Multispectral Image Classification Based on Morphological Watershed Algorithm of a Remote Sensing Image Multidimensional Histogram

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الملخص:

الخوارزميات الكلاسيكية لتصنيف الصور متعددة القنوات تحدث تجزئة مفرطة لمكونات الصورة، وتداخل في الألوان حيث يرجع إلى الضوء المنعكس على كائنات الصورة. كما تعتمد معالجة صور الاستشعار عن بعد بشكل كبير على أحجام البيانات الكبيرة المرتبطة غالباً بالصور متعددة القنوات، بما في ذلك التصوير عبر الأقمار الاصطناعية والصور الجوية. يوفر هذا النوع من البيانات قدراً هائلاً من المعلومات، وهذا بدوره، وبشكل واضح، ينشئ تزايد الطلب على الخوارزميات التلقائية القادرة على معالجة مجموعات البيانات الهائلة متعددة القنوات. تلك الخوارزميات التي توفر السرعة الكافية والدقة العالية للاستخدام العملي. تبحث هذه الورقة في خوارزمية محسّنة لتجزئة الصور متعددة القنوات لتنفيذ إجراءات تصنيف وكوناتها، ولها القدرة على جمع المعلومات التي توفرها جميع قنوات البيانات. التقنية المقترحة تقوم على ببناء الرسوم البيانية المورفولوجية متعددة القنوات، وتنشر الشبكات العصبية لوظيفة القواعد الشعاعية لتحديد علامات مستجمعات المياه المورفولوجية التي تحدد تجمعات البيانات المستهدفة. تم تنفيذ هذه التقنية على بيانات الاستشعار عن بعد متعددة النطاقات الملتقطة من القمر الصناعي Landsat 9.

Abstract:

Classical Multichannel image classification algorithms represent excessive segmentation and color intervention reflected from light on picture objects. Remote sensing image processing highly depends on the large data volumes often associated with multichannel imagery, including satellite imaging and aerial photos. This sort of data provides huge amount of information which is clearly arises the demand for automatic algorithms that are able to process these multi-channel data sets fast enough for practical use and more accurately. This paper examines an improved image segmentation algorithm for the implementation of a multichannel classification procedure that brings together the information provided by all data channels. The proposed technique constructs multichannel morphological histograms, and deploys Radial Bases Function neural networks to define the morphological watershed markers that identify target datasets. The technique has been implemented on Landsat 9 multiband remotely sensed data.

Keywords—Multichannel image classification; remote sensing; morphological watershed; RBF neural networks.

I. INTRODUCTION

Multichannel image segmentation has a significant application value in the realm of picture content analysis and pattern identification. The advantages of the watershed approach over various traditional edge detection techniques are its low computer complexity and good computational accuracy. It uses the image's gradient as its input and produces continuous edge lines that are one pixel wide (Nallaperumal and Krishnaveni, 2007). However, because of the impact of quantization error, gradient noise, and the sensitive texture inside the object (Wu and Li, 2022). States regional planning, research and environmental monitoring applications relay heavily on land use and land cover information. Therefore, multispectral remotely sensed image classification has been recognized as one of the key data information resources over the last four decades. The development of land use and land cover information extraction from satellite remote sensing data has been an active and interesting research in the remote sensing discipline, as well as algorithm development displine. Many of classifiers have been in use in remote sensing researches including the ISODATA, KMeans unsupervised classifiers, the Maximum Likelihood, Minimum Distance, Mahalanobis Distance, Parallelepiped, Spectral Angle Mapper, Neural Network and Decision Tree classifiers, and most of them have been integrated in the remotely sensed image processing software such as PCI, ERDAS and ENVI (Liu *et. al.*, 2014). Watershed transformation in mathematical morphology is considered as a powerful image classification tool which is usually applied on gradient magnitude of grayscale images. In mathematical morphology, an image is usually considered as a topographical surface where the gray level of each pixel correspond to an altitude, pixels having the highest gradient magnitude intensities (GMIs) correspond to watershed lines representing object boundaries (Shi and Milk, 1997). Interpreting images this way makes its features seen as mountains where the highest brightness values, peaks, are considered as tops and the lowest values as valleys. A watershed is defined as a side from where a drop of water flows from a top sliding down until it reaches a valley's minima. The optimum contours of the image are these watersheds (Braccini *et. al.*, 1995), and watershed transformation algorithm is a technique used for extracting these lines from the modulus of the gradient image (Vincent and Soille, 1991).

