Object-based classification of hyperspectral data using Random Forest algorithm

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ABSTRACT
This paper presents a new framework for object-based classification of high-resolution hyperspectral data. This multi-step framework is based on multi-resolution segmentation (MRS) and Random Forest classifier (RFC) algorithms. The first step is to determine the importance of weights of the input features while using the object-based approach with MRS to processing such images. Given the high number of input features, an automatic method is needed for estimation of this parameter. Moreover, we used the Variable Importance (VI), one of the outputs of the RFC, to determine the importance of each image band. Then, based on this parameter and other required parameters, the image is segmented into some homogenous regions. Finally, the RFC is carried out based on the characteristics of segments for converting them into meaningful objects. The proposed method, as well as, the conventional pixel-based RFC and Support Vector Machine (SVM) method was applied to three different hyperspectral data-sets with various spectral and spatial characteristics. These data were acquired by the HyMap, the Airborne Prism Experiment (APEX), and the Compact Airborne Spectrographic Imager (CASI) hyperspectral sensors. The experimental results show that the proposed method is more consistent for land cover mapping in various areas. The overall classification accuracy (OA), obtained by the proposed method was 95.48, 86.57, and 84.29% for the HyMap, the APEX, and the CASI data-sets, respectively. Moreover, this method showed better efficiency in comparison to the spectral-based classifications because the OAs of the proposed method was 5.67 and 3.75% higher than the conventional RFC and SVM classifiers, respectively.

1. Introduction
Classification is one of the most used analysis of remotely sensed data for the Earth observation applications. Numerous methods are presented in the literature which can be categorized based on different criteria, such as pixel-wise, sub-pixel-wise object-based image classification (Li et al. 2014). During the past decades, due to the coarse resolution of satellite imagery, the analysis was at the pixel level in most classification techniques. These techniques were only based on the spectral information of individual pixels. Minimum Distance Classifier, Mahalanobis Distance Classifier, Parallelepiped, Maximum-Likelihood Classifier, Support Vector Machine (SVM), Decision Tree, Random Forest (RF), and Artificial Neural Network are some supervised pixel-based methods (Perakis, Kyririmis, and Kungolos 2000; Deer and Eklund 2003; Dwivedi, Kandrika, and Ramana 2004; Marconcini, Camps-Valls, and Bruzzone 2009; Jiang et al. 2012; Adam et al. 2014), while ISODATA and K-means are the two most popular unsupervised techniques for remotely sensed data (Zhang, Cao, and Gu 2005; Alajlan et al. 2012; Li et al. 2014).

Due to the limitations of the medium and coarse spatial resolution imageries in heterogeneous areas, the traditional pixel-based classifiers are not sufficiently accurate (Blaschke, Lang, and Hay 2008). As a result, sub-pixel methods, such as fuzzy classification and spectral mixture analysis techniques, have been proposed to address the spectral mixing problem (Adams, Smith, and Johnson 1986; Wu et al. 2003; Li et al. 2014). Very High-resolution (VHR) sensors can acquire hyperspectral images, and the spectral and spatial information provide the opportunity of better land cover mapping (Bioucas-Dias et al. 2013; Fauvel et al. 2013; Liu and Bo 2015). In this context, this paper proposes a method using an object-based classification method (OBBCM). Unlike previous methods, an object-based technique incorporates geographic features and objects as the fundamental components of the image classification. The object-based image analysis (OBIA) not only tries to
imitate the human thought procedure for getting better results, but also decreases the level of details, reduces image complexity and abundance of spatial detail, and process an enormous amount of data accordingly (Blaschke, Lang, and Hay 2008).

The OBCM is applied on the extracted segments from the images instead of working on pixels (Petropoulos, Kontoes, and Keramitsoglou 2011). Using either spectral or spatial information, a degree of spatial details always get lost in the final classification of an OBCM (Darwish, Leukert, and Reinhardt 2003; O’Neil-Dunne et al. 2009). Indeed, the integration of both spectral and spatial data in pattern recognition techniques results in more reliable information extraction, and thus more accurate land cover classification (Darwish, Leukert, and Reinhardt 2003; Cui et al. 2008). OBCMs effectively overcome the limitations of traditional pixel-based classification method by incorporating the shape and spectrum of formed segments (O’Neil-Dunne et al. 2009). These methods build the classification rules, which not only take advantage of various relationships between feature objects on different levels but also extract more features (e.g. geometric and textural features) from the extracted segments. Consequently, the OBCM can be more flexible and accurate than pixel-based classifications methods (Moser, Serpico, and Benediktsson 2013).

