مجله کاربرد سیستم اطلاعات جغرافیایی وسنجش از دوردر برنامه ریزی،دوره۱۱،شماره۳،پاییز ۹۹

Object-Based Classification by using Hierarchical Segmentation and Weighted Genetic Algorithm

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Date of receiving the article: ۲۰۲۰,۱۰,۱۶ **Date of receiving the article:** ۲۰۲۰,۱۱,۱۸

Pages: 68-77

Abstract

Recently, an effective approach for spectral-spatial classification has been proposed using Hierarchical SEGmentation (HSEG) grown form automatically selected markers. This paper aims at improving this approach for classification of hyperspectral images in urban areas. The Weighted Genetic (WG) algorithm is first used to obtain the subspace of hyperspectral data. The obtained features are then fed into the marker-based HSEG algorithm. Then, the contextual features from segmented images are extracted. For spatial features, area, entropy, shape, adjacency and relation features are considered as the potential components in feature space. Finally, using both spectral and spatial features, the image objects are classified by a rule-based classifier. The experimental tests are applied to two datasets: the Berlin, and Quebec City, which are two known and benchmark datasets in hyperspectral imagery. The evaluation of results showed that the proposed approach achieves approximately ۱۶٪ and ۹٪ better overall accuracy than the Original-HSEG algorithm for these datasets respectively.

Key words: Hyperspectral image, Object-based Classification, Weighted Genetic Algorithm, Marker selection, Hierarchical segmentation, Feature extraction.

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١. Introduction

Hyperspectral imaging concerns measurement and interpretation of spectral imagery acquired by satellite, airborne, terrestrial, or laboratory sensors over visible, infrared and sometime thermal spectral regions of electromagnetic spectrum (Shippert, ٢٠٠٤). There are two major approaches for classification of hyperspectral images: the spectral or pixel-based techniques, and the spectral-spatial or object-based techniques. The pixel-based techniques, e.g. support vector machines (SVMs), apply exclusively to the spectral information (Watanachaturaporn et al., ٢٠٠٨). However, the second category considers both the spectral information of the pixels and their spatial context (Fauvel et al., ٢٠٠٨; Li et al., ٢٠١٧). Because of the complex nature and diverse composition of land cover types existing within the urban environment, the classification of high-resolution hyperspectral imagery is a difficult task (Akbari, ٢٠١٩; Lu et al., ٢٠١٠). For example, the “Meadow” and “Tree” classes are spectrally similar and have a significant amount of spectral overlap (Zhang and Qiu, ٢٠١٢). This is the primary reason for the large number of misclassifications between these classes. Traditional classification methods that only take into account the spectral information are unable to differentiate between these classes with a high degree of accuracy. Consequently, the methods that utilize the spatial information, in addition to the spectral information, are needed to produce more accurate land cover maps in urban areas (Carleer and Wolff, ٢٠٠٦; Chen et al., ٢٠١٩; Liu et al., ٢٠١٨; Shackelford and Davis, ٢٠٠٣).

Segmentation techniques are powerful means for defining the spatial dependencies among the pixels, as well as for finding the homogeneous regions in an image (Borzov and Potaturkin, ٢٠١٨; Gonzalez and Woods, ٢٠٠٢). An alternative way to achieve accurate segmentations consists of performing a marker-controlled segmentation (Gonzalez and Woods, ٢٠٠٢; Soille, ٢٠٠٣). The marker-based segmentation significantly reduced over-segmentation and led to better accuracy rate. Recently, an efficient approach is proposed for spectral-spatial classification using the Hierarchical SEGmentation (HSEG) grown from automatically selected markers (Tarabalka et al. ٢٠١٢). It uses a pixel-wise SVM classification, in order to select pixels with the highest probability of each class membership as markers for corresponding class. In this approach, a connected components labelling is, first, applied on the classification map. Then, the markers are considered to be p% of the pixels with the highest probability estimated for large regions, and pixels with an estimated probability higher than a pre-defined threshold for small regions.

For classification of hyperspectral images, the large number of bands sometimes causes intense computational complexities and generates inappropriate results. Many methods have been presented in the hyperspectral literature in order to effectively reduce the dimensions of input space, and achieve better performance. The genetic algorithm, which seeks to solve the optimization problems using the evolution methods, specifically survival of the fittest, can be used to optimize band subset of hyperspectral data. This algorithm is commonly used in binary form. The limitation of binary genetic is that it removes some of the bands despite having a small amount of information.

