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# Tree detection using UAV-based imagery based on Random Forest classification

**Fatemeh Moradi[1], Farhad Samadzadegan[1], Farzaneh Dadrass Javan[1, 2, *] and Ahmad Toosi[1]**

[1] School of Surveying and Geospatial Engineering, College of Engineering, University of Tehran, Tehran, Iran
[2] Faculty of Geo-Information Science and Earth Observation (ITC), University of Twente, 7522 NB Enschede, the Netherlands

* Correspondence: School of Surveying and Geospatial Engineering, College of Engineering, University of Tehran, Tehran, Iran; fdadrasjavan@ut.ac.ir
*Email addresses*: fatemeh.moradii@ut.ac.ir (F. Moradi), samadz@ut.ac.ir (F. Samadzadegan), fdadrasjavan@ut.ac.ir, f.dadrassjavan@utwente.nl (F. Dadrass Javan), (A. Toosi), ahmadtoosi71@ut.ac.ir

**Abstract**: Mapping trees using UAVs is one of the most effective methods in urban planning and management. In this paper, the objective is to present an accurate hybrid method using Random Forest classification to extract urban trees. The classification process has been carried out with two different approaches. In the first approach, spectral and textural features, and the second one, in addition to these features, the digital surface model has also been used. The Random Forest algorithm is evaluated with these two approaches in two urban areas in Iran, which with the addition of DSM, the Kappa accuracy level in the study areas improves by 21%, and 36%, respectively. Furthermore, the effect of reducing the space of textural features is also evaluated using principal component analysis. Based on the obtained results, kappa accuracy is reduced if all textural features are used.

**Keywords:** Remote Sensing, Tree Extraction, Random Forest, UAV

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## 1. Introduction

Urban tree canopy plays an important role in sustainable urban development and planning, offers a variety of environmental services and social and economic benefits [1] (P.1). Therefore, having the statistics and information of existing trees can be an essential step in managing urban greenbelt. Due to a large number of trees and the extent and distribution of urban greenbelts, updating the statistics and information of trees cannot be limited to using the traditional methods. Therefore, utilizing Remote Sensing can be an effective method to generate maps of tree canopies.

A variety of studies were conducted using different Remote Sensing data in the field of tree detection, in which some scholars have used Light Detection and Ranging (LiDAR) point cloud or a combination of LiDAR height data with other data sources to identify tree classes with other features [2-4]. Another study showed that hyperspectral images have a high potential to distinguish trees from other urban objects [5]. Due to the complexities of the urban environment, the use of hyperspectral images or LiDAR data leads to high acquisition and computational costs. In other researches, Unmanned Aerial Vehicle (UAV)-derived optical images have been used to detect trees [6-9], which has advantages over other Remote Sensing methods such as lower operating costs, altitude control, sensor angle control, and overlapping adjustment [10]. UAV data also provides several prominent characteristics that can be of great help such as high-resolution images, dense point clouds of the area, and high-quality digital surface models (DSMs) [2].

To map trees, image classification techniques, both object-based [11] and pixel-based methods have been widely used. One of the problems with pixel-based classification is the noise generated in the output classified map which is caused by ignoring the pixels' spatial information. The researchers showed that the Random Forest algorithm provides advantages to overcome the problems of pixel-based classification [12]. Also, by using the Random Forest method and texture-based features the results revealed that this algorithm offers an accuracy close to the object-based classification method [9]. According to [13] it can be deduced that the Random Forest method has a performance advantage over other machine learning algorithms such as the Support Vector Machine (SVM) and can provide higher accuracy.

Considering the results of previous researches, this paper pursues two main objectives: 1) Evaluating the performance of DSM's features in addition to textural and spectral features to extract the tree using the Random Forest classification method. 2) Evaluation of the effect of reducing feature space using principal component analysis (PCA) and comparing it with the case where all textural properties have been used for classification.

## 2. Materials and Methods

Based on the objectives of the current research and according to Figure 1, the proposed method includes four steps: 1) Obtaining UAV data and pre-processing them, 2) Extracting spectral features, image-based texture, and DSM from UAV images, 3) Applying Random Forest method for tree extraction in urban areas, 4) Evaluation and analysis of results.

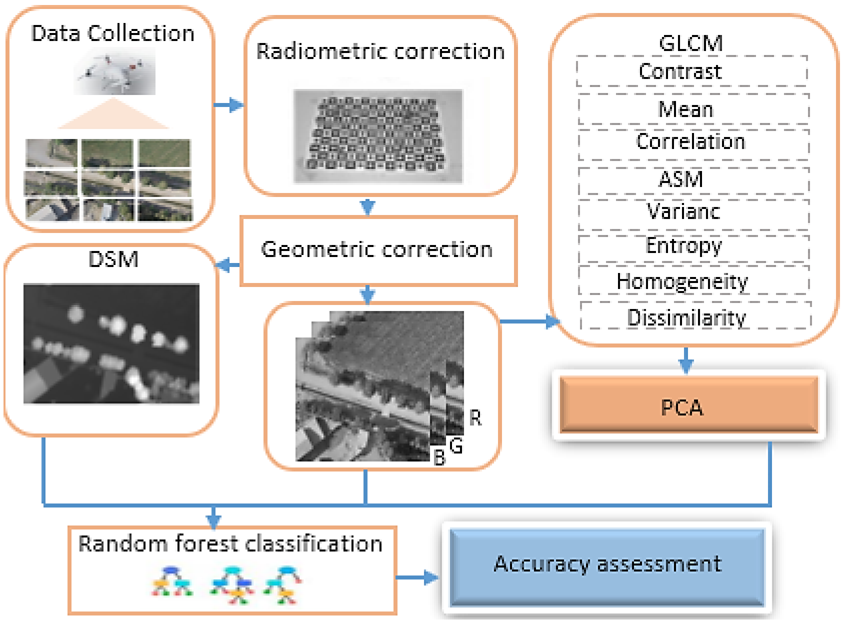


**Figure 1**. Workflow of the proposed method

### *2.1. Data Acquisition and Pre-processing*

In this study, a multicopter drone equipped with a GoPro Hero 4 camera with a focal length of 3 mm was used to obtain data. The first part of the data, with a spatial resolution of 2.23 cm, was obtained from Philestan village located in the central part of Pakdasht city with geographical characteristics as WGS-84 35° 26' 7'' N and 51° 40' 22'' E which covers an area of 3.07 hectares. The second part of the data was obtained from Charmshahr industrial town located in Varaamin city with geographical characteristics as WGS-84 35° 12' 17'' N and 51° 34' 58'' E which covers an area of 104.5 hectares and a spatial resolution of 8.75 cm. All the data were optical images (containing red, green, and blue channels).

first, the flight path was set and then radiometric calibration was performed using special boards at the flight site before and after the flight. Also, geometric correction of UAV images was carried out using Agisoft Metashape software to extract ortho-mosaic and DSM for the two study areas.

### *2.2. Feature Extraction*

According to the previous research, image-based texture features play an important role in extracting trees from UAV images [9]. The use of image-based texture properties will be effective if the parameters related to the extraction of texture properties such as direction, pixel distance, and filter size are well selected for the task [14]. According to [14] to solve the direction problem in this study, all of the eight statistical properties extracted from the Grey Level Co-occurrence Matrix (GLCM) were estimated in four directions such as 0, 45, 90, and 135 degrees, then by averaging these four directions for each statistical characteristics, the direction parameter related to the GLCM was calculated. The dimensions of the selected filter are very important to define the spatial relationships between the pixels. If selected too small, the extracted spatial information is not statistically reliable and if selected too large, it produces textural information with numerous features and overlapping terrain features [15]. In this study, the filter size was set to 5×5 and the distance was set to one pixel based on trial and error. By determining these values for each of the image bands, eight texture properties were generated, so there would be a total of 24 textural properties for the whole three bands. Generating high-dimensional features will usually result in data redundancy and noise [16]. Therefore, in this study, to reduce the dependency between class and noise, the PCA method was applied on image-based textural properties, and the four properties with the most variance were selected including entropy, Angular Second Moment (ASM), homogeneity, and mean value. In the last step, four selected bands obtained from the PCA method along with three main image channels and a DSM band were given as data to the Random Forest classification to separate the tree class from other urban features (Table 1). For the training and testing process of the Random Forest algorithm performance, 50% of the data were randomly selected for training and 50% for testing.

**Table 1**. Extraction of spectral, textural, and elevation features

| Textural features | Formula | Textural features | Formula | Spectral & elevation features |
|---|---|---|---|---|
| Contrast | $\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}(i-j)^2P(i,j)$ * | Variance | $\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}\left(j-\mu_j\right)^2P(i,j)$ | Green band |
| Mean | $\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}P(i,j)$ | Entropy | $\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}P(i,j)ln\left(P(i,j)\right)$ | Red band |
| Correlation | $\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}\frac{(i-\mu_i)(j-\mu_j)P(i.j)}{\sigma_i\sigma_j}$ | Homogeneity | $\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}\frac{P(i,j)}{1+(i-j)^2}$ | Blue band |
| ASM | $\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}\left(P(i,j)\right)^2$ | Dissimilarity | $\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}\lvert i-j\rvert\,P(i,j)$ | DSM |

* ***Ng***: number of image gray value; ***P (i, j):*** image gray value in (i, j) cell in GLCM; $\boldsymbol{\mu_i}$ and $\boldsymbol{\mu_j}$: mean in the i and j directions, respectively; $\boldsymbol{\sigma_i}$ and $\boldsymbol{\sigma_j}$: standard deviation in the i and j directions, respectively.