Image segmentation methods, in general, fall into two main domains: knowledge-driven methods (top-down) vs. data-driven methods (bottom-up) (Sohlbach, Weber, and Willhauck 2004). In the top-down approach, the user already knows what information is needed to be extracted from the image. Whereas in the bottom-up approach, the segments are generated based on a set of statistical methods and parameters for processing the entire image (Sohlbach, Weber, and Willhauck 2004). Various segmentation methods are presented for remote sensing images, including region-growing, Markovian methods, watershed methods, hierarchical algorithms, and multi-resolution segmentation (MRS) (Li et al. 2014). The classification based on segmentation, usually, consists of two main steps. In the first phase, the image is decomposed into certain segments and then in the second step, the classification is applied to these segments using the extracted features (Darwish, Leukert, and Reinhardt 2003; Hay et al. 2005).

Acquiring images with both high spatial and high spectral information in the past, prevented the remote sensing community from reaching maximum abilities for better classification of satellite images using OB algorithms. However in the recent years, through the introduction of high spatial resolution hyperspectral images, the OB algorithms became more attractive in remote sensing community (Bioucas-Dias et al. 2013; Fauvel et al. 2013; Liu and Bo 2015). MRS is one of the most efficient algorithms for segmentation purposes (Happ et al. 2010). Although segmentation is one of the most important steps in OBCM, it requires an additional step for converting these segments into meaningful objects.

Rule-based methods are normally built on transferring existing knowledge in machine-executable rule sets (Stumpf and Kerle 2011). An expert in rule-based methods is of the essence because his role is to introduce the rules and their priorities. These limitations prevent the application of an automatic method. Moreover, in many cases, the results might not be entirely acceptable. In an attempt to find a replacement for such rule-based methods, the RF algorithm was used in order to improve the classification accuracy and to reduce the human effort, as well as to facilitate the choice of classification thresholds and object features (Stumpf and Kerle 2011). In recent years, the random forest (RF) algorithm has become one of the most popular methods for classification tasks. RF has been used in many applications, such as mapping application using object-based methods (Stumpf and Kerle 2011; Puissant, Rougier, and Stumpf 2014), high-resolution image processing (Immitzer, Atzberger, and Koukal 2012), hyperspectral image processing (Ham et al. 2005; Amini, Homayouni, and Safari 2014), and many other applications.

In this paper, we employed RF algorithm to create the image objects. However, despite the acceptable results of segmentation algorithms on multispectral images, the MRS algorithm cannot easily be used for hyperspectral images. It is mainly because, determining the weight or importance of input bands, as one of its inputs, requires great effort. As a result, this algorithm does not work with its maximum ability. In other words, the better these parameters are set, the better results can be achieved.

Moreover, OB methods require a significant computational effort for image classification. To overcome these problems, RF algorithm can help the estimation of the importance of spectral bands, as the optimum inputs. The novelty of this approach is in the automatic determination of the weight parameter, which is one of the segmentation parameters, for the data with a high number of input features (bands). In previous studies (Hay et al. 2005; Puissant, Rougier, and Stumpf 2014), there is less effort for determination of the weight parameter because of less number of input features. However, using a large number of input features, such as hyperspectral data, requires an automatic method for assigning a weight for each input feature (band).

This paper is organized as follows: Section 2 describes the study areas and data-sets, followed by describing the framework of the proposed method. Section 3 presents experimental results and related analysis, followed by discussion. Finally, the conclusions of this research in presented in Section 4.
2. Material and methodology

Figure 1 shows an overview of this method. In the first step, RF is applied on the images in order to estimate the Variable Importance (VI). This criterion will help in the selection of the optimum features or bands to be used for segmentation. The MRS is then used to break down the image into several segments. Then, based on extracted information from segments using the RF classifier, these segments are finally classified and converted into the meaningful objects.