In this paper, we propose an innovative object-based classification approach based on the subspace analysis of hyperspectral remote sensing data. In the proposed approach, the Weighted Genetic (WG) algorithm is used for subspace analysis of hyperspectral images. WG algorithm uses the information of all bands, by assigning a value between zero and one in each band, as the weight of the band. Afterwards, the marker-based HSEG algorithm is used to segment the obtained features. The segmented images are then used in an object-based classification method that considers the spectral and contextual information. Therefore, we extracted different contextual features. Then, image objects, using spectral and contextual features, are subsequently classified by rule-based classifier. The proposed framework not only makes the best use of characteristics obtained from high-resolution hyperspectral imagery, but also increases significantly the classification accuracy.

٢. Proposed approach

The proposed approach contains four main steps: ١) subspace analysis, ٢) marker-based HSEG, ٣) feature extraction, and ٤) object-based classification. The scheme of the proposed classification is presented in Fig.١.

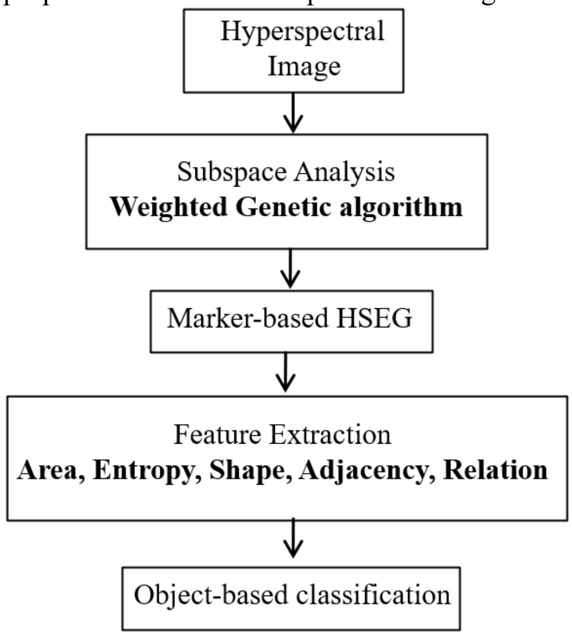


Figure ١. Scheme of the proposed method.

٢,١ Subspace Analysis

The genetic algorithm is an adaptive optimization search method based on a direct analogy to Darwinian natural selection and genetics in biological systems (Huang and Wang, 2006). It starts from an initial population which is composed of a set of possible solutions called individuals (chromosomes), and then evaluates the quality of each individual based on a fitness function. In the binary genetic algorithm, each chromosome has one and zero values, while, in WG algorithm, the weighted values are between zero and one. We use the Kappa coefficient accuracy parameter of SVM classification as the fitness function. The fitter solutions have a better chance to survive or reproduce in the next generations. The population during consecutive generations evolves to be fit in the problem's conditions. Selection, crossover, and mutation are the main genetic algorithm's operators for reproducing the future generations. The evolutionary process will not stop until the termination conditions satisfy (Zhuo and Zheng, 2008).

٢,٢ Marker-based HSEG

The HSEG algorithm is a segmentation technique based on the iterative hierarchical stepwise optimization (HSWO) region-growing method. Furthermore, it allows for the merging of nonadjacent regions using a input parameter $S_{wg\square t}$ (Tilton, ٢٠٠٣). The optional parameter $S_{wg\square t}$ tunes the relative importance of spectral clustering versus region growing. For $S_{wg\square t}$ =٠, HSEG is essentially the same as HSWO, wherein only the spatially adjacent regions are allowed to merge. For $S_{wg\square t}$=١, the spatially adjacent and non-adjacent regions are given equal weight for merging. Lastly, for the values of $S_{wg\square t}$ between ٠ and ١, spatially adjacent merges are favoured compared with spatially nonadjacent merges by a factor of ١/$S_{wg\square t}$.

The HSEG algorithm can be summarized in four steps :

١) Initialize the segmentation by assigning a region label to each pixel. If a pre-segmentation is provided, label each pixel according to the pre-segmentation. Otherwise, label each pixel as a separate region.

٢) Calculate the dissimilarity criterion value amongst all pairs of spatially adjacent regions ($S_{wg\square t}$ =٠), find the pair of spatially adjacent regions with the smallest dissimilarity criterion value, and merge that pair of regions.

٣) If the parameter $S_{wg\square t}$ > ٠, merge all pairs of spatially non-adjacent regions with dissimilarity criterion Values less than or equal to the multiplication of the smallest dissimilarity criterion value of spatially adjacent regions and $S_{wg\square t}$

٤) Stop; if no more merges are required. Otherwise, return to step (٢).

For determining most similar pair of regions, we use the standard spectral angle mapper (SAM) between the region mean vectors as a dissimilarity criterion (Tilton, ٢٠٠٨). The SAM measure determines the spectral similarity between two vectors $u_i = (u_{i1}, u_{i2}, \ldots, u_{iB})^T$ and $u_j = (u_{j1}, u_{j2}, \ldots, u_{jB})^T$by computing the angle between them as follows:

$$SAM(u_i, u_j) = arccos(\frac{\sum_{b=١}^{B} u_{ib}u_{jb}}{[\sum_{b=١}^{B} u_{ib}^{٢}]^{١/٢}[\sum_{b=١}^{B} u_j^{٢}} \quad (١)$$

Where B is the number of hyperspectral image bands.

The marker-based HSEG algorithm can be summarized as follows. Each pixel is considered one region. If the given pixel is marked, the corresponding region obtains a new non-zero marker label, which corresponds to the information class. For non-marked regions, the label is equal to zero. Thus, at the initialization step, all the markers are split into one-pixel markers. The HSEG algorithm is then performed. When a marked region is merged with a non-marked region, the resulting region keeps the marker label inherited from the marked region. The process is stopped when the number of regions is equal to the number of markers. In the final step, the class of each marker is assigned to all pixels in the region containing this marker. The main idea behind the marker-based HSEG algorithm consists in assigning a marker label for each region containing the marker pixels, and then merging the regions with an additional condition. This condition requires that two regions with different marker labels cannot be merged together.

٢,٣ Feature Extraction

The contextual information extracted from objects can help decrease the number of misclassifications amongst spectrally similar classes. In this paper, we use the area, entropy, shape, adjacency, and relation features.

Area: In an segmented image, the "area" is the number of pixels that an object has (Chen, ٢٠٠٦; Nghi and Mai, ٢٠٠٨).

Entropy: Entropy is a measure of texture and is calculated as follows:

$$H = -\sum_{i=٠}^{L-١} p(z_i)\, log_٢\, p\,(z_i) \quad (٢)$$

Where L is the number of distinct gray levels, z is a random variable denoting image gray level and $p(z_i)$ is the normalized gray level histogram.

Shape: We define shape feature as follows (Li et al., ٢٠٠٧):

$$L = \sqrt{S}/P \quad (٣)$$

In this formula, S is the area of a certain polygon object and P is the perimeter. L is the shape index of an object. This index can distinguish different shapes. The shape index of a rectangle or a square is bigger than the linear objects.

Adjacency: The adjacency feature is appropriated information used to distinguish the image's objects from one another. The "building" and "road" classes in the image are, in some cases, spectrally similar and have a significant amount of spectral overlap; we normally cannot reliably distinguish them from one another. However, the shadow objects in any direction around the high buildings make these two objects dissimilar. Here, the shadow is considered the adjacency information (Chen, ٢٠٠٦; Nghi and Mai, ٢٠٠٨).

Relation: We define the relation feature as follows. If the objects A and B are two adjacent objects, and, A and B are in the same class, then A has a relation with B. If B has a relation with C and C is not adjacent with A, then A has a relation with C. Relation feature is the number of objects that has a relation with A (Nghi and Mai, ٢٠٠٨). Like the similarity between two pixels, there is also the similarity between two objects; this means that some objects have the same similar features such as the shape and the area. As a result, there will most likely be a misclassification of these features. However, the relation feature can provide a solution to this problem (Li et al., ٢٠٠٧).

٢,٤ Object-Based Classification

In this paper, we developed an object-based classification scheme that allows the image to be classified using different contextual measures for different sets of classes. The rule-based approach allows the analyst to combine different features of objects in order to assign a class membership degree (between ٠ and ١) to each object based on a fuzzy membership function or strict thresholds (Benz et al., ۲۰۰٤; Walker and Blaschke, ۲۰۰۸). The membership functions used in this study are based on the logical operator AND (&) and thresholds. Furthermore, it has a hierarchical capability to classify the entire scene into general classes (e.g., vegetation and non-vegetation areas). These general classes are called parent classes. Then, each parent class is divided to sub classes (child class) containing more detailed land cover types (e.g., buildings and roads). This hierarchical capability allows the developer to incorporate objects in different levels of segmentation for individual levels of class hierarchy. In this paper, we developed a rule-based classification scheme that allows the image to be hierarchically classified using different spatial measures for different sets of classes.