The most common segmentation approach is thresholding (Yahya *et. al.*, 2013). It has a high speed of operation and ease of implementation. However its performance is relatively limited since image pixels with similar gray level value will invariably be segmented into the same class, resulting in what so called over-segmentation (Sin and Leung, 2001). Simple watershed transformation methodologies mostly cause over-segmentation (Hill *et. al.*, 2003). In order to prevent this over-segmentation, the watershed method passed through several stages of evolution. The original watershed method was developed by Lantuejoul (Lantuejoul, 1978) and was widely described together with its applications by Beucher and Meyer (Beucher and Meyer, 1993). Segmentation by morphological watersheds embodies different principal segmentation concepts such as edge detection, region growing, and thresholding. It provides more stable segmentation results, as well as providing simple framework (Han *et. al.*, 2012). To reduce over segmentation, marker based techniques are implemented (Sharma *et. al.*, 2015). Use of region markers is proposed in (Lewis and Dong, 2012), where the desired local minima are designated as markers. The set of points of the surface whose steepest slope path reach that found minimum constitutes the catchment basin associated with that marker, while the watersheds are the zones dividing adjacent catchment basins (Plaza, 2008). Geodesic reconstruction is then applied to fill the other plateaus. Presence of variable shaped regions with imperfect and overlapped boundaries makes it more complex to find appropriate markers representing the desired region of interest (Grau *et. al.*, 2004). This makes automatic segmentation of masses a challenging and interesting problem. Artificial intelligence techniques such as neural networks have been applied to overcome the over-segmentation drawback. Masoumi *et al*. in 2012 used trained Multi-Layer Perceptron (MLP) neural networks to extract features of the liver region in CT images, and adjust the required parameters automatically. Middleton and Damper in (Middleton and

Damper, 2004) proposed a segmentation algorithm based on neural networks to classify image pixel as a boundary or a non-boundary pixel.

Another important issue is the fact that employing watersheds straightforward on an image requires the image to have clear and sharp regions, where each region should have a peak and gradient in its color distribution (Russ, 1995). In general, the original image does not have these kinds of features. Therefore, prior image processing is needed to provide high contrast contours, and to create the high value of gradient (Russ, 1995), (Zayane *et. al.*, 2011), and (Sharma *et. al.*, 2015). The contrast of the gradient image can be enhanced by top/bottom hat transformation and subject the combination to the watershed algorithm (Yahya *et. al.*, 2013).

In this paper, the watershed technique is applied on the image histogram instead of the image itself. The histogram is considered as another way of representing the features of an image depending on the number of reputations of each pixel's brightness value. The image features are represented as regions with peaks in the image's histogram (Russ, 1995). To solve the over-segmentation, neural networks Radial Bases Function (RBF) will be trained online to locate the two local minima markers of each segment in the image. RBF networks are able to adaptively model or identify a dynamical complex process online while the process is changing (Narendra and Parathasathy, 1990) and (Park *et. al.*, 2002). The RBF NNs ability to uniformly approximate smooth functions over compact sets is well documented, see for examples (Sanner and Slotine, 1992), (Li *et. al.*, 2004), and (. Seshagiri and Khalil, 2000). From mathematical prospective, RBF NNs represent one class of linear in the weight approximators. Compared to the MLP network, the RBF network is simpler to implement, needs less computational memory, converges faster, and global minimum convergence is achieved even when operating conditions change or fault occurred during testing with frozen weights. The RBF

NN also required less training time to converge and fewer computational complexities to train the network online (Park *et. al.*, 2002).

II. METHODOLOGY

In this paper classification of image regional segments is organized in the form of three phases. In the first phase, the grey-scale image is pre-processed by morphology reconstruction to clarify the actual image regions. The second phase works on building the pre-processed image histogram which will be constructed in stages divided in intervals depending on the image height. Also, the histogram will be smoothed to remove noisy peak spikes. During this phase, an RBF neural network will be trained at each interval in order to set the Gaussian bases centers, widths, and weights. The final Gaussian widths will serve as references for image region markers. A clustering based approach is applied in the third phase to obtain the final segmented target regions.