2.1. Hyperspectral data

Three data-sets are used to evaluate the efficiency of the proposed method. The details about the data and sensors are mentioned in Table 1. The first data-set is a hyperspectral image acquired by the HyMap sensor with a spatial resolution of 3.5 m and 114 spectral bands in the visible and near-infrared spectral regions over Berlin, Germany (see Figure 5(a)). In this image, five different land cover classes namely, Vegetable, Building, Pavement, Sand, and Water are identified to be mapped. In this data-set, the ground truth data were available for the whole image. Therefore, we randomly grouped them into training and test data. This proportion is calculated through the ratio of the number of training data to the total number of pixels in the image and multiplying the numeric value by 100. The percentage of training and test data for each class in HyMap data-set are mentioned in Table 2.

The second data-set is a hyperspectral image acquired by the Airborne Prism Experiment (APEX) imager. The data-set has a spatial resolution of 1.8 m with 285 spectral bands in the visible and near-infrared spectral regions acquired in 2011 over of the area surrounding Baden, Switzerland (see Figure 6(a)) (Schaepman et al. 2015). Given the small number of available reference data for this data-set (i.e. 54 samples in total), training data were selected from the image by visually identifying and manually digitizing multiple polygons for each land cover class. The spectral signature of several classes was provided by the APEX Open Science Data team on the day of the over-flight using an Analytical Spectral Devices (ASD) Field Spec 3 Spectroradiometer operating in radiance mode. Based on the spectrometry data, additional training data were extracted from the image. In this image, seven different land cover classes namely, Black Roof, Vegetation, Yellow Tartan, Sand, Water, Concrete, and Tree were selected. The percentage of training and test data for each class in APEX data-set are mentioned in Table 3.

The third data-set is a hyperspectral image acquired by the CASI over the University of Houston campus and the neighboring urban area, which was provided by the IEEE GRSS (2013) Data Fusion Technical Committee for organizing the 2013 Data Fusion Contest (see Figure 7(a)). This third image has 144 bands in the 380–1050 nm spectral region with a pixel size of 2.5 m. In this image, 15 different land cover classes namely, Healthy grass, Stressed grass, Synthetic grass, Trees, Soil, Water, Residential, Commercial, Roads, Highways, Railways, Parking 1, Parking 2, Tennis courts, and Running tracks were selected. The percentage of training and test data for each class in CASI data-set are mentioned in Table 4.

2.2. Random Forest classification

The Random Forest classifier (RFC) is an ensemble learning technique developed by Breiman (2001) based on an original version introduces by Bell Labs in 1995. RF has recently been proposed for hyperspectral image classification and has raised much interest, attributed to its speed of processing and limited parameters need to be established (Breiman 2001). RFC is an ensemble classifier which combines weaker classification trees that are de-correlated (Xiong 2014). RF classifier has two main benefits: the relatively high accuracy and the speed of processing (Breiman 2001; Joelsson, Benediktsson, and Sveinsson 2010). The strength and correlation among individual classification trees are significant and will affect the ensemble performance of RF. The RF classifier is comprised of a collection of treelike classifiers which train several classifiers, where each tree contributes a
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First, we used it to determine the weight for each band. To this end, we used the variable importance (VI) which is one of the RF’s outputs. It can be defined as the average of correctly cast votes for the randomly permuted variable in the Out-of-Bag (OOB) cases data. This is, then, subtracted from the number of correctly cast votes for the original OOB data over all the trees in the forest. In other words, VI is the average lower margin across all OOB cases and all trees in the forest (Breiman 2001; Breiman and Cutler 2004). Second, RF was applied in order to obtain the final classification map from the extracted segments.

### 2.3. Multi-resolution segmentation

Object-based image classification includes two main procedures. The first is to segment the entire image into several regions of different sizes based on unique spectral and textural characteristics. The segments are, then, combined in order to create much larger objects and land cover classes. The procedure of object creation benefits from the geometric features, topology and adjacency relationships of the objects. The hope is that these objects can be more easily related to the land cover types rather than individual pixels.

For this purpose, the image is broken down into several segments using MRS. MRS is a bottom-up region-merging technique that is regarded as a region-based algorithm. MRS starts by considering each pixel as a separate object. Subsequently, pairs of image pixels are merged to form larger segments (Darwish, Leukert, and Reinhardt 2003). Smoothness and compactness are in general considered as the shape factors in an image, which can also be seen as homogeneity parameters. The color parameter is defined as the change of weighted standard deviation from the spectral values. Shape parameters, i.e. smoothness and compactness, aim to identify and find the segments that represent the best objects (Sohlbach, Weber, and Willhauck 2004). Smoothness and compactness are complementary parameters. The sum of the coefficients of these parameters is always equal to one. The compactness is the ratio between the perimeter of the segment and the square root of its area. The smoothness is the ratio between the perimeter of the object and the perimeter of the minimum bounding rectangle (i.e. the bounding box) (Happ et al. 2010).