### *2.3. Random Forest*

The Random Forest algorithm was proposed by Bryman in 2001 [17]. It is a supervised machine learning algorithm that achieves better classification results by combining the output of several classifiers [18]. This algorithm is implemented in two stages: The first step is related to the creation of learners, and the second step is devoted to combining the outputs. There are several methods for combining the output of classifiers, one of the simplest and most common of which is the "majority vote" mechanism [19]. Random Forest has fewer hyper-parameters compared to other machine learning algorithms and has higher speed and accuracy [9].

### *2.4. Accuracy Assessment*

The performance evaluation of the proposed algorithm is performed using the criteria obtained from the confusion (error) matrix, which is an accurate and pixel-based evaluation and compares the result obtained with the ground truth data. In this paper, Overall Accuracy (OA), Positive Predictive Value (PPV), and Kappa coefficient were selected as metrics to evaluate the accuracy [20]. Eq. 1-3 defines the mentioned metrics, respectively.

$$\mathrm{OA} = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}} \tag{1}$$

$$\mathrm{PPV} = \frac{TP}{TP+FP} \tag{2}$$

$$\mathrm{Kappa} = \frac{\mathrm{OA-expected\ agreement}}{\mathrm{1-expected\ agreement}} \tag{3}$$

Where TP, FN, FP, and TN represent a situation that "in reality, the object is a tree and detected as a tree", "in reality the object is a tree but not detected as a tree", "in reality the object is not a tree but detected as a tree" and "in reality, the object is not a tree and not detected as a tree", respectively.

## 3. Results and Discussions

As presented in Figure 2, in this research, three different regions have been selected to further evaluate the proposed algorithm for the test data.

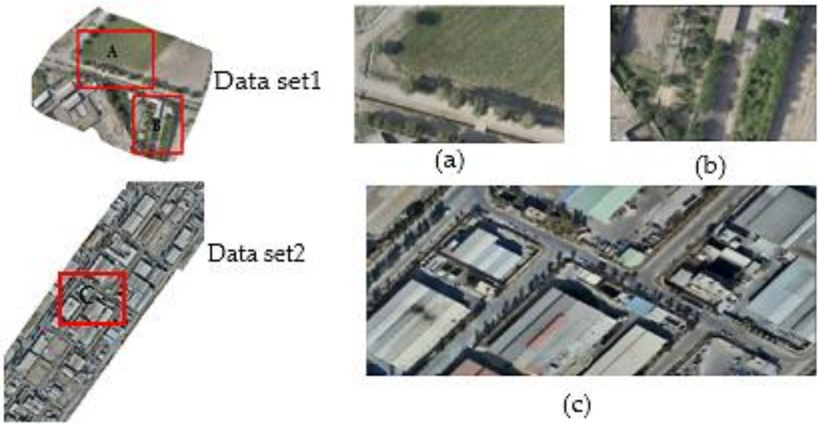


**Figure 2.** Test data. (**a**) An urban area with detached trees and simple background; (**b**) An urban area with dense trees and tall boxwoods; (**c**) A complex urban area with trees of different ages and heights and urban objects.

Also, the separation of trees from other urban objects has been done in three different approaches (Figure3). In the first approach, only the visible image bands and four textural features obtained from the PCA method were utilized for the classification. For the second one, considering that both study sites are urban areas and the land is almost flat, the DSM (as a feature vector) was used in addition to visible image bands and four textural features. From a visual comparison standpoint of the obtained results, it is observed that with the addition of DSM, the ability to separate trees from other urban objects in three areas increases. Textural features are very effective in separating trees from vegetation, but in the first region, these features have not been able to distinguish tree canopies from their shadows on the lawn. Also, in the second region, which contains dense vegetation and tall boxwoods, by using DSM, trees are better distinguished from boxwoods. About the third region, which has trees of different ages and heights, if in the first approach only the textural features and spectral bands are used, small trees will be lost in the classification process, but in the second approach, in addition to these features, importing DSM as a feature vector in the classification process helps to better identify small trees and separate them from other objects. In the third approach, the visible image bands and all textural features were used for classification to study the efficiency of using PCA in the classification process. Using all textural features with the conditions mentioned in the previous sections, despite dependencies in some feature spaces, reduces the accuracy of the classification and also generates noises (Figure 3). Furthermore, if all the textural features are used it consumes much running time and the computational expense will drastically increase.

