Self-adaptive Image Segmentation Optimization for Hierarchal Object-based Classification of Drone-based Images

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Abstract. This study proposes an approach for the quality improvement of feature extraction in unmanned aerial vehicle (UAV)-based images through object-based image analysis (OBIA). A fixed-wing UAV system equipped with an optical (red–green–blue) camera was used to capture very high spatial resolution images over urban and agricultural areas in an arid environment. A self-adaptive image segmentation optimization aided by an orthogonal array from the experimental design was used to optimize and systematically evaluate how OBIA classification results are affected by different settings of image segmentation parameters, feature selection, and single and multiscale feature extraction approaches. The first phase encompassed data acquisition and preparation, which included the planning of the flight mission, data capturing, orthorectification, mosaicking, and derivation of a digital surface model. In the second phase, 25 settings of multiresolution image segmentation (MRS) parameters, namely, scale, shape, and compactness, were suggested through the adoption of an L25 orthogonal array. In the third phase, the correlation-based feature selection technique was used in each experiment to select the most significant features from a set of computed spectral, geometrical, and textural features. In the fourth phase, the ensemble adaptive boosting algorithm (AdaBoost) was used to classify the image objects of segmentation levels in the orthogonal array. The overall accuracy measure (OA) and kappa coefficient (K) were computed to represent a quality indicator of each experiment. The OA and K values ranged from 89% to 95%, whereas the K values ranged from 0.75 to 0.95. The MRS parameter settings that provided the highest classification results (>94%) were analyzed, and class-specific accuracy measures and F-measure were computed. Multiscale AdaBoost classification was conducted on the basis of the computed F-measure values. Results of the multiscale AdaBoost classification demonstrated an improvement in OA, K, and F-measure.

1. Introduction
Given the latest and ongoing advances in the field of unmanned aerial vehicles (UAVs), which are also widely referred to as drones, UAV systems have been acknowledged as effective, versatile, and cost-effective platforms for remote sensing data acquisition. Growing attention has recently been given to UAVs in a wide range of nonmilitary applications. The increasing adoption of UAV platforms in the remote sensing community is due to their capability of capturing very-high-resolution (e.g., spatial, spectral, and temporal) images from multiple sensors based on the demand at low cost compared with manned aerial systems and satellite platforms. They have been integrated across a wide spectrum of
varied disciplines that include, but not limited to, land cover feature extraction [1], [2], photogrammetry and topographic mapping [3]–[5], vegetation mapping [6]–[9], archaeology [10]–[12], and disaster management and assessment [13]–[15].

UAV-based images are often acquired at low altitude with high image overlap and maximum flight height that is permitted up to 120 m within the United Arab Emirates law. Very-high-spatial-resolution (VHSR) images that can reveal fine details with a centimetric spatial resolution are provided. One issue in the feature extraction from drone-based images is the high intraclass variability among classes, which poses several challenges when pixel-based image analysis is used because single pixels do not capture the characteristics of ground targets compared with high-spatial-resolution images [16], [17]. The process is timely, expensive and memory intensive and portrays difficulties in analyzing large areas that are covered by multiple images with partial overlap [18]. The geographic object-based image analysis (GEOBIA) is a paradigm that has previously emerged to mimic human visual perception of real-world objects, address the spectral heterogeneity between classes, and allows better classification results than per-pixel classification [19]. The fundamental concept of GEOBIA is the aggregation of spectrally similar neighbouring pixels into homogeneous, contiguous, and nonintersecting meaningful image segments. The spectral, spatial, textural, geometrical, and contextual attributes of the generated image objects are incorporated in the classification phase. The GEOBIA framework usually consists of two main stages: (1) image segmentation, which is the process of producing homogenous and nonintersecting meaningful image segments from image pixels, and (2) feature selection and classification, which include the selection of the appropriate feature space and classification algorithm to classify image objects. The accuracy of the final output of the image object classification greatly depends on the quality of the output in the image segmentation phase. Multiresolution segmentation (MRS), which is governed by three user-defined parameters, namely, (i) scale, (ii) shape color/weight, and (ii) compactness/smoothness weight, is a widely used region-growing segmentation algorithm in the remote sensing community [20]. The size and shape of the generated image objects rely on the combinations of MRS parameters. Therefore, the adoption of an optimization approach to find the optimum MRS parameter is imperative to achieve high-quality classification from UAV-based images. The optimum scale parameter in segmenting a VHSR image is affected by various factors [21]. For instance, diverse classes can vary in size and require different optimum segmentation scales, objects that belong to the same class might correspond to different optimal scales due to their diverse surrounding contrast, and different components within an object might require to be analyzed at multiple scales [17], [21]. Multiple optimal scale values should be considered while segmenting UAV-based images. Various unsupervised and supervised methods have been used to select the optimum multiscale parameters [22]–[25].

