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Image Processing Techniques based Feature Extraction for Insect Damage Areas[1]

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Abstract

Monitoring of forests is important for the diagnosis of insect damage to vegetation. Detection and monitoring of damaged areas facilitates the control of pests for practitioners. For this purpose, Unmanned Aerial Vehicles (UAVs) have been recently used to detect damaged areas. In order to distinguish damage areas from healthy areas on UAV images, it is necessary to extract the feature parameters of the images. Therefore, feature extraction is an important step in Computer Aided Diagnosis of insect damage monitored with UAV images. By reducing the size of the UAV image data, it is possible to distinguish between damaged and healthy areas from the extracted features. The accuracy of the classification algorithm depends on the segmentation method and the extracted features. The Grey-Level Co-occurrence Matrix (GLCM) characterizes areas texture based on the number of pixel pairs with specific intensity values arranged in specific spatial relationships. In this paper, texture characteristics of insect damage areas were extracted from UAV images using with GLCM. The 3000*4000 resolution UAV images containing damaged and healthy larch trees were analyzed using Definiens Developer (e-Cognition software) for multiresolution segmentation to detect the damaged areas. In this analysis, scale parameters were applied as 500, shape 0.1, color 0.9 and compactness 0.5. As a result of segmentation, GLCM homogeneity, GLCM contrast and GLCM entropy texture parameters were calculated for each segment. When calculating the texturing parameters, neighborhoods in different angular directions (0,45,90,135) are taken into account. As a result of the calculations made by considering all directions, it was found that GLCM homogeneity values ranged between 0.08 - 0.2, GLCM contrast values ranged between 82.86 - 303.58 and GLCM entropy values ranged between 7.81 - 8.51. On the other hand, GLCM homogeneity for healthy areas varies between 0.05 - 0.08, GLCM contrast between 441.70 - 888.80 and GLCM entropy between 8.93 - 9.40. The study demonstrated that GLCM technique can be a reliable method to detection of insect damage areas from UAV imagery.

Keywords: Image processing, Insect damage, Gray level co-occurrence matrix

1. Introduction

Unmanned **A**erial **V**ehicles (UAVs) have been frequently used in forestry applications such as measuring structural characteristics of individual trees (Bayat et al., 2019; Finn et al., 2019), calculating and mapping forest parameters (Williams et al., 2022; Lin et al., 2023), estimating biodiversity (Milz et al., 2023), as well as detecting insect damage on individual trees (Jung et al., 2019; Lin et al., 2019; Junttila et al., 2022). If there are stressed trees in forests due to insect damage, healthy and decayed trees can be distinguished from UAV images using the spectral reflectance characteristics of tree canopies. For example, *Thaumetopoea pityocampa* (pine beetle) causes mass reproduction on coniferous trees, destroying all the needles and leaving the tree bare. In these damages, accurate and timely forest health monitoring is required to support sustainable forest management (Lausch et al., 2018). UAVs provide timely forest health monitoring and spatially precise data against such damages (Torresan et al., 2018; Manfreda et al., 2018). Image Segmentation techniques are used to find infected areas in high- resolution UAV images. However, even in the same image for geo-classification, the same object has different reflectance value, which can cause texture complexity (Lan and Liu, 2018). To resolve this pixel complexity and capture morphological variations in high-resolution images, researchers have developed color and texture descriptors, the two main features of image segmentation that can be associated with geographic information (Haralick et al., 1973; Qin, 2000; Liu., 2008). One of the descriptors used to classify complex and variable scenes is Gray Level Co-Occurrence Matrix (GLCM) based texture and color descriptors. In the literature, many studies have been conducted using remote sensing images, showing that GLCM texture parameters including Energy, Contrast, Homogeneity, Entropy statistics are sensitive to scale parameters in land cover and can improve classification accuracy (Franklin et al., 1996; Stasolla and Gamba, 2008; Kuffer et al., 2017; Lan and Liu, 2018; Kupidura et al, 2019; Mugiraneza et al., 2019, Fallatah et al., 2020; Lai and Yang, 2020). In addition, in recent years, GLCM

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texture parameters have started to be used in the calculation of structural parameters of forests (Ozdemir et al., 2012; Ozdemir et al., 2018).

The aim of this study was to calculate texture parameters for the detection of pine beetle damage without going to the field. In the application, pine beetle damage parameters were calculated on a larch stand using unmanned aerial vehicle images. Gray Level Co-occurrence Matrices (GLCM) method was used to extract the feature vectors of the images. The images were classified into two groups; 1) healthy and 2) diseased.

2. Material and Methods

2. 1. Study Area and Data Capture

The study area covers an area of approximately five hectares located in Kaynaslı district of Düzce province. The study area is a pure larch plantation and the approximate coordinates are 40°47'39.44"N, 31°16'38.26"E, 40°47'29.59"N, 31°16'45.14"E (Figure 1). As a result of the field study in April 2018, intense pine beetle damage was observed on the larch stand and serious discoloration of the trees was observed. Therefore, this area was selected as the study area where pine beetle damage can be detected using UAV data.

DJI Phantom 4 RTK UAV was used to collect aerial photos of the study. The DJI Phantom 4 RTK platform has a 12-megapixel resolution camera that can take photos in the visible range (RGB) provided by the manufacturer (DJI, 2023). A total of 10 photographs covering the damage areas on the larch stand were taken. Among these photographs, three photographs of the most intensive damage area were selected as sample areas. The photographs obtained were 4000x3000 pixels in size, 72 dpi resolution and 24-bit capacity. Definiens Developer (e-Cognition software) was used for data analysis.

2.3. Method

For the classification of very high-resolution images, a multiresolution segmentation process was utilized. This process enables the calculation of GLCM matrices. In this study, UAV images in JPEG format were analyzed in two stages: the pine beetle damage area and the undamaged area. The e-Cognition software was employed to perform multiresolution segmentation, followed by the calculation of GLCM matrices. Specifically, the minimum and maximum values of the feature vectors for three parameters, namely contrast, homogeneity, and entropy, were computed.