Furthermore, the selection of appropriate scales for the segmentation is one of the most important parts in the object-based classification approach. After the primary segments are formed, the neighbor segments are evaluated whether each two of them are suitable for being merged. This process is evaluated based on color homogeneity as well as scale parameter. The average object size indirectly will be influenced by the scale parameter, and a smaller value leads to smaller objects, and vice versa (Sohlbach, Weber, and Willhauck 2004). Selection of these parameters often relies on subjective trial-and-error methods (Blaschke, Lang, and Hay 2008). In recent years, several methods are introduced for automatic selection of these parameters (Drăguț et al. 2014). Given the lack of standard evaluation method for assessing the quality of image segments, the final

### Table 1. The details about data and sensors.

| Details | Data-set | Details | Data-set | Details | Data-set |
|---------|----------|---------|----------|---------|----------|
| Sensor  | HyMap    | APEX    | CASI     | Sensor  | APEX    | CASI     |
| Context | Urban     | Urban    | Urban    | Context | Urban    | Urban    |
| Spatial coverage | 300 × 300 pixels | 1000 × 1500 pixels | 1400 × 349 pixels | Spatial coverage | 3.5 m    | 1.8 m    | 2.5 m    |
| Spatial resolution | 114       | 285      | 144      | Spatial resolution | 5       | 7        | 15       |
| Number of bands | 114       | 285      | 144      | Number of bands | 5       | 7        | 15       |
| Number of classes | 5        | 7        | 15       | Number of classes | 5       | 7        | 15       |

### Table 2. The percentage of training and test data for HyMap data-set.

| Class       | Training data | Test data |
|-------------|---------------|-----------|
| Vegetation  | 8.95%         | 13.43%    |
| Building    | 12.78%        | 19.17%    |
| Pavement    | 13.60%        | 20.39%    |
| Sand        | 2.59%         | 3.89%     |
| Water       | 2.08%         | 3.12%     |

### Table 3. The percentage of training and test data for APEX data-set.

| Class              | Training data | Test data |
|--------------------|---------------|-----------|
| BlackRoof          | 0.49%         | 0.80%     |
| Vegetation         | 0.72%         | 0.44%     |
| Yellow Tartan      | 0.47%         | 0.52%     |
| Sand               | 0.96%         | 0.90%     |
| Water              | 0.47%         | 0.65%     |
| Concrete           | 0.75%         | 0.38%     |
| Tree               | 0.67%         | 0.73%     |

### Table 4. The percentage of training and test data for CASI data-set.

| Class            | Training data | Test data |
|------------------|---------------|-----------|
| Healthy grass    | 0.08%         | 0.07%     |
| Stress grass     | 0.06%         | 0.06%     |
| Synthetic grass  | 0.03%         | 0.06%     |
| Tree             | 0.03%         | 0.06%     |
| Soil             | 0.05%         | 0.06%     |
| Water            | 0.02%         | 0.02%     |
| Residential      | 0.03%         | 0.04%     |
| Commercial       | 0.12%         | 0.18%     |
| Road             | 0.09%         | 0.11%     |
| Highway          | 0.03%         | 0.05%     |
| Railway          | 0.03%         | 0.03%     |
| Parking lot 1    | 0.11%         | 0.13%     |
| Parking lot 2    | 0.06%         | 0.06%     |
| Tennis court     | 0.02%         | 0.04%     |
| Running track    | 0.10%         | 0.07%     |
result of segmentation might be less reliable (Van Den Eeckhaut et al. 2012). To overcome this problem and obtain better results, the final decision must be made based on visual interpretation. The recognized restrictions of automatic approaches make it impossible to expect successful automation in many cases, especially when aiming semantically complicated categories of image objects. However, first approximations of some of the parameters, such as scale and color weight are possible (Drăguţ et al. 2014). The range of these parameters further depends on the size of the objects of interest (Meinel and Neubert 2004; Hay and Castilla 2006). In addition to the scale parameter, shape and compactness weighting may highly affect the segmentation results. Particularly, the segmentation results will be affected when classifying spectrally similar objects (Sohlbach, Weber, and Willhauck 2004; Frauman and Wolff 2005; Hay and Castilla 2006). The value of the shape parameter modifies the relationship between shape and color criteria; therefore, by altering the shape criterion, one defines the color criteria (color = 1 − shape). In other words, when building each object, one can use the shape information, the spectral information or both.