The availability of hundreds of spectral, textural, geometrical, and contextual features can be computed for each image object and utilized in the classification phase. The processing time is increased, a computational burden is added, and classification accuracy is affected if a large number of features are used in the classification. Feature selection, which is the process of finding remarkable features, is a vital step prior to the classification of image objects to remove redundant features, increase the processing time, and achieve higher classification accuracy than or equal classification accuracy to that when utilizing all computed features. The computed feature value (i.e., spectral or geometrical feature) generally varies according to the MRS parameter settings [26]. Thus, significant features may vary from segmentation level to another if they are selected as a part of a classification phase (wrapper method), because classification results are influenced by the selection of MRS parameters. This study attempts to (i) utilize a self-adaptive image segmentation optimization approach through the aid of an orthogonal array to design the experiment and select the optimal settings of MRS parameters for single and multiscale levels, (2) integrate the correlation-based feature selection (CFS) in the optimization, and (3) assess the performance of adaptive boosting (AdaBoost) algorithm at single and multiple level.
2. Methodology

2.1 Overview
Five steps were considered in the methodological framework of the study (Figure 1). The first step included flight planning, data acquisition, and preprocessing. The second step included the selection of the possible ranges and the number of levels to segment UAV imagery. The third step comprised the selection of an appropriate orthogonal array from the experimental design based on the number of levels and image segmentation. The fourth step consisted of feature computations and selection for every segmentation level in the orthogonal array. The fifth step was to perform AdaBoost classification and select the optimum segmentation level for each class.

Figure 1. Workflow of the analysis.

2.2 Experimental site and UAV data acquisition
The study was conducted in mixed urban and agricultural areas located around the academic city in Dubai City, United Arab Emirates, which covers an area of 0.5 km$^2$ (coordinates, latitude 25.095° N, and longitude 55.393° E, World Geodetic System 1984 datum). The data were acquired in May 2019 at a maximum flight height of 120 m using a fixed-wing eBee plus RTK drone equipped with S.O.D.A. 5472 × 3648 RGB camera (https://www.sensefly.com/). A total of 298 images were acquired with 70% lateral and longitudinal overlaps and an average ground sampling distance of 2.89 cm. For succeeding mission-planning and data acquisition steps, Pix4D software, which is photogrammetric software, was used to import the acquired images, perform image pair matching, and generate point clouds, digital surface model (DSM), and orthomosaic (Figure 2).

2.3 Experimental design
The experimental design is a systematic statistical approach that is used to determine the relationship between variables that affect the quality of output and optimize the final output. The orthogonal array design, which is a branch of factorial experimental design, is a widely used approach in versatile discipline because of its effectiveness [27], [28]. The independent variables in the orthogonal array are represented orthogonally to one another in columns to allow the examination of variables simultaneously.
in a few numbers of experiments and balance the different variables in such a way that the interactions and first-order effects are estimated [27].

Figure 2. Drone-based dataset used in this analysis: (a) orthophoto image and (b) generated DSM.

The selection of the dimension of an orthogonal array depends on the numbers of levels and the examined parameters. A preliminary analysis of segmentation output showed that the possible scale level might range from 100 to 500, and the values of the shape and compactness range from 0.1 to 0.9. In this study, the L25 orthogonal array experiment that comprised the three MRS parameters (scale, shape, and compactness) at five different levels was adopted to find the optimal level for extracting the classes existing in the UAV image.

2.4 Feature selection and classification

Classification using a large number of features in the classification phase is formidable and computationally intensive considering the VHSR of the UAV-based imagery. Thus, feature selection is imperative to reduce the processing time and improve the classification result. In this study, 30 various spectral, geometrical, and textural attributes were computed for the examined levels proposed by the orthogonal array and listed in Table 1. The CFS technique was adopted in this study to select discriminative features due to its simplicity and efficiency [20]. As a typical feature selection technique, CFS selects significant features using a search algorithm with a heuristic evaluation function; the merit of each feature is measured to predict the class label and the intercorrelation level of the features [29].

In this study, the AdaBoost classifier was used to classify the 25 segmentation levels proposed by the orthogonal array (Table 2) as an output of each experiment. AdaBoost is an iterative ensemble machine-learning algorithm that combines multiple classifiers (weak classifiers) to improve classification accuracy. The iterative process commences by training a classifier while giving equal weights to all instances in building a classification model. A new model is subsequently built by giving higher weights to the erroneously classified samples. The weights of the correctly classified training image objects are minimized, whereas the weights of the misclassified objects are increased after each iteration. This process forces the weak learner to improve the prediction of the problematic instances until a terminated condition is met, and the final classifier is generated from the linear combinations of the classifiers from each iteration. The overall accuracy (OA) and kappa coefficient (K) were derived from the error matrix and used to evaluate the performance of the integration of image segmentation, feature selection, and AdaBoost classifier at single-level and multilevel combinations of MRS parameters. In each experiment in the orthogonal array, 900 reference samples, with 100 samples per class, were divided into 70% and 30% to train and test the output of each experiment, respectively.
3. Results and discussion
As explained in the Methodology, the L25 orthogonal array was used in this analysis to minimize the number of trials into 25 possible experiments to examine the effects of the combinations of the MRS parameters, namely, scale, shape, and compactness, and feature selection on the classification results. The first three columns in Table 2 show the 25 MRS parameter combinations that should be examined. First, the UAV-based imagery was segmented using the combinations of MRS parameters in each experiment. Second, 30 features (Table 1) were computed for each experiment and exported along with the segmentation result of each level. Third, the representative stratified training samples were selected at the pixel-level for nine classes and then superimposed with each segmentation level. The attribute tables of every exported segmentation level that contains the computed features were spatially joined with the label attribute of the training samples to be used in the feature selection step. Fourth, the CFS feature selection technique was used to select the significant features for each experiment. Finally, the AdaBoost classification algorithm was used to classify the image objects of each experiment. The performance of each experiment was evaluated for each class by computing a class-specific accuracy measure (F-measure) (Table 3). The CFS algorithm was implemented to find the discriminative features in every experiment prior to the classification phase to lessen the computational burden and improve classification accuracy. The quality of each experiment, which integrates a combination of MRS parameters, CFS, and AdaBoost classifier, was measured by computing OA and K. The OA ranged between 89.72 and 95.64, and the values of K ranged from 0.75 to 0.95. The highest classification accuracies were found at different levels, as highlighted in bold in Table 3 (experiment numbers 2, 13, 20, and 25). Figure 3 shows the segmentation results that yield high classification results. The number of the selected feature and the spectral, textural, and geometrical values computed for the different combinations of MRS segmentation vary largely in every experiment based on the MRS parameter settings.

