A new Wavelet based Multi-Resolution Texture Segmentation scheme of Remotely Sensed Images for Vegetation Extraction

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Abstract

Texture segmentation via wavelet transform traditionally adopts textural features based approach. However, applying this method can lead to over-segmentation problems. To overcome this limitation, we propose a new scheme of texture segmentation. The proposed approach will be applied to remotely sensed images for vegetation extraction. The key idea is that we precede wavelet transform by a preliminary step for increasing the homogeneity of each texture region and removing noise, consisting on smoothing the image by means of anisotropic diffusion technique. The smoothed image is then decomposed into sub-images with different spatial frequencies. Separating the high spatial frequency details corresponding to vegetations, from the other spatial low frequencies, dictates a wavelet reconstruction while neglecting the approximation coefficients. Then, by applying a triangle algorithm based thresholding, we isolate regions corresponding to vegetations. Natural remote sensed images of olive trees parcels with different geometries and different characteristics were considered for texture segmentation. Simulation results prove that trees textures are successfully extracted.

1. Introduction

Reproducing the aptitude of the human, to recognize the objects in images by analysing the form and texture of the entities in view, by developing appropriate algorithms, is an important feature in image processing. Texture segmentation of remote-sensed images has been widely used as a powerful means to extract different sets of information related to the earth environment. Remote sensing (RS) is an invaluable information source for the plants investigation, since very high spatial resolution (VHR) images became widely accessible. Accordingly, the objective of texture segmentation in remote sensing is to identify and separate the pixels forming the noisy image of an area with respect to its class (nature of plants). Usually, the spectral signature is the main feature used to classify the pixels. For multi-spectral images, data acquired by remote sensing devices are very complex entities which have not only spectral characteristics but also spatial characteristics. Exploitation of this spatial related information, in addition to spectral information, can improve the segmentation performance in many applications. Our attention here is focused on using spatial features for texture segmentation aiming at vegetations extraction. Numerous vegetations are planted according to a complex spatial pattern: olive tree and almond tree are examples covering millions of hectares, representing an obviously economic interest. For these crops, inspection from a high altitude shows regularly spaced individuals, generally separated from each other by uncovered soil. Such regularity of the investigated plants suggests strongly the use of spatial frequency based analysis methods.

Various feature extraction and segmentation techniques have been suggested in the past for the purpose of texture analysis. More recently methods based on multi-resolution or multi-channel analysis such as wavelet transform has received a lot of attention in diverse areas such as pattern recognition and signal processing. In wavelet representations, the images are decomposed using basis functions localised in spatial position, orientation, and spatial frequency (scale) [9,10]. These specific characteristics of satellite images and the characteristics of the wavelet transform motivate the investigation of use of the wavelet transform in plants texture segmentation. Accordingly, proper noise removal techniques should be applied to improve the segmentation performances such as anisotropic diffusion [7,8].

This paper is organized as follows: in section 2, the proposed method is described in detail. In section 3, experimental results and discussion are presented. Finally, in Section 4, we provide a conclusion.

2. Proposed method

Our proposed approach is summarized in the system block depicted in Fig.1. To increase the homogeneity of each texture region and for noise removal, the image is smoothed applying anisotropic diffusion technique. Then through packet structured wavelet transform, the image is first decomposed into sub-images with different spatial frequency channels and orientations. Looking for isolating the details of the image corresponding to olive trees, we make cancel the approximation coefficients for a further Wavelet reconstruction. Lastly, the reconstructed image is enhanced and an automatic thresholding procedure is used for texture segmentation and trees extraction. In the following, the proposed method will be described in detail.

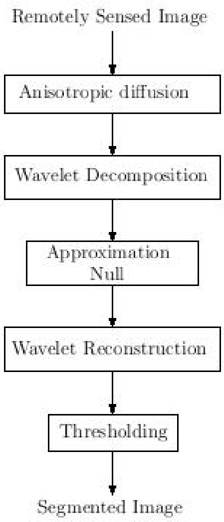


Figure 1: The system block of the proposed method.

2.1. Anisotropic diffusion

Remotely sensed images are generally affected by small variations in intensity such as noise or shading that appear as local anomalies in textured surfaces and background. A suitable denoising scheme is undoubtedly required for a further accurate processing of the images. When the smoothing/denoising scheme is adapted to the spatiotemporal image structure as much as possible, the accuracy achieved is maximal and reliable results are obtained in case of further image processing. The idea of anisotropic diffusion, based on the partial derivative equations (PDE), is to adaptively smooth the image such that intra-regions become smooth while edges of inter-regions are preserved. The diffusion process is generally selected so that small variations in intensity such as noise or shading can be well smoothed, and edges with large intensity transition are particularly retained.