A. Morphological Reconstruction pre-processing

Morphological Reconstruction is a transformation process involves dilating and eroding the original image, and involves a structuring element (SE). Dilation and erosion are operations that thicken and thin the objects in the image, respectively. This pre-processing procedure smoothen the interior objects as well as preserve the boundary of the objects, (Yahya *et. al.*, 2013) and (Platt, 1991). The dilation and erosion of the image f by structuring element B denoted by $f \oplus B$ and $f \ominus B$, respectively, are defined as follows:

$$(f \oplus B)\,(x, y) = \max \{(x - x1, y - y1) + (x1, y1) \mid (x - x1, y - y1) \in Z, (x1, y1) \in Z\},$$

$$(f \ominus B)(x, y) = \min\{(x + x1, y + y1) - (x1, y1) \mid (x + x1, y + y1) \in Z, (x1, y1) \in Z\},$$

where Z is the size of the structuring window. The opening of image f by structuring element B is defined as follows:

$$\vartheta(f) = f \circ B = (f \ominus B) \oplus B.$$

The closing of image f by structuring element B is defined as follows:

$$\theta(f) = f \cdot B = (f \oplus B) \ominus B.$$

To smooth the image f by reconstruction operator, we use the following equation:

$$R(f) = (\theta l, (f \oplus B)),\ 0 \leq l \leq n,$$

where β is reconstruction operator, θl is reference image which is obtained by closing the image f, l times, and n is the size of the structure element B (Platt, 1991).

B. RBF Neural Networks for Image Histogram Marking

As discussed above, watershed algorithm is a powerful tool used for image segmentation; nevertheless it often suffers from over-segmentation. Conventionally, markers of desired object size are computed and then watershed algorithm is applied on the gradient image. However, in this work we propose to reduce this over-segmentation problem so that the objects of interest are needed to be marked on their target image histogram clusters. Therefore, during this phase the histogram will be built in step by step mode where at each step an RBF neural network will be trained to identify the final markers of image region. Fig. 1 below simplifies the algorithm.

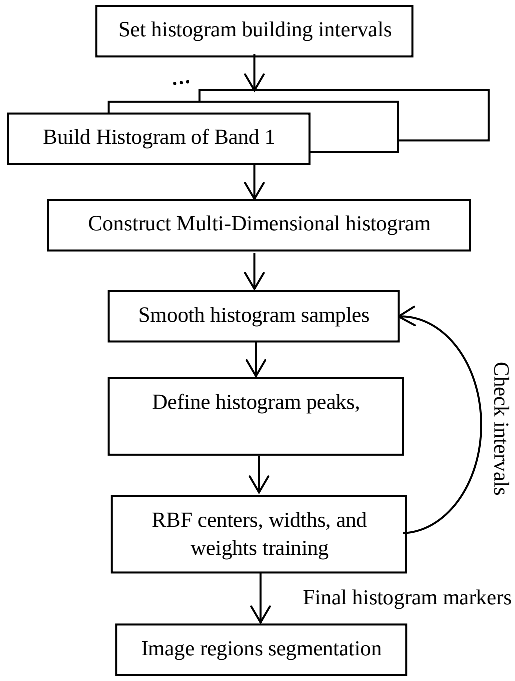

Figure 1. Proposed methodolgy scheme

An image histogram sample is built for every 5 image rows. Though, every new histogram sample will take into account all previous samples. Each sample is smoothed and scanned to identify its peaks, and to recognize left and right minima for each peak. An RBF neuron is associated for each peak. The position of the peak will be the center of the neuron, whereas the left and right minima will define its start and end, as a result its width. The parameters setting and tuning of the RBF network is performed online including tuning neurons' centers and widths, and tuning the network weights. The adaptive centers were fine-tuned using the back-propagation method proposed in (Platt, 1991):

$$\Delta c_j^i = 2\frac{\alpha}{\sigma_j^i}(x_i - c_j^i)z_j[(T - f_0)w_j],$$

$$z_j = \exp\left(-\sum_l \frac{(c_j^l - x_l)^2}{(\sigma_j^l)^2}\right),$$

where $\alpha > 0$ which is set to 0.02, T is the desired output and f_0 is the network output. The width of the RBF units (σ_j^i) strongly affects the performance of the RBF NNs, and in practice it is difficult to estimate the appropriate value of the RBF width (Mai-Duy and Tran-Cong, 2006). Unfortunately, the literature of RBF NNs lacks the theory regarding tuning the unit width, which remains a challenging task in using RBF NNs. Haykin in 1994 used the Delta rule to adjust the width of the RBF hidden layer units. In (Mai-Duy and Tran-Cong, 2006) used the relation $\sigma_i = \beta d_i$ where σ_i is the width of i^{th} neuron, β is a positive scalar and d_i is the minimum of distances from the i^{th} center to its neighbors. This paper proposes a simple technique for adjusting the neurons' width (σ_j^i) of RBF network

$$\sigma_j^i = \beta c_j^i ,$$

where σ_j^i is the width of the j^{th} neuron in the RBF hidden layer, c_j^i is the position of the center of the j^{th} neuron and β is a positive scalar. The proposed technique gives promising results in improving the RBF nonlinearities. The output layer weights were updated online using the Delta rule.

Fig. 2 demonstrates the construction process during which the image Multidimensional histogram is being built until the final histogram is formed. At each building interval, the RBF neural network is trained according to histogram peak positions and left and right minima. For any new peaks new neurons are added to the network. Fig. 3 shows sample training history of an RBG neuron. The figure also shows an image cluster region final markers. Fig. 4 illustrates the final distribution of Gaussian bases functions forming the trained RBF neural network.

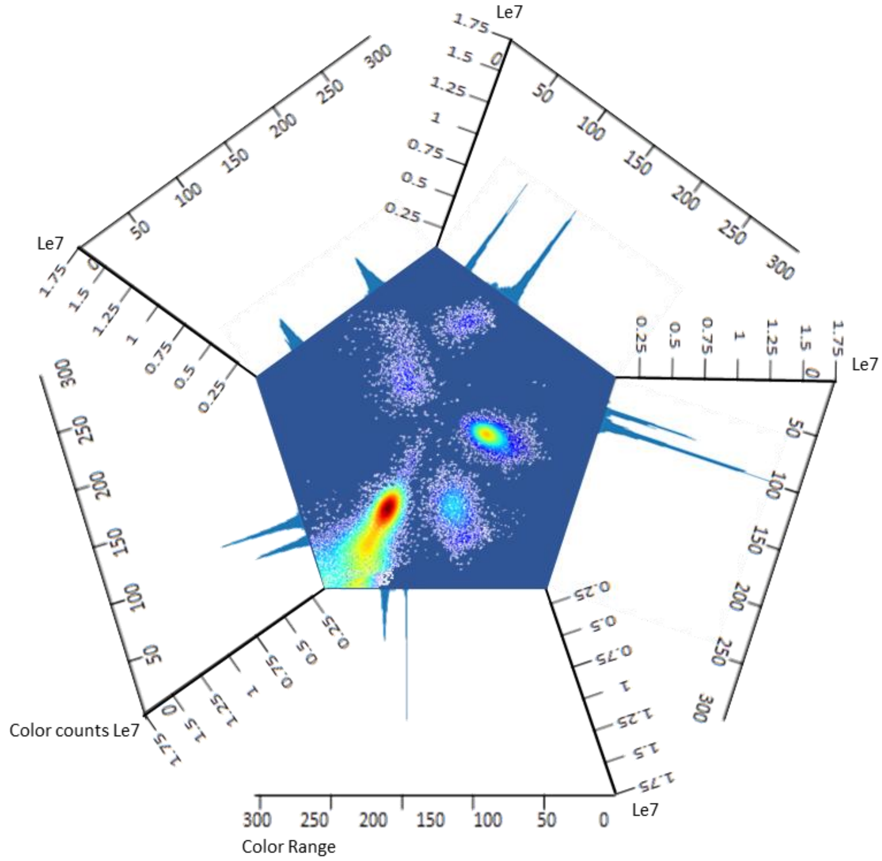

Figure 2. Multidimensional image histogram

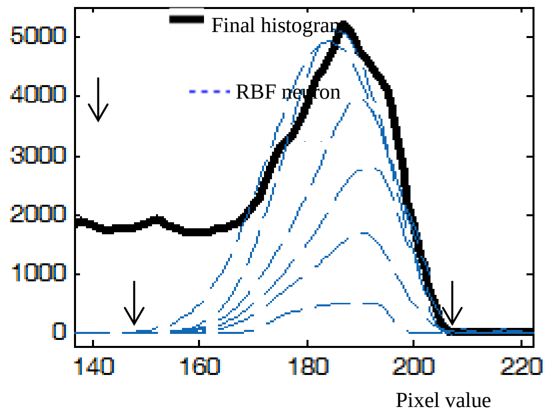

Figure 3. Traing of RBF neuron to identify image region markers

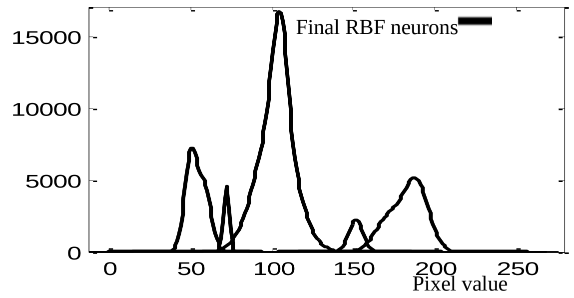

Figure 4. Final RBF neurons distribution

C. Image Regions Segmentation

In the final created neural network, every neuron's left and right minima define the positions of two histogram cluster markers, assuming that similar image regions are represented in a single histogram cluster, and will be segmented accordingly. Therefore, clustering procedure proposed here is automatically defining markers as an input to watershed algorithm to segment the target image regions. Sample region markers identified using this approach is shown in Fig. 3.

III. EXPERIMENTAL RESULTS

The proposed segmentation algorithm was tested on a remotely sensed Landsat 9 image acquired in October 2015. The algorithm gave interesting results when experimented upon this diverse application images. The outcome of the proposed segmentation algorithm is shown in Figures 5.

Figure 5a. Location of Testing Area

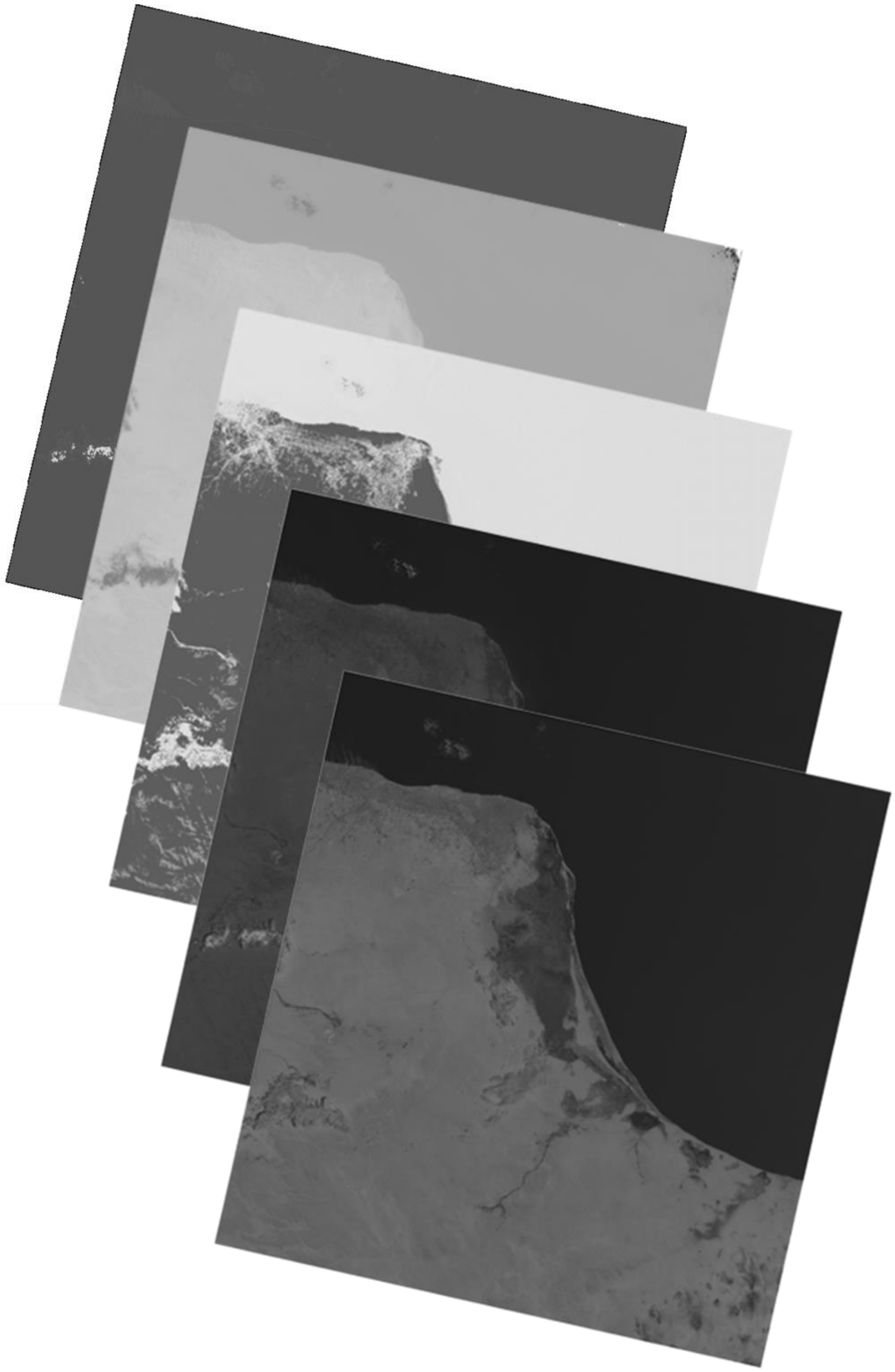

Figure 5b. Landsat 9 Multispectral source images

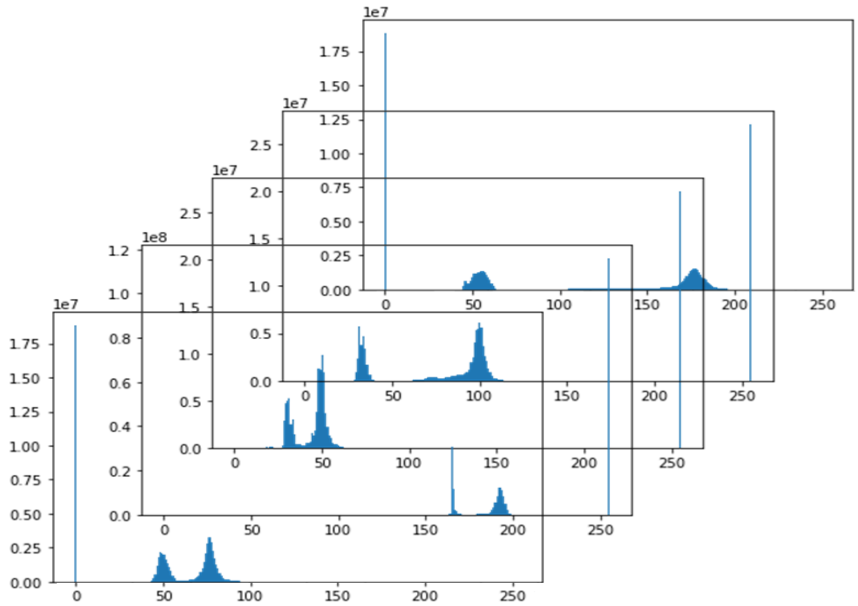

Figure 5c. Histogram of Landsat 9 Multispectral source image bands

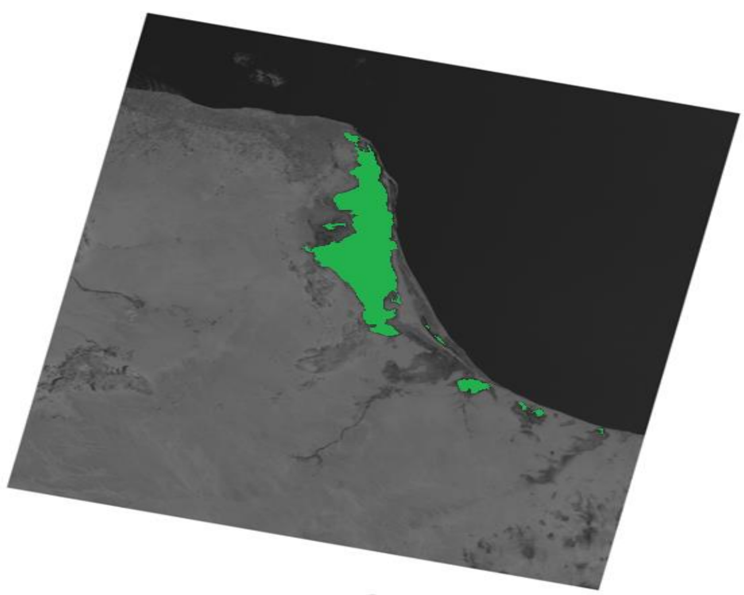

Figure 5d. Marsh classification with RBF NN marking watershed algorithm

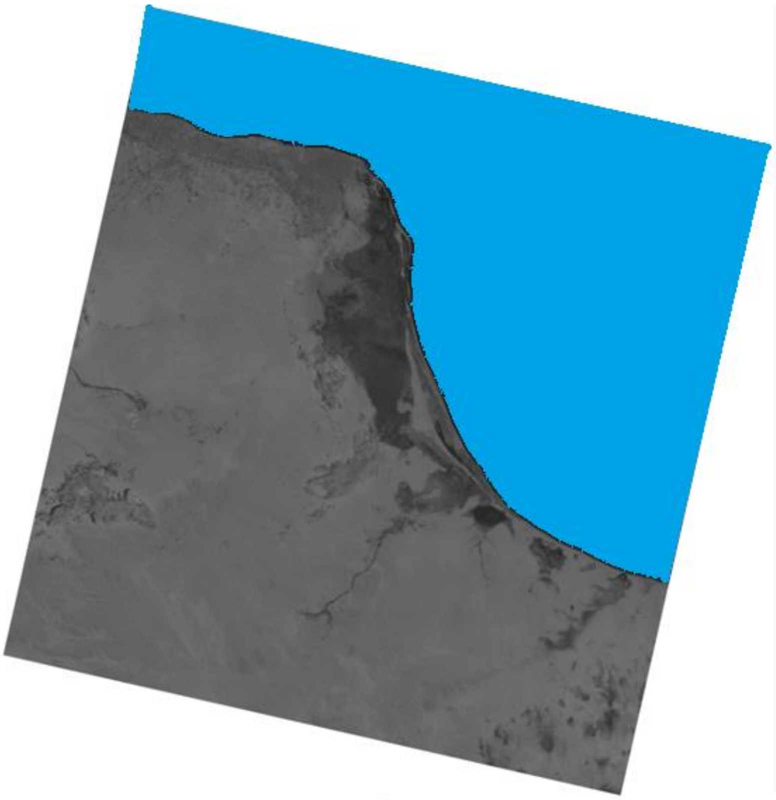

Figure 5e. Sea Water classification with RBF NN marking watershed algorithm

IV. CONCLUSIONS

Towards improving the accuracy of the classification of multiband remote sensing images, this paper applied a multidimensional watershed based histogram, which was built using image segmentation algorithm that applied RBF neural networks to set image cluster boundaries. The reported approach trained RBF neural network Gaussian functions on the image histogram clusters in order to generate appropriate target region markers. These markers work as input to a final segmentation phase. The proposed segmentation algorithm was tested on Landsat multiband images and produced satisfactory results with respect to suppression of over-segmentation and under-segmentation. Thus, the proposed algorithm could be considered as an effective tool to define suitable target regions markers, and it can contribute to overcome the conventional watershed segmentation problems.

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