| Feature type | Feature name |
|--------------|--------------|
| Spectral (17) | Mean red, mean blue, mean green, mean DSM, max difference, brightness, standard deviation (SD) red, SD-green, SD-blue, SD-DSM |
|              | Ratio-R = (R)/(G + B + R), |
|              | Ratio-G = (G)/(G + B + R), |
|              | Ratio-B = (B)/(G + B + R), |
|              | NDRG = (R − G)/(R + G), |
|              | NDGB = (G − B)/(G + B), |
|              | NDBG = (B − G)/(B + G), |
|              | NDRB = (R − B)/(R + B), |
|              | NDBR = (B − R)/(B + R), |
|              | NDGR = (G − R)/(G + R), |
|              | RB = R/B, |
|              | V = 4/π . arctan ((G − B)/(G + B )), |
|              | S = 4/π. arctan ((1 − sqr (R^2 + G^2 + B^2)) / (1 + sqr (R^2 + G^2 + B^2))) |
| Texture (6)  | GLCM (Gray level co-occurrence matrix) mean, GLCM contrast, GLCM homogeneity, GLCM standard deviation, GLCM entropy, and GLCM correlation. |
| Shape (7)    | Shape index, density, rectangular fit, length/width, compactness, elliptic fit, border index. |
The number of the selected attributes by CFS in the orthogonal array generally ranged from 12 to 18 attributes out of 30 attributes. Significant features that contributed in improvement of the performance of the highlighted experiments in Table 3 ranged from 15 to 18 features (Table 3). The common features in the four levels were GLCM_Entropy, GLCM_Mean, Mean_DSM, Mean_G, Ratio_G, Ratio_R, NDGR, NDBG, SD_G, SD_B, and SD_DSM. Table 3 shows that the single-scale classification of a UAV-based imagery with a great amount of details can yield varied classification results with appropriate prediction of several classes in a certain level(s) but poor prediction in other level(s). Multiscale classification improves feature extraction results from VHSR images. Thus, a class-specific accuracy measure, F-measure, was first computed for the selected levels to determine the appropriate level(s) that should be used to extract each class accurately. A multiscale AdaBoost model was then used on the basis of the suggested classes. Table 4 shows the F-measure values for single-scale and multiscale classification.

The analysis of Table 4 suggests that the optimum MRS settings and the significant features are selected on the basis of the F-measure values to perform hierarchal AdaBoost classification. For instance, asphalt, buildings, and trees were extracted at a large scale (500: 0.1: 0.7), whereas small trees were extracted from a small level (100: 0.7: 0.3). Vegetation classes, including palm trees, crops, and grass, were extracted from the 13th experiment (300: 0.5: 0.9), whereas the bare soil and pavement classes were extracted from the 20th experiment (400: 0.1: 0.5). The results of multiscale AdaBoost classification demonstrated an improvement in the OA, K, and F-measure. Figure 4 displays the result of a hierarchal AdaBoost classification algorithm of an image subset.

| No. | MRS parameters | # No. of selected features by CFS | OA   | K   |
|-----|----------------|-----------------------------------|------|-----|
| 1   | 100 0.9 0.1    | 17                                | 91.27| 0.89|
| 2   | 100 0.7 0.3    | 17                                | 94.70| 0.93|
| 3   | 100 0.5 0.5    | 16                                | 91.59| 0.89|
| 4   | 100 0.3 0.7    | 19                                | 91.90| 0.90|
| 5   | 100 0.1 0.9    | 19                                | 91.60| 0.89|
| 6   | 200 0.9 0.3    | 18                                | 89.72| 0.87|
| 7   | 200 0.7 0.5    | 16                                | 93.15| 0.917|
| 8   | 200 0.5 0.7    | 17                                | 93.77| 0.92|
| 9   | 200 0.3 0.9    | 17                                | 92.83| 0.91|
| 10  | 200 0.1 0.1    | 15                                | 93.77| 0.92|
| 11  | 300 0.9 0.5    | 15                                | 89.72| 0.87|
| 12  | 300 0.7 0.7    | 16                                | 91.59| 0.89|
| 13  | 300 0.5 0.9    | 18                                | 94.08| 0.93|
| 14  | 300 0.3 0.1    | 15                                | 92.52| 0.91|
| 15  | 300 0.1 0.3    | 18                                | 92.83| 0.91|
| 16  | 400 0.9 0.7    | 16                                | 91.56| 0.89|
| 17  | 400 0.7 0.9    | 18                                | 91.58| 0.9|
| 18  | 400 0.5 0.1    | 15                                | 92.21| 0.9|
| 19  | 400 0.3 0.3    | 17                                | 90.96| 0.89|
| 20  | 400 0.1 0.5    | 14                                | 94.08| 0.93|
| 21  | 500 0.9 0.9    | 12                                | 79.75| 0.75|
| 22  | 500 0.7 0.1    | 17                                | 90.96| 0.89|
| 23  | 500 0.5 0.3    | 16                                | 91.90| 0.9|
| 24  | 500 0.3 0.5    | 15                                | 91.28| 0.895|
| 25  | 500 0.1 0.7    | 16                                | 95.64| 0.95|