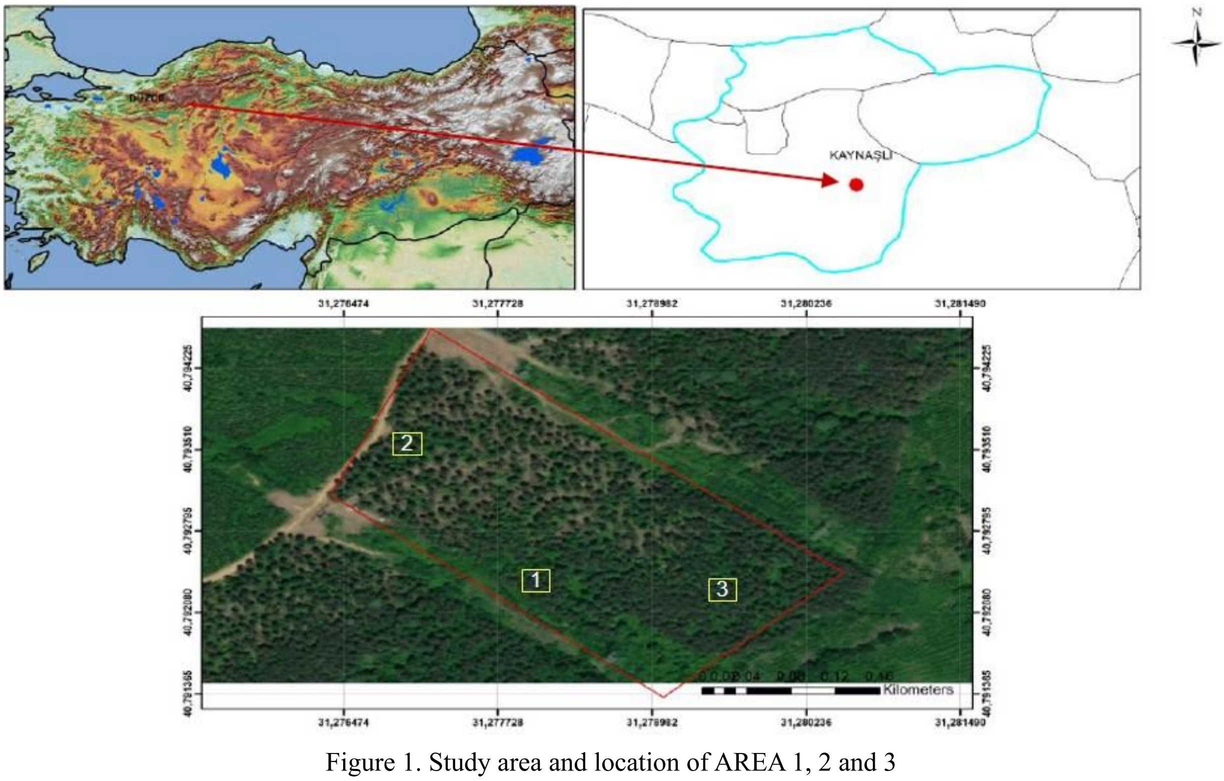

Figure 1. Study area and location of AREA 1, 2 and 3

GLCM (Gray Level Co-occurrence Matrix) is a feature extraction method introduced by M. Haralick in 1973. It is utilized to extract features such as GLCM Homogeneity, GLCM Contrast, and GLCM Entropy from grayscale images. GLCM establishes the relationship between two adjacent pixels in an image. The first pixel is referred to as the reference pixel, while the second is called the neighbor pixel (Horng et al., 2003). GLCM generates a frequency matrix that represents the occurrences of pixel value pairs at a specified distance and angle within the image. This matrix is a square matrix of size Ng, where each element indicates the frequency of pairs of pixel values i and j at a distance d (Roumi, 2009). From these matrices, three texture features, namely contrast, homogeneity, and entropy, can be computed to describe the texture characteristics of the image. These textural features are derived from GLCM.

Contrast*:* Contrast is a measure of heterogeneity and represents the amount of local variation within an image. It is determined by evaluating the differences between neighboring pixels. An increase in contrast leads to an increase in the number of distinct pixel value pairs (i, j) in the GLCM matrix (Haralick et al., 1973). The parameters required for calculating contrast are as follows:

$$\sum_{N=0}^{N_g-1} n^2 \left(\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i,j)\, IIi - jI = n\right) \qquad (1)$$

Homogeneity: Homogeneity refers to the uniformity or similarity of pixel values within a given region. In regions with high homogeneity, the GLCM values tend to be concentrated in the corners of the matrix. This concentration indicates a higher degree of similarity between neighboring pixels. Conversely, in heterogeneous regions, the GLCM values are distributed more evenly across the matrix. This difference in GLCM distribution between homogeneous and heterogeneous areas results in contrasting color values. The color values decrease as we transition from heterogeneous to homogeneous areas (Haralick et al., 1973). The parameters required for calculating homogeneity are as follows:

$$\sum_{i,j} \frac{p(i,j)}{1+(i-j)^2} \qquad (2)$$

Entropy: Entropy in GLCM calculations quantifies the degree of uncertainty or randomness in the distribution of GLCM values. An even distribution of GLCM values across the matrix leads to a higher entropy value, indicating greater complexity or variability in the texture of the image (Haralick et al., 1973). The parameter used for entropy calculation is as follows:

$$\sum_{i,j} \frac{p(i,j)}{1+(i-j)^2} \qquad (3)$$

In the segmentation process, the aim is to group pixels with similar characteristics together and utilize texture features to differentiate damage areas. The image is segmented into image objects using the segmentation algorithm integrated into the Definiens software. The bottom-up field merging method was employed for the segmentation of UAV data. Segmentation scale, color, shape, integrity and transitivity parameters were used as inputs for multiresolution segmentation. In this method, color and shape parameters, integrity and transitivity parameters take complementary values of 1 (Tian and Chen, 2007). Three features including contrast, homogeneity and entropy were calculated to characterize the texture of the image. To find the appropriate parameter values, many combinations of values were assigned to the segmentation parameters and decided through visual analysis. The visual analysis evaluates the spatial and morphological suitability of the image objects obtained for the region and prefers segmentations that effectively separate different damaged and undamaged regions.

3. Results and Discussion

The "spectral variation hypothesis" proposed by Palmer et al. (2000) and Palmer et al. (2002) suggests that higher spectral heterogeneity in an image corresponds to higher diversity. In the case of GLCM-based pine beetle damage detection, the texture parameters we calculated supported this hypothesis. The three texture parameters, GLCM homogeneity, GLCM contrast, and GLCM entropy, were computed for each segment. The analysis applied scale parameters of 500, shape 0.1, color 0.9, and density 0.5. As a result of the multiresolution segmentation, AREA 1 was divided into two categories: damage areas and non-damaged areas, as shown in Figure 2.