This approach is basically a modification of the linear diffusion (or heat equation), and the continuous isotropic diffusion. Indeed, isotropic diffusion of heat in a material is managed according to the following PDE:

$$\frac{\partial u}{\partial t} = c\Delta u \qquad \textbf{(1)}$$

where c is a diffusion coefficient and Δ is the Laplacian operator.

Eqn.1 can be locally expressed by :

$$\begin{cases} \frac{\partial u}{\partial t}(x,y,t) = u_{\eta\eta}(x,y,t) + u_{\varepsilon\varepsilon}(x,y,t) \\ u(x,y,0) = u_0(x,y) \end{cases} \qquad \textbf{(2)}$$

Where $u_{\eta\eta}$ and $u_{\varepsilon\varepsilon}$ are respectively the u second order derivative with respect to directions η and ε.

Koenderink [1] was the first to apply a filter based on eqn.1 to a two D image. He proved that it is equivalent to the convolution of the corresponding image by a Gaussian core h, of standard deviation σ given by:

$$h(x,y) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{x^2+y^2}{2\sigma^2}} \qquad \textbf{(3)}$$

This filter repeatedly diffuses the intensity of a pixel of the image around its neighbors during a time T. T corresponds in this process to the level of details chosen on the space-scale in order to preserve the physical evolution of the diffusion.

The Gaussian operator diffuses the image in isotropic way, without taking into account its geometry. Thus it eliminates well noise. However it smoothes by the way contours, which degrades the useful information in the image. Fig.8 illustrates the result of an iterative isotropic filtering for different values of σ.

To carry out a good morphological analysis of the image, it is necessary to adapt the equation of diffusion to full-fill the two following conditions:

- Smoothing of the image by diffusion.
- Preserving the morphological structure of the image, i.e. discontinuities of differential elements having an intrinsic geometrical significance such as contours. Indeed contours delimit the homogeneous fields of an image and are essential with the definition of its components.

Since contours result in discontinuities in the gradient of an image, preserving the discontinuous character of contours in the diffusion process suggests an anisotropic diffusion technique, so that it can be inhibited in the direction of the corresponding gradient.

The revolution is brought by Perona and Malik [2, 3] by introducing coefficients of diffusion which depend on the position and time (time is confused with the space-scale in order to preserve the evolution of the diffusion). Thus the diffusion becomes anisotropic and will be described by the following equation:

$$\begin{cases} \dfrac{\partial I}{\partial t}(x,y,t) = div\left(c(x,y,t)\nabla I(x,y,t)\right) \\ I(x,y,0) = I_0(x,y) \end{cases} \qquad \textbf{(4)}$$

where div and ∇ represent respectively the operators divergence and gradient, I_0 (x,y) is the initial image and c(x, y, t) is variable with respect to space and time.

By developing eqn.4, we get the following equations:

$$\begin{cases} \dfrac{\partial I}{\partial t}(x,y,t) = c(x,y,t)\Delta I(x,y,t) + \nabla c(x,y,t)\nabla I(x,y,t) \\ \qquad I(x,y,0) = I_0(x,y) \end{cases} \qquad \textbf{(5)}$$

For a small variation of t, assuming that c(x, y, t) remains constant between t and t+dt and. The best mean describing the space geometry of an image is the gradient of the image g, we thus get:

$$\begin{cases} \dfrac{\partial I}{\partial t}(x,y,t) = g\left(\left|\nabla I(x,y,t)\right|\right)\Delta I(x,y,t) \\ I(x,y,0) = I_0(x,y) \end{cases} \qquad \textbf{(6)}$$

In order to filter the homogeneous zones and preserve discontinuities corresponding to contours, g should full-fill the two following boundary conditions:

$$\begin{cases} \lim\limits_{|\nabla I|\to 0} g = 1 \\ \lim\limits_{|\nabla I|\to \infty} g = 0 \end{cases} \qquad \textbf{(7)}$$

Thus g is a decreasing function of $|\nabla I|$. A function which comes to mind is undoubtedly the negative exponential function g defined by:

$$g\left(\left|\nabla I\right|\right) = e^{-\left(|\nabla I|/k\right)^2} \qquad \textbf{(8)}$$

where k is a slope parameter representing a threshold of transition. For $|\nabla I|<k$, g can be approximated to one and diffusion is enhanced, whereas for $|\nabla I|>k$, g is approximated to 0 and the diffusion process is inhibited.