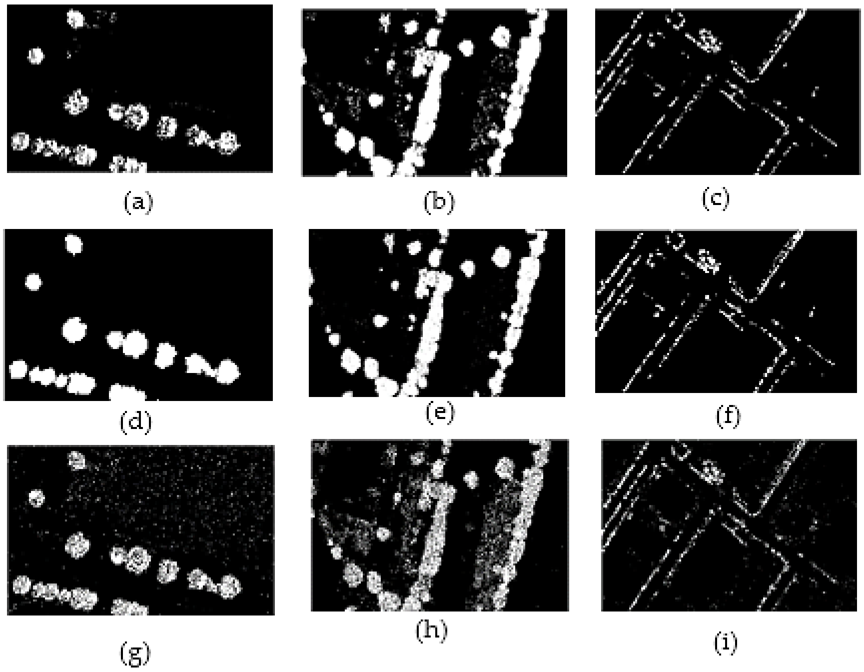


**Figure 3.** Classification result. (**a**) RGB + 4 textures for the 1st image; (**b**) RGB + 4 textures for the 2nd image; (**c**) RGB + 4 textures for the 3rd image; (**d**) RGB + 4 textures + DSM for the 1st image; (**e**) RGB + 4 textures+ DSM for the 2nd image; (**f**) RGB + 4 textures + DSM for the 3rd image; (**g**) RGB + 24 textures + DSM for the 1st image; (**h**) RGB + 24 textures + DSM for the 2nd image; (**i**) RGB + 24 textures + DSM for the 3rd image.

As can be seen in Table 2, quantitative evaluation of the results confirms the qualitative assessment, therefore the proposed method has been able to achieve the highest accuracy in three different areas. Finally, the second approach in the proposed method resulted in the highest accuracy in the study areas with the overall accuracy of 98%, 97%, and 98%, respectively.

**Table 2.** Accuracy assessment of Random Forests in three different modes

| Image | Features Used | OA (%) | Kappa (%) | PPV (%) |
|---|---|---|---|---|
| | RGB + 4 Textures | 94 | 79 | 93 |
| **a** | RGB + 4 Textures + DSM | 98 | 90 | 98 |
| | RGB + 24 Textures | 93 | 70 | 76 |
| | RGB + 4 Textures | 94 | 64 | 86 |
| **b** | RGB + 4 Textures + DSM | 97 | 90 | 97 |
| | RGB + 24 Textures | 91 | 59 | 76 |
| | RGB + 4 Textures | 97 | 88 | 94 |
| **c** | RGB + 4 Textures + DSM | 98 | 91 | 99 |
| | RGB + 24 Textures | 91 | 74 | 82 |

## 4. **Conclusions**

Greenbelts and trees play an important role in urban areas, so preparing a map of urban trees helps the policymakers and corresponding officials to make propitious decisions about the city. Therefore, in this research, UAV-based optical images were used to separate trees from other urban objects. It should be noted that in optical images, trees and other vegetation have high spectral similarity, which leads to a decrease in classification accuracy. In this research, by proposing an accurate combined method of Random Forest, textural features, spectral bands of the visible image, and DSM, high accuracy results were achieved for tree extraction in urban areas. It has also shown that DSM has a significant role in increasing the classification accuracy so that with the addition of DSM as a feature vector, an increase of 21%, 36%, and 3% accuracy was revealed in the first, second, and third study areas, respectively. In the second part of this study, the effect of using PCA in the classification process was examined and it was showed that if all the textural properties are used, the classification accuracy will decrease. Considering the advantages of UAVs compared to other Remote Sensing platforms, it is suggested to utilize UAV-derived multi-spectral images (images that include invisible channels in addition to the RGB visible bands) to monitor urban vegetation in future researches and the effect of the near infra-red band in separating trees from other objects should be evaluated.

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