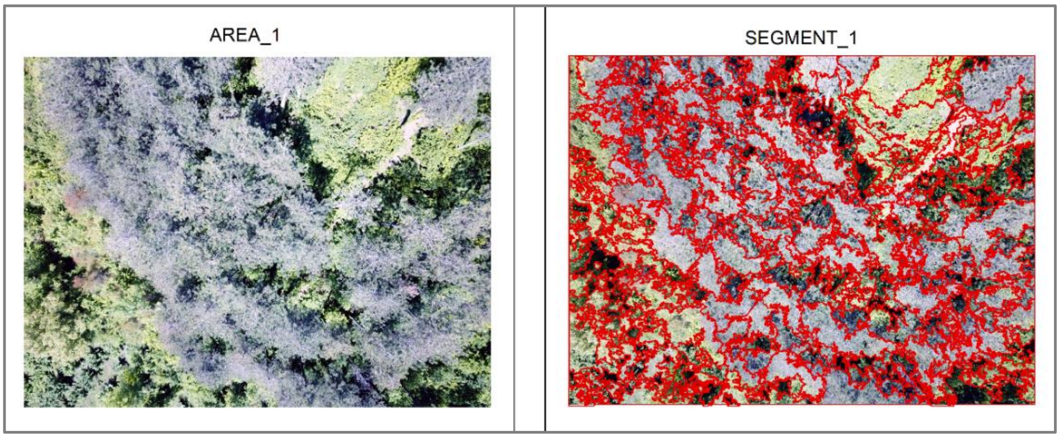

Figure 2. AREA 1

In study AREA 1, the calculations for all directions (GLCM homogeneity, GLCM contrast, and GLCM entropy) revealed the following ranges of values for the damaged segments: GLCM homogeneity ranged from 0.064 to 0.129, GLCM contrast ranged from 95.11 to 376.58, and GLCM entropy ranged from 8.12 to 8.59. On the other hand, for the healthy areas, the ranges were as follows: GLCM homogeneity ranged between 0.050 and 0.064, GLCM contrast ranged between 414.73 and 476.15, and GLCM entropy ranged between 8.65 and 8.94. Similarly, for study AREA 2, the result of multiresolution segmentation separated the area into damage areas and non-damaged areas, as indicated in Figure 3.

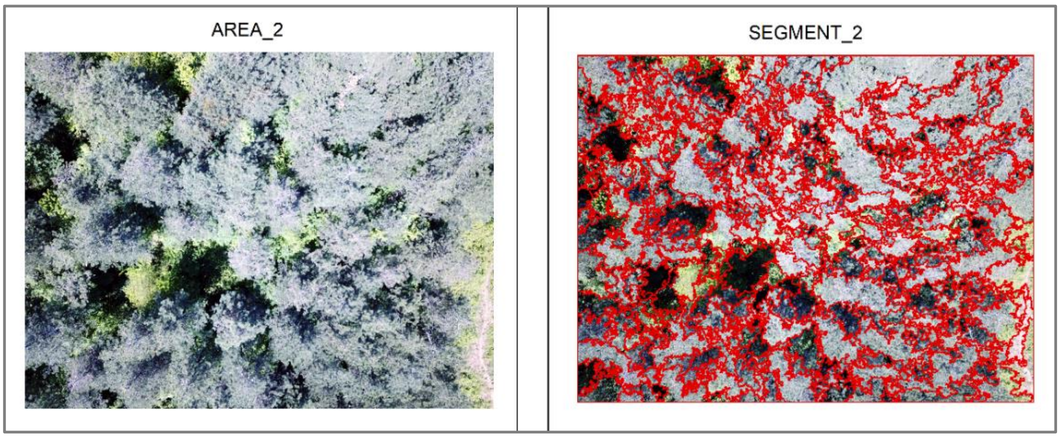

Figure 3. AREA 2

In study AREA 2, the calculations for all directions (GLCM homogeneity, GLCM contrast, and GLCM entropy) indicated the following ranges of values for the damaged segments: GLCM homogeneity ranged from 0.08 to 0.2, GLCM contrast ranged from 82.86 to 303.58, and GLCM entropy ranged from 7.81 to 8.51. On the other hand, for the healthy areas, the ranges were as follows: GLCM homogeneity ranged between 0.05 and 0.08, GLCM contrast ranged between 441.70 and 888.80, and GLCM entropy ranged between 8.93 and 9.40. Furthermore, the result of multiresolution segmentation for AREA 2 separated the area into damage areas and non-damaged areas, as illustrated in Figure 4.