After generating the segments, the RF algorithm is used in order to convert these segments into meaningful objects. This algorithm draws on bootstrap samples for each tree from the original data, and randomly selects some features at each node. The best feature in each node is chosen by indices, such as GINI index and Information Gain (Breiman 2001; Joelsson, Benediktsson, and Sveinsson 2010; Adam et al. 2014). This procedure is applied in each tree until the stopping criteria reached. The stopping criterion is condition being used in order to verify the growing procedure should stop or continue at each specific node. One Sample in Node is one of the most used conditions for stopping criteria. Finally, the classification is applied by majority votes on all of the trees (Joelsson, Benediktsson, and Sveinsson 2010).

In addition to the proposed algorithm, classical RF algorithms and SVM were also used in this research for the evaluation and comparison study. SVM is a supervised machine learning classifier that finds an optimal hyperplane through minimizing the upper bound of the classification error (Chapelle et al. 2002). The SVM Classifier requires more parameters to be initialized compared to the other classifiers. To tune these parameters, different methods are proposed in the literature (Chapelle et al. 2002; Hosseini, Homayouni, and Safari 2012).

### 3. Results and discussion

The proposed method, as well as the competitor methods, were applied to the three previously introduced data-sets. The initial processing step is image classification by the RFC using the EnMAP toolbox (Held et al. 2012). EnMAP is an available public toolbox. This toolbox is platform-independent software for hyperspectral data analysis. The toolbox is particularly developed to handle data from the EnMAP satellite sensor but can process any multispectral or hyperspectral image data. Based on the estimated VI, we assigned weights for the features/bands (see Table 5 and Figures 2–4). Multi-resolution segmentation parameters are mentioned in Table 6. According to the results, it was observed that six weight classes are enough. Selecting more weights can adversely affect the results and vice versa.

Due to the different object sizes (e.g. the individual houses with small sizes) and the heterogeneity in this area, the shape parameter is important and is required to be set precisely. The best segmentation parameters can be estimated due to the size of objects in the images. To this purpose, all three data-sets were segmented using eCognition Developer 5 software’ (Sohlbach, Weber, and Willhauck 2004) by introducing different scale parameters such as 140, 100 120. The similarity between scale parameters in these data-sets can be related to the similarity between the study areas, which are all from urban areas where the structures are almost alike. The color and the shape are set to 0.7, and 0.3 for the HyMap data and 0.6, and 0.4 for two latter data-sets, respectively. The reason for this setting was that there were fewer features in the first data-set than the others (about two-thirds). Therefore, it can be concluded that for getting better results in segmentation, by increasing the number of features in high-resolution images, the assigned weight to the color parameter has to be increased. However, in high-resolution hyperspectral image data, the weights for color and shape become very close to each other. Smoothness and compactness in all three data-sets were set to 0.5 and the reason might be the structure of the building is almost similar in all study area. As a result, smoothness and compactness play equal share in the final segments in these data-sets.

There are several automatic methods for setting these parameters. Some of these methods are based on a grid search method. The required parameters are set through some criteria, like mathematical modeling and visual interpretation. Nevertheless, in some cases, the results of such modeling are not acceptable. As results, the final

### Table 5. Assigned weight based on VI.

| No. | Range of VI | Final weight | Range of VI | Final weight | Range of VI | Final weight |
|-----|-------------|--------------|-------------|--------------|-------------|--------------|
| 1   | 0.483–0.697 | 0.043–0.075  | 0.576–0.700 | 0            |
| 2   | 0.700–0.898 | 0.081–0.189  | 0.701–0.991 | 1            |
| 3   | 0.900–1.005 | 0.190–0.394  | 1.229–0.991 | 2            |
| 4   | 1.030–1.180 | 0.400–0.698  | 1.230–1.694 | 3            |
| 5   | 1.189–1.180 | 0.700–1.180  | 1.719–1.719 | 4            |
| 6   | 1.410–2.405 | 0.942–3.673  | 5 more      | 7            |
data-sets, respectively. In total, 342 features for the first data, 855 features for the second data, and 432 features for the third data were extracted.