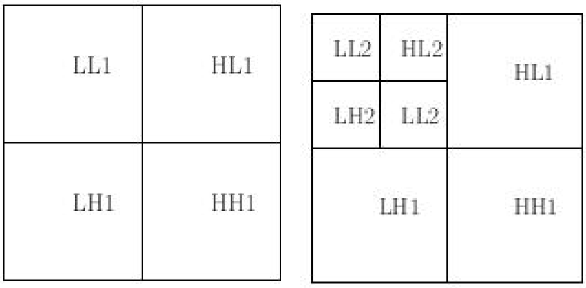
Accordingly, implementation of anisotropic diffusion makes use of a discrete representation of eqn.6 as follows:

$$I_{t+1}(x,y)=I_t(x,y)+dt\left(g\left(\left|\nabla I_t(x,y)\right|\right)\Delta I_t(x,y)\right)_t \qquad \textbf{(9)}$$

Applying the anisotropic diffusion technique to olive trees image of Fig.9-a, we get the smoothed result in Fig.9-b. Uncovered soil is well homogenized and granulations due to noise are eliminated while preserving the general sight of olive-trees parcels. Fig.9-c illustrates the profile of the original image and that of the diffused one. The diffused profile reproduces the original one while minimizing its fluctuations.

2.2. Discrete wavelet transforms (DWT)

Wavelets are functions generated from one single function Ψ by dilations and translations. The basic idea of the wavelet transform is to represent any arbitrary function as superposition of wavelets. The discrete wavelet transform (DWT) is identical to a hierarchical sub band system where the sub-bands are logarithmically spaced in frequency. Any such superposition decomposes the given function into different scale levels where each level is further decomposed with a resolution adapted to that level [5].



(a) (b)

Figure 2: Image decomposition. a. one level. b. two levels.

As shown in Fig.2-a, by applying DWT, the image is essentially decomposed into four sub-bands and critically sub-sampled. The sub-bands labeled LH1, HL1 and HH1 represent the finest scale wavelet coefficients related to details in the images while the sub-band LL1 corresponds to coarse level coefficients related to rough approximations of the image. These sub-bands come up from independent applications of horizontal and vertical filters. To obtain the next coarse level of wavelet coefficients, as shown in Fig.2-b, the sub-band LL1 alone is further decomposed and critically sampled. This results in two level wavelet decompositions. Similarly, to obtain further decomposition, LL2 will be further decomposed. These subsequent decompositions continue until some final scale is reached. The values or transformed coefficients in approximation, and detail images (sub-band images) are the essential features, which are useful for texture discrimination and segmentation. Since textures, either micro or macro, have non-uniform gray level variations, they are statistically characterized by the values in the DWT transformed sub band images or the features derived from these sub-band images or their combinations [6]. In other words, the features derived from these detail sub-band images can characterize a finest texture. The features obtained from these DWT transformed images are shown here as useful for texture analysis, namely segmentation, and are discussed in the following section.

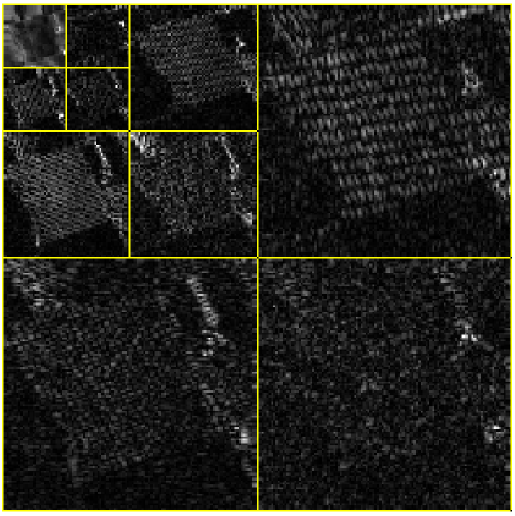


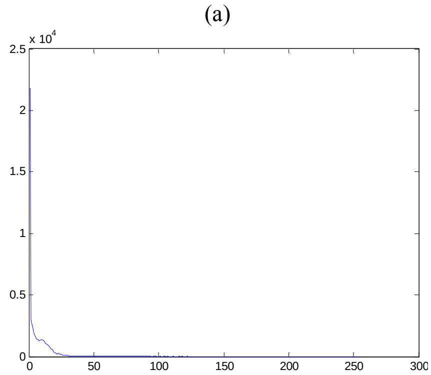
Figure 3: An example of three levels wavelet decomposition of an olive trees parcel image.