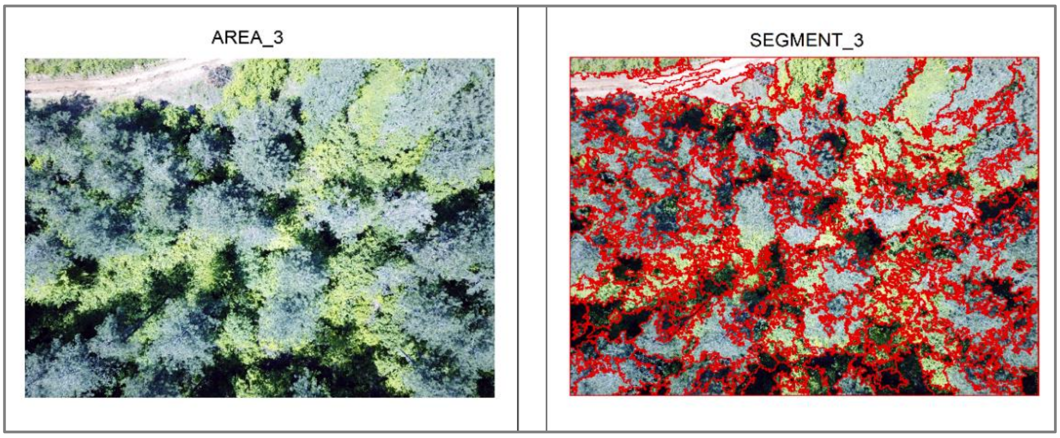

Figure 4: AREA 3

In study AREA 3, the calculations for all directions (GLCM homogeneity, GLCM contrast, and GLCM entropy) revealed the following ranges of values for the damaged segments: GLCM homogeneity ranged from 0.101 to 0.32, GLCM contrast ranged from 229.85 to 351.25, and GLCM entropy ranged from 6.67 to 7.69. On the other hand, for the healthy areas, the ranges were as follows: GLCM homogeneity ranged between 0.07 and 0.09, GLCM contrast ranged between 352.58 and 682.8, and GLCM entropy ranged between 8.80 and 9.08.

The GLCM-based classification parameters for pine beetle damage and non-damage areas were observed for all three study areas, as presented in Table 1. It was observed that the more structurally homogeneous regions in the images corresponded to the pine beetle damage areas. In the study areas, where the objective was to differentiate between damaged and undamaged areas, the contrast values of the image pixels were lower in the damaged areas (Table 1).

Table 1. Tabular view of Texture Parameters

	AREA 1		AREA 2		AREA 3	
GRUPS	Entropy		Homogeneity		Contrast	
	min	max	min	max	min	max
Damaged	8.12	8.59	0.064	0.129	95.11	376.51
Non-damaged	8.65	8.94	0.050	0.064	414.73	476.15
Damaged	7.81	8.51	0.08	0.20	82.86	303.58
Non-damaged	8.93	9.40	0.050	0.08	441.70	888.80
Damaged	6.67	7.69	0.101	0.32	229.85	351.25
Non-damaged	8.80	9.08	0.070	0.09	352.58	682.8

Based on the GLCM homogeneity values used for pine beetle damage detection, a range of 0.064 to 0.32 was calculated, while the GLCM contrast ranged from 82.86 to 376.51, and GLCM entropy ranged from 6.67 to 8.59. This indicates that the homogeneity of the damaged areas on the larch stand allows them to be easily differentiated from the non-damaged areas in the image, as the pixel values are close to each other. Therefore, it can be concluded that spectral variance in UAV images is an effective method for distinguishing insect damage. Although this study used different remote sensing data and species diversity compared to previous studies, the results are consistent with findings from previous studies on structural diversity in forests using GLCM. These studies include Seto et al. (2004), St. Louis et al. (2006, 2009), Culbert et al. (2012), Wood et al. (2012), and De Ocampo and Dadios (2021). According to extent of our literature review, this study is the first comprehensive assessment of the usefulness of pine beetle damage tissue measurements, calculated from UAV data, for distinguishing pine beetle damage. Therefore, it was not possible to directly compare the texture parameters with those of other published studies. In conclusion, by using image texture metrics for pine beetle damage, it is possible to predict and map the damage areas from UAV imagery.

6. Conclusion

In this study, the performance of each texture criterion was evaluated by examining their relationship with different damage regions. It was observed that the reflection values of the damaged areas were close to each other, resulting in lower entropy and contrast values, and higher homogeneity values due to the similarity of neighboring pixels. These findings indicate that damage areas were more homogeneous compared to non-damaged areas. While none of the three images represented a unique texture feature for the region based on different criteria, the GLCM parameters allowed for distinguishing pine beetle damage in larch species as auxiliary data. Clear results were obtained for the pure stand region. As a next step, future studies should be planned to use the average texture criterion values obtained for mixed stands to establish correlations and derive damage texture criterion values in mixed stands. Although the use of high-resolution UAV data provides an advantage in differentiating damage zones, it is recommended for future studies to incorporate multi-temporal data as a separate texture layer for larch species. This can be achieved by utilizing differences in phenological periods, which may further enhance the accuracy of distinguishing pine beetle damage.

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