The RF parameters that are required to be set consist of the number of trees, number of features, an impurity function, and stop criteria. In general, the primary values used for this method are the square root of all features at each node, the GINI coefficients as an impurity function, and one sample in each node as a stop criterion. The only parameter which changes in this experimental test is the number of trees. Based on our experiment, the classification accuracy does not significantly improve when the number of trees is greater than 400. However, it increases the computation time. For this reason, we run the RFC by setting the number of trees to 400 (see Table 7).

The quantitative analysis of the results has been applied over several test areas for each data-set. Confusion matrices are calculated through the available reference data. To this purpose, we used 36,001 pixels, 6811, and 4220 as training data and 53,999, 6629, and 5274 pixels as test data for these three data-sets, respectively. Then, relevant statistical parameters, such as overall classification accuracy (OA), Kappa parameter, Producer Accuracy (PA), User Accuracy (UA) are extracted. It worth noting that this reference data are not 100% accurate, and there is an error in the validation and training data. However, our objective here is to evaluate one classifier relative to another. Thus, the absolute accuracies are not as important in the evaluation. In this study, the accuracies are calculated based on the number of pixels instead of the number of segments. For this purpose, we used the same test data for both object and pixel based methods. However, the training data were slightly different. The reason for changing some of the training data are that, after generating segments, because of the possibility of over-segmentation, some training data might lead to misleading in the final results. Consequently, modifying the training data to be fitted to the segments is of the essence. Moreover, at each tree one-thirds of the training data (known as OOB) for all the trees are used to calculate VI. To this purpose, we used 4,800,133, 908,133, and 563,867 pixels as data for these three data-sets, respectively.

Two main strategies can be used for accuracy assessment of the object-based methods. First, the number of correctly classified segments or objects can be considered as a measure of efficiency. Second, the classical confusion or error matrix of pixel-based classification methods can be calculated and utilized for accuracy assessment. The latter strategy has two advantages: first, it enables us to compare the results with the results of the pixel-based methods, and secondly, it avoids the over-segmentation problem.

In this paper, we used OBRF strategy. The classification accuracy of each data are presented in Table 8. In general, the proposed method has not only better Kappa,
i.e. 0.07 and 0.05 higher, but also better OA, which is 5.66 and 3.75% higher compared to the conventional RFC and SVM, respectively. This could be related to the ability of the object-based methods for deciding on the extracted segments instead of pixels.

The accuracy in object-based classification is increased as shown in the classified maps. This method

| Data-set | RF OA | Kappa | SVM OA | Kappa | OBRF OA | Kappa |
|----------|-------|-------|--------|-------|---------|-------|
| HyMap    | 89.91 | 0.86  | 91.65  | 0.88  | 95.48   | 0.94  |
| APEX     | 81.43 | 0.78  | 81.94  | 0.79  | 86.57   | 0.84  |
| CASI     | 77.95 | 0.76  | 81.42  | 0.80  | 84.22   | 0.90  |

**Figure 5.** (a) Natural color image of the HyMap data (RGB: 633.5, 556.8, and 464.4 nm), (b) Random Forest Classified Image, (c) OBRF Classified Image, (d) Support Vector Machine Classified Image.
In addition to comparing OA and Kappa coefficients for each data-sets, we compared PA and UA for each class for all the classifiers (see Figures 8–10). In this paper, we used the EnMAP package which employs a grid search for estimating the best parameters for the SVM. The radial-based function (RBF) kernel for the SVM normally results in better classification efficiency and it requires less computational time compared to other kernel functions (Mountrakis, Im, and Ogole 2011; Hosseini, Homayouni, and Safari 2012). Then, a grid search method based on RBF kernel was used for estimating the best value for the Gaussian RBF Kernel (g) and the regularization parameter (c) of SVM classifier. The range of potential values of the SVM parameters is

Figure 6. (a) Natural color image of the APEX data (RGB: 639.8 nm, 551.5 nm, and 461.11 nm), (b) Random Forest Classified Image, (c) OBRF Classified Image, (d) Support Vector Machine Classified Image.

also effectively avoids the isolated pixel and identifies some classes better than other methods in Figures 5–7, which is shown in these figures through the zoomed area, respectively. Although in some cases, since the size of segments were bigger than the pixel size, the objects were not allocated into their real classes, and as a result, the accuracy of classification in those areas is decreased according to the central area in Figures 5–7. In other words, selecting just one value as the scale parameter for all of the classes will limit our capability of extracting different objects of interest. Given this fact, obtaining the acceptable results for all classes is at the expense of accuracy degradation for certain classes.