An example of three levels wavelet decomposition is depicted in Fig.3. We can observe the details corresponding to each level of decomposition and approximation. High spatial frequencies associated to the trees appearing in the details can be easily distinguished from low spatial frequencies representing ground and parcel contour appearing in approximation. To get rid of unusual information for texture segmentation of olive trees, one can make null the coefficients of the approximation. Hence, image rebuilding by wavelet reconstruction preserve the trees entities. Fig.4 illustrates the output of the wavelet reconstruction process after cancelling the approximation coefficients and its corresponding histogram. We can note that the image has a very weak contrast which makes difficult its segmentation. We describe in the following a histogram enhancement technique to overcome this limitation.

2.3. Histogram enhancement

Faced to a very weak contrast of the images resulting from the wavelet reconstruction process, an histogram enhancement must be applied to increase the contrast of the image without modifying its morphology. A linear transformation of the dynamic range of the image is then applied. The new pixels dynamic range is made maximum comprised between 0 and 255. The histogram enhancement function is depicted in Fig.5. Fig.6 illustrates the results of histogram enhancement on the considered image.

(a)



(b)

Figure 4: Wavelet reconstruction output after cancelling the approximation coefficients. a. Reconstructed image. b. Its corresponding histogram.

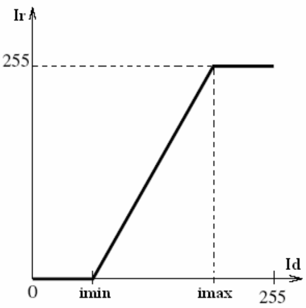
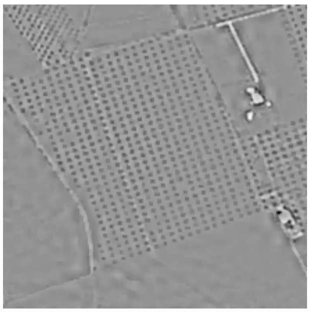


Figure 5: Histogram enhancement function.

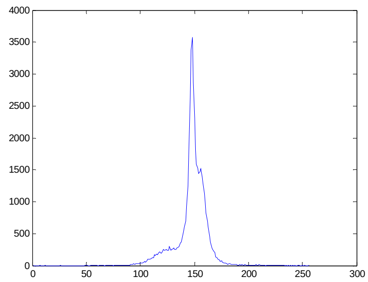
2.4. Segmentation by pixels classification

Segmentation is an operation whose objective is to divide an image into areas with similar pixels characteristics. In our case, the image comprises two classes: an object class referring to olive-trees and a background class referring to uncovered soil. Texture segmentation is thus a simple allocation of pixels to one of the two classes. For olive-trees images, these two classes correspond to slightly different gray levels. The level characterizing the olive trees is darker than that of the background; however, the different is not so obvious. Given that the two classes of the image overlap too much in our case what makes difficult the determination of the threshold of classification, we applied the method of the triangle for histogram thresholding [4]. Based on the principle illustrated in Fig.7, this method consists on determining the maximum distance between the histogram and the line D connecting the first point of this histogram with its maximum, having respectively as grey level values imin and imax. Let D be described by the following equation:

$$D: y=a.x+b \quad \textbf{(10)}$$



(a)



(b)

Figure 6: Histogram enhancement results.a. Enhanced image. b. Its corresponding histogram.

The distance d can be computed as follows:

$$d = \frac{|a.i - h(i) + b|}{\sqrt{a^2 + b^2}} \quad \textbf{(11)}$$

The threshold allowing image segmentation s can be fixed as the value of I which maximizes d.

3. Results and interpretation

Our method has been tested on several remote sensed images with different parcel geometries and different characteristics. We use a panchromatic SPOT 5 images with a 2.5 m resolution. The studied region is situated in Sfax a town of the middle east of Tunisia. Sfax contains about 57 million of olive trees which is the third of the whole of Tunisian olive trees. Moreover, in this region, two neighbouring olive trees are spaced by 24 m which favourites keeping a good quality images with minimal atmospheric distortions (this distance becomes 6m for the north of Tunisia).