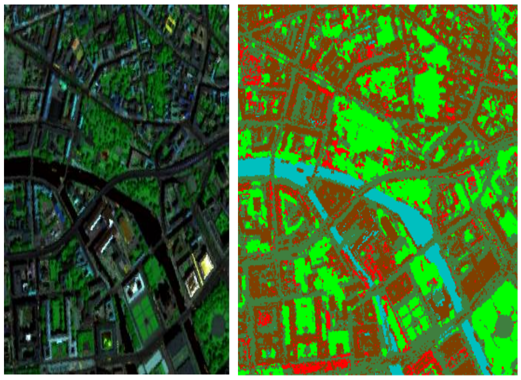
۳. Experimental results and discussions

۳,۱ Hyperspectral Data

To evaluate the proposed method, two hyperspectral datasets are selected. The first imaged the Berlin urban area, Germany, acquired by Hymap. The second dataset was collected by Hyper-Cam LWIR over the city of Quebec, Canada. The Berlin image is acquired in visible and infrared spectral regions, while the image of the Quebec City is acquired in the thermal region of electromagnetic spectrum. In this image data, the pixels' digital numbers represent the radiance. Therefore, it requires atmospheric correction prior to perform the classification. To this end, ENVI's Thermal Atmospheric Correction algorithm was applied on this dataset. Table 1 describes the main characteristics of these two datasets. The color composite image and the reference map of these datasets is shown in Figures 2 and 3.

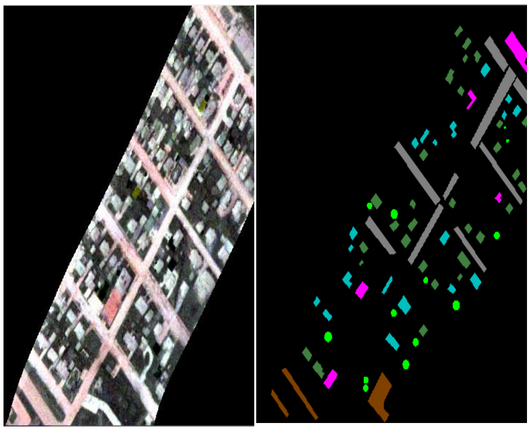
Table ۱. The main characteristics of the datasets used

Dataset	Berlin	Quebec City
Sensor	HyMap	Hyper-Cam LWIR
Spectral range (um)	۰,٤-۲,٥	۷,۸-۱۲,٥
Spatial coverage (pixel)	۳۰۰×۳۰۰	۷۹٥× ٥٦٤
Spatial resolution (m)	۳,٥	۱
Number of bands	۱۱٤	۸٤
Number of classes	٥	٦



(a) (b)

Figure ۲. Berlin dataset; (a) Color composite image (b) Reference map.



(a) (b)

Figure ۳. Quebec City dataset; (a) Color composite image (b) Reference map.

۳,۲. Experimental results

Table 2 presents the value of parameters used in proposed WG algorithm, which are actually the same for the two datasets.

Table ۲. The WG's Parameters for datasets used

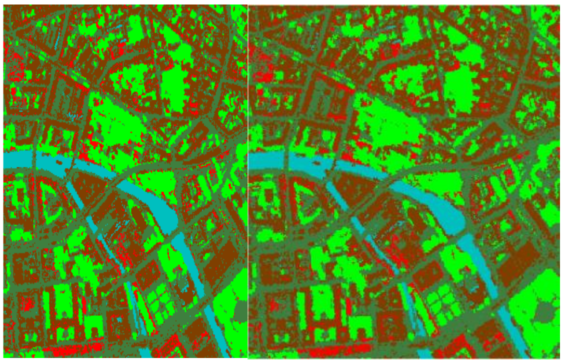
Parameters	data
Population	۱۰۰
Crossover probability	۸۰٪
Mutation probability	۰,۹٪
K-tournament	۲
K-elitism	۲

For marker selection, a pixel-based classification is performed, using the multiclass SVM classifier with the Gaussian radial basis function (RBF) kernel. The penalty parameter C and γ (spread of the RBF kernel) are chosen by five-fold cross validation. Furthermore, the marker-based HSEG segmentation algorithm is applied. For this purpose, since, the images of urban areas contain the classes with mostly unlike spectral responses, we chose S_{wght} = [٠,٠.٢,٠.٥]. In order to compare the results of the proposed method, we have implemented the Original-HSEG algorithm.

The accuracies of the classification maps are assessed by computing the confusion matrices using the reference data. Based on these matrices, several criteria have been estimated to evaluate the efficiency of algorithms (Congalton, ١٩٩١; Story and Congalton, ١٩٨٦). These measures are a) the overall accuracy (OA), which is the percentage of correctly classified pixels, b) the Kappa coefficient (κ), which is the percentage of agreement corrected by the amount of agreement that could be expected due to chance alone, and c) the class-specific producer's accuracy, which is the percentage of correctly classified samples for a given class.

٣,٢,١ Berlin Dataset

In this dataset for each class, we randomly choose ١٠٪ of the labelled samples for training and the rest for testing procedures. The values of RBF kernel's parameters are: C = ٢٢٨ and γ = ٢$^{-٤}$. Fig. ٤ shows the classification maps of Original-HSEG and the proposed approach, for Berlin data. As can be seen, the proposed approach map contains many more homogeneous regions when compared with the map obtained by other approach. These results prove the superiority of WG algorithm and the importance of the use of contextual information throughout the classification procedure.



(a) (b)

Figure ٤. Berlin dataset, classification maps by (a) Original-HSEG, and (b) the proposed approach (S_{wght} = ٠,٢).

The global (overall and kappa coefficient) and class-specific producer's accuracy parameters of the Berlin dataset are reported in Table ٣. As can be seen, the proposed approach has resulted in up to an approximately ١٦٪ higher rate of accuracy for Original-HSEG in OA. Also, with $S_{wg\square t}$= ٠,٢ the proposed approach performs—in most cases—better than when $S_{wg\square t}$= ٠ is used. If $S_{wg\square t}$= ٠, only spatially adjacent regions are allowed to merge. If, ٠ < $S_{wg\square t}$ < ١ spatially adjacent merges are done with spatially nonadjacent merges. If $S_{wg\square t}$=١, the spatially adjacent and non-adjacent regions are given equal weight for merging. As can be seen, classification accuracy rates decrease with a further increase of the $S_{wg\square t}$value (i.e.$s_{wg\square t}$ = ٠.٥).

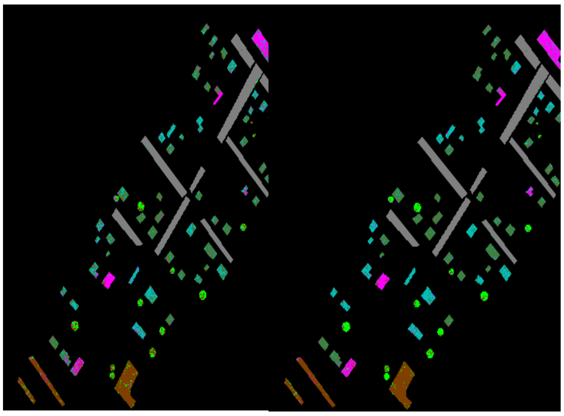
Table ٣. Accuracy measures for the Berlin dataset.

	Original-HSEG	Proposed approach		
S_{wght}	٠,٠	٠,٠	٠,٢	٠,٥
OA(%)	٨٢,٩	٩٨,٨	٩٨,٩	٩٨,٠
κ (%)	٨٠,٨	٩٢,٧	٩٣,٠	٩٢,٢
Vegetation	٨٧,٤	٩٨,٦	٩٩,٠	٩٧,٣
Build-up	٨٢,٩	٩٠,٩	٩١,٨	٩١,٢
Impervious	٨٣,٦	٩٩,٥	٩٩,٩	٩٩,٤
Soil	٧٥,٦	٩٩,٣	٩٩,٣	٩٧,٧
Water	٩١,٨	٩٦,٣	٩٦,٨	٩٥,٧

In Table ٣, All the class-specific accuracy rates for the proposed approach are higher than the Original- HSEG approach, which are more than ٩٠٪.

٣,٢,٢ Quebec City Dataset

In this dataset, for each class, we randomly choose ١٠٪ of the labelled samples for training and the rest for testing. The values of RBF kernel's parameters are C = ٣٠ and γ = $e^{-٥}$. Fig. ٥ shows the classification maps. As can be seen, the map obtained by proposed approach is much less noisy than the map obtained by Original-HSEG.



(a) (b)

Figure ٥. Quebec City dataset, Classification maps by (a) Original-HSEG, and (b) the proposed approach (S_{wght} = ٠,٢).

Table ٤ reports the accuracies obtained on the Quebec City dataset. As can be seen, the global accuracies are improved by proposed approach.

Table ٤. Accuracy measures for the Quebec City dataset.

	Original-HSEG	Proposed method		
S_{wght}	٠,٠	٠,٠	٠,٢	٠,٥
OA(%)	٨٢,٢	٩٠,٤	٩١,٥	٩٠,٨
κ (%)	٧٨,٨	٨٧,٤	٨٨,٢	٨٧,٩
Road	٩١,٢	٩١,٦	٩١,٦	٩١,٦
Trees	٨٥,١	٩١,٨	٩٤,٣	٩٣,٧
Blue roof	٧٨,٤	٨٨,٨	٨٨,٩	٨٨,٨
Gray roof	٨٤,٥	٨٤,٠	٨٤,٤	٨٤,٢
Concrete roof	٨٢,٩	٩٠,٢	٩١,٩	٩٠,٢
Vegetation	٩٠,٩	٩٦,٩	٩٨,٤	٩٨,٠

As Table ٤ demonstrates, all of the class-specific producer's accuracies, except for “Gray roof” class are considerably increased by the proposed approach compared to Original-HSEG. In the case of “Gray roof” class, this reduction in accuracy seems to be due to the complexity of the Quebec City image.

٤. Conclusions

Hyperspectral sensors capture images in hundreds of narrow spectral channels. The detailed spectral signatures for each spatial location provide rich information about an image scene, leading to better discrimination amongst physical materials and objects. Although pixel-based classification techniques have resulted in high classification accuracy rates when dealing with hyperspectral data, the incorporation of the spatial context into classification procedures yields even better accuracy rates.

In this paper, a new method for the object-based classification of hyperspectral images has been proposed. This work follows two main objectives; first is to propose an efficient dimensionality reduction method that finds and selects informative features from hyperspectral data which maximum the classification accuracy, and the second is the use of maximum spatial information for hyperspectral image classification. Additional information from image objects also allows us to get neighborhood characteristics.

Experimental results on two hyperspectral datasets showed that the proposed method could significantly improve the classification accuracy. It has increased the Original-HSEG classification accuracy from ٨٢,٩٪ to ٩٨,٩٪ in Berlin image and ٨٢,٢٪ to ٩١,٥٪ in Quebec City image. It is thus evident that reducing dimensions and contextual features for classification are very important. Further work is needed to improve the proposed method. It is necessary to take advantage of the available data in order to automate the whole classification process.

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طبقه بندی مبتنی بر هدف با استفاده از قطعه بندی هرمی و الگوریتم ژنتیک وزن دار

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چکیده:

اخیرا، یک روش موثر برای طبقه بندی طیفی-مکانی با استفاده از قطعه بندی هرمی (HSEG) رشد یافته از نشانه های انتخاب شده ارائه شده است. هدف این مقاله بهبود این روش برای طبقه بندی تصاویر فراطیفی در مناطق شهری است .ابتدا الگوریتم ژنتیک وزن دار (WG) برای بدست آوردن باندهای بهینه داده های فراطیفی استفاده می شود .الگوریتم HSEG مبتنی بر نشانه سپس بر ویژگی های بدست آمده پیاده سازی می شوند. در ادامه، ویژگی های زمینه ای از تصاویر قطعه بندی شده استخراج می شوند. برای ویژگی های مکانی، ویژگی های مساحت، آنتروپی، شکل، مجاورت و رابطه به عنوان اجزای بالقوه در فضای ویژگی در نظر گرفته شده اند. سرانجام ، با استفاده از هر دو ویژگی طیفی و مکانی، اشیا تصویر توسط یک طبقه بندی کننده مبتنی بر قانون طبقه بندی می شوند. آزمون ها بر روی دو مجموعه داده اعمال شد Berlin :وQuebec City ، که دو مجموعه داده شناخته شده و بنچ مارک در تصاویر فراطیفی هستند. ارزیابی نتایج نشان داد که روش پیشنهادی به ترتیب برای این مجموعه داده ها به ترتیب از ۱۶٪ و ۹٪ دقت کلی بهتری نسبت به الگوریتم HSEG اولیه به دست می آورد.

کلید واژه:

تصویر فراطیفی ، طبقه بندی مبتنی بر شی ، الگوریتم ژنتیک وزن دار ، انتخاب نشانه ، قطعه بندی هرمی