In addition to comparing OA and Kappa coefficients for each data-sets, we compared PA and UA for each class for all the classifiers (see Figures 8–10). In this paper, we used the EnMAP package which employs a grid search for estimating the best parameters for the SVM. The radial-based function (RBF) kernel for the SVM normally results in better classification efficiency and it requires less computational time compared to other kernel functions (Mountrakis, Im, and Ogole 2011; Hosseini, Homayouni, and Safari 2012). Then, a grid search method based on RBF kernel was used for estimating the best value for the Gaussian RBF Kernel (g) and the regularization parameter (c) of SVM classifier. The range of potential values of the SVM parameters is
Figure 7. (a) Natural color image of the CASI data (RGB: 640.70, 550.20, and 459.60 nm), (b) Random Forest Classified Image, (c) OBRF Classified Image, (d) SVM Classified Image.

Figure 8. User accuracy (a) and producer accuracy (b) of HyMap data.

Figure 9. User accuracy (a) and producer accuracy (b) of APEX data.
make them difficult to distinguish, while working with supervised classification method (Di Palma et al. 2016). By introducing more features (such as textural or spectral features) into classification algorithm, we can expect that the algorithm would achieve the capability of better distinguishing the classes in some degree (Blaschke, Lang, and Hay 2008).

4. Conclusions

This paper proposed a new object-based framework for the classification of hyperspectral data. This framework was based on MRS and RFC. Moreover, the automatic detection of the parameters for segmentation, i.e. the weights of input features, was proposed and evaluated. The results of experiments showed that the high-resolution hyperspectral data, which have more features (spectral bands), require more weight for color parameter than high-resolution multispectral images. The reason might be the high information content in spectral features of such images. Moreover, we observed that the scale parameter for the urban area in the high-resolution hyperspectral image could approximately be 100. As a result, this value can be considered as an initial value to begin the segmentation. However, according to the data-set and study area, the scale parameter must be changed to find its best value.

The evaluation of the results based on the OAs and Kappa coefficients demonstrated the efficiency and relative superiority of the proposed method, although some under- and over-segmentation errors are evident. The problem is evident specifically where the classes are so different from each other regarding the shape and spectral properties. In many applications, under-segmentation would decrease the speed of processing. However, over-segmentation would lead to less accurate results.

Table 9. SVM parameters.

| Parameters             | Range (Multiplier) | Selected value | Range (Multiplier) | Selected value | Range (Multiplier) | Selected value |
|------------------------|--------------------|----------------|--------------------|----------------|--------------------|----------------|
| Gaussian RBF Kernel (g) | 0.1–1000 (10)      | 1              | 0.1–1000 (10)      | 0.1            | 0.1–1000 (10)      | 1              |
| Regularization (c)     | 0.1–1000 (10)      | 1000           | 0.1–1000 (10)      | 100            | 0.1–1000 (10)      | 1000           |

Figure 10. User accuracy (a) and producer accuracy (b) of CASI data.
Therefore, there must be a balance between these two errors. Based on these experiments, a suitable segmentation scale will lead to accurate feature object identification. Furthermore, a proper band weight and a homogeneous factor are crucial to improve the classification efficiency. Moreover, the choice of parameters which are used depends on the extracted features types. In this paper, we have employed only the color features (the mean, the standard deviation, and the skewness) of the pixels inside each segment as the outputs of each segmentation. In addition to the color features, taking full advantages of both geometrical and textural features is proposed to be investigated. Moreover, different targets require different segmentation scale parameters, which are important and should be investigated in the future. Moreover, by increasing the number of input features, the Hughes Phenomenon might happen, and as a result, the introduction of appropriate input features is of the essence in the final results.

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