6th Intercontinental Geoinformation Days

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Improving the accuracy of classification of multispectral Images using an anisotropic diffusion neural network algorithm (ADNNA) and machine learning SVM algorithm

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Keywords
Unsupervised classification
ADNN
Multi-Level classification
Multispectral Images
Remote Sensing

Abstract

To improve image classification accuracy, one common practice is to add specific information like image texture, DEM and different indices to satellite image datasets. Here, an attempt has been made to include outputs of Anisotropic Diffusion Neural Network algorithm (ADNNA) to satellite image datasets during classification stages. The unsupervised multi-level neural network (or anisotropic diffusion neural network) modifies the pixel values of the input image by consecutive weighted averaging with neighboring pixels. It performs simultaneous modification of all input multi-spectral image at five level of scale/resolution. The algorithm can process both spectral information of the image and textural details resulting from wavelet transformation simultaneously in a multi-scale representation. To perform this task Landsat 8 Surface reflectance images pertaining to Miandoab region have classified with and without adding outputs of ADNNA (five levