a pixel that belongs to a particular class that can either be buildings or vehicles. It is noted that for classifiers, the performance has to be augmented with the help of optimization of different parameters (Fig. 7).

Fig. 3 Weka classifier image 1

Fig. 4 Weka classifier image 2

The results obtained are after different stages of optimization techniques. A commonly employed technique used in machine learning is Bayesian optimization. When there are different hyper-parameters that deal with machine learning problems, there arises tuning of the classifier which results in costly evaluations with respect to time and computational resources, respectively. Bayesian optimization is useful to overcome this short coming. A probabilistic model is built, and the posterior predictive distribution is computed that integrates the various true functions. This leads to an optimized proxy function that is cheaper when compared with the true objective.

Fig. 5 Weka test results image 1

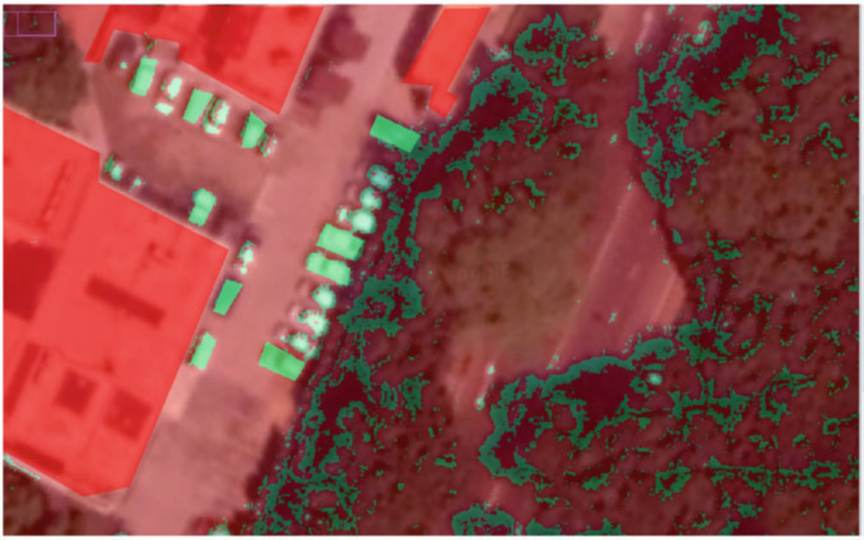

Fig. 6 Weka test results image 2

The idea behind this approach is to exploit the amount of randomness to balance the exploration. This approach may not give the best results with respect to neural networks [26] because optimization that is based on a manual scheme is applied.

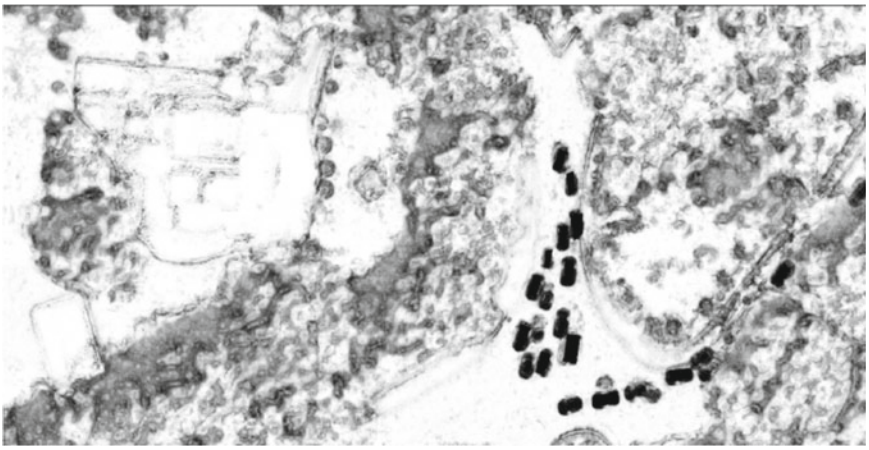

Fig. 7 Weka probability map of the test results

The random forest approach produces the value of accuracy as 0.87 which is computed as the number of true predictions to the entire number of input images. The specificity obtained is 0.91 which matches the negative samples wrongly identified as positive to the whole set of incorrect samples. The precision value obtained is 0.93 which is equal to the proportion of correct positive samples to the whole set of samples that are positive. The recall results come to 0.91 which is denoted as the right positive samples that are predicted to the entire set of samples irrespective of prediction. The F_1 measure that corresponds to the harmonic mean involving both precision as well as recall is 0.92 which depends on the precision of the classifier. The geometric mean comes out to be 0.94 which is related to both sensitivity and specificity.

5 Conclusion

The detection of roads is a critical problem. This is due to complication of road segments like occlusions, discontinuities, different boundaries, and sharp bends. This makes the classification of both buildings and vehicles also difficult. This research article discusses about an approach that classifies buildings and vehicles in Google Map satellite images based on the random forest approach. This provides an informative approach for the classification of both buildings and vehicles. The random forest classifier is employed for this purpose. This research article discusses about an approach in classifying buildings and vehicles with relatively high accuracies. The results can be further improved if the images are processed using deep neural networks that employs deep learning.

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