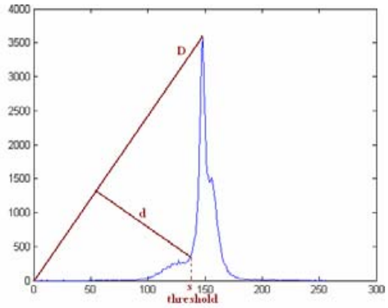


Figure 7: Threshold based on the triangle algorithm.

Packet structured wavelet transform is used up to three levels in all experiments. Fig.10 shows the segmentation results for four remote sensed images. The processing results are finally illustrated in the original image by drawing with green colour the segmented trees texture. For each case, the thresholded image can reveal the different trees in the parcel of interest. Fig.10 (b) is an example of a remote sensed image which is highly affected by local shading noise. Although this noise is localized in the parcel of interest, anisotropic diffusion allows noise removal without affecting texture segmentation process and trees situated in the noisy regions were correctly segmented. Fig.10 (c) is an example of a remote sensed image with poor contrast and local low noise level in the parcels of interest. As seen from the segmentation results, trees textures are successfully extracted without being affected by those conditions and the results are quite accurate.

4. Conclusion

In this paper, a new texture segmentation scheme for vegetation extraction is proposed. It consists on anisotropic diffusion based noise removal process preceding a three level wavelet decomposition step. A key idea in our approach was to neglect approximation coefficients for further wavelet reconstruction. Based on a triangle algorithm, the reconstructed image is thresholded for discriminating the interior parts of texture regions from background. Natural remotely sensed images with different parcel geometries and different characteristics were considered for texture segmentation. An example of remotely sensed image which is highly affected by local noise due to shading shows that our approach undergoes these noise effect limitations. Simulation results prove that olive trees textures are successfully extracted without being affected by those conditions and the results are quite accurate.

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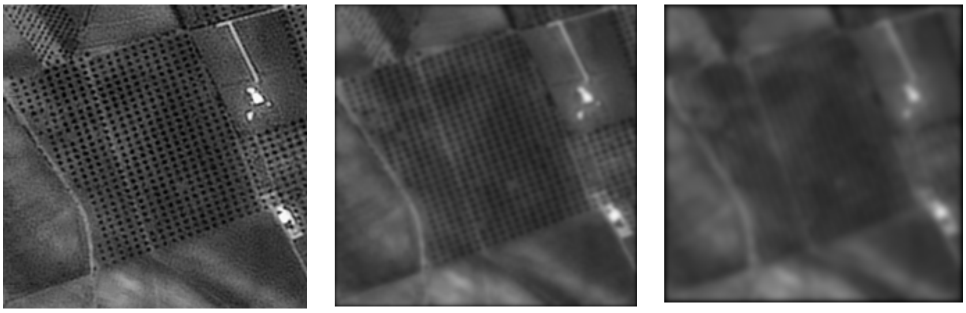
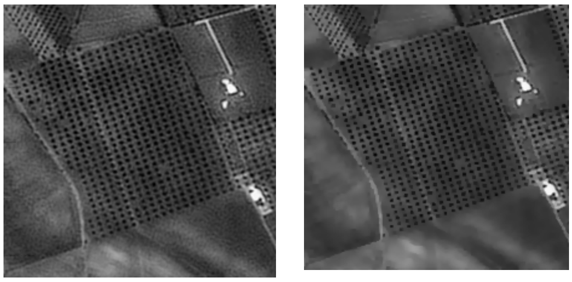
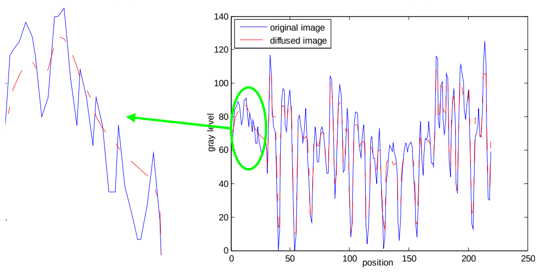


(a) (b) **(c)**

Figure 8 : Isotropic diffusion after 10 iterations. a. Original image. b. $\sigma=0.5$. c. $\sigma=1.5$

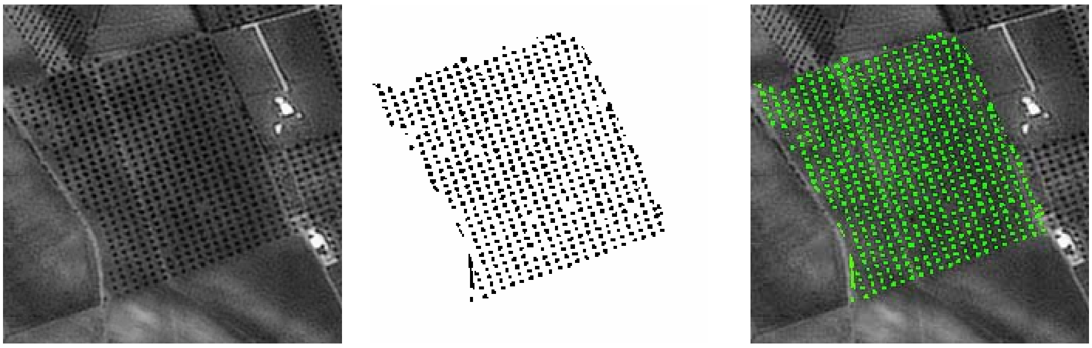


(a) (b)



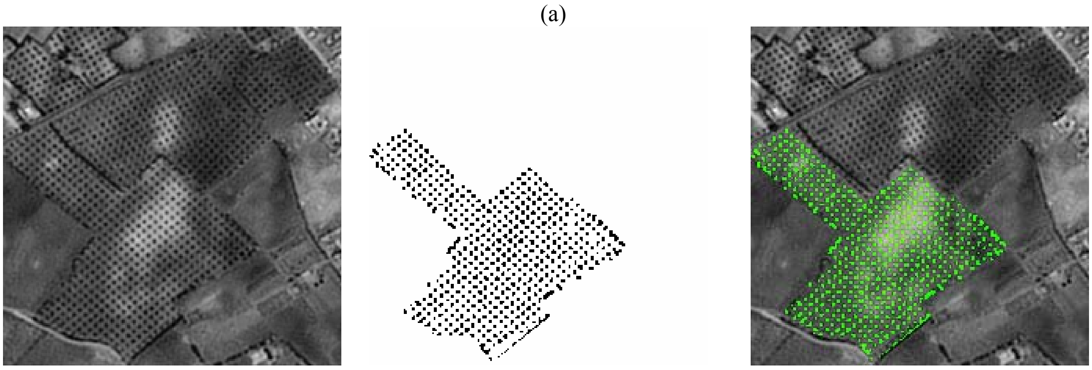
(c)

Figure 9 : Anisotropic diffusion. a. Original image. b. Diffused image. . Central profile of the original image and the diffused one



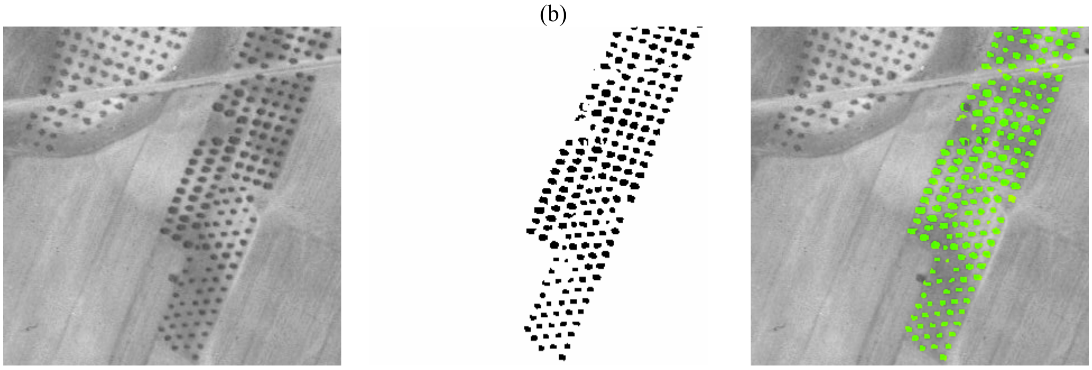
1. Original image. 2. Segmented image. 3. Extracted trees in the original image.

(a)



1. Original noisy image. 2. Segmented image. 3. Extracted trees in the original image.

(b)



1. Original image with low contrast. 2. Segmented image. 3. Extracted trees in the original image.

(c)

Figure 10: Segmentation results of the proposed method. a. Image with good contrast. b. Image affected with shading effects. c. Image with poor contrast