Note: Values in bold indicate the best result.
Figure 3. Results of image segmentation obtained by different MRS parameter settings based on the best classification results: (a) 500, 0.1, 0.7, (b) 400, 0.1, 0.5, (c) 300, 0.5, 0.9, and (d) 100, 0.7, 0.3.

Table 3. Significant features selected by CFS for the highlighted experiments (Experiment no. 2, 13, 20, 25)

| # of Exp. | 2          | 13         | 20          | 25          |
|-----------|------------|------------|-------------|-------------|
| MRS settings | 100: 0.7: 0.3 | 300: 0.5: 0.9 | 400:0.1: 0.5 | 500: 0.1: 0.7 |
| 1         | GLCM_Entropy | GLCM_Entropy | GLCM_Entropy | GLCM_Entropy |
| 2         | GLCM_Mean   | GLCM_Mean   | GLCM_Mean   | GLCM_Mean   |
| 3         | Mean_DSM   | Mean_DSM   | Mean_DSM   | Mean_DSM   |
| 4         | Mean_G     | Mean_G     | Mean_G     | Mean_G     |
| 5         | Ratio_G    | Ratio_G    | Ratio_G    | Ratio_G    |
| 6         | Ratio_R    | Ratio_R    | Ratio_R    | Ratio_R    |
| 7         | NDGR       | NDGR       | NDGR       | NDGR       |
| 8         | NDBG       | NDBG       | NDBG       | NDBG       |
| 9         | SD_G       | SD_G       | SD_G       | SD_G       |
| 10        | SD_B       | SD_B       | SD_B       | SD_B       |
| 11        | SD_DSM     | SD_DSM     | SD_DSM     | SD_DSM     |
| 12        | S          | Brightness | Brightness | Brightness |
| 13        | GLCM_Contrast | Density    | Density    | Density    |
| 14        | Mean_R     | Ratio_B    | Ratio_B    | Ratio_B    |
| 15        | Shape_index | Shape_index | -           | Shape_index |
| 16        | Standard_R | Standard_R | -           | Mean_R     |
| 17        | NDRB       | Mean_R     | -           | -          |
| 18        | -          | Max_diff.  | -           | -          |
Figure 4. Classification result of AdaBoost classifier.

4. Conclusion
With the technological advancement in UAV platforms, sensors, and techniques and in consideration of their temporal flexibility and cost effectiveness, numerous remote sensing applications have been initiated. The processing of very high spatial resolution of UAV-based images is challenging if a traditional per-pixel classification approach is used. The OBIA approach has been effectively utilized in various applications for feature extraction from UAV-based images. The quality of the final output obtained through OBIA greatly depends on the selection of optimal segmentation parameters, feature selection, and the number and quality of the training samples and classification algorithm. A systematic self-adaptive optimization technique that utilizes an orthogonal array was proposed to evaluate the effects of image segmentation parameter selection, feature selection, and AdaBoost algorithms on OBIA.
output. The K values were used to evaluate the quality of OBIA output from multiple parameter settings of image segmentation and varied from 0.75 to 0.95; thus, the selection of the optimum combinations of multiscale segmentation parameters (scale, shape, and compactness) significantly affect OBIA classification output. The best results of single-scale classifications were selected to perform a hierarchical AdaBoost classification, which yielded an improvement of 2% in OA and demonstrated improvement in class-specific accuracy measures. The orthogonal array provides a supervised method to evaluate the effect of image segmentation parameter settings in the classification output, thereby ultimately allowing the selection of the optimum single and multiscale parameter settings of MRS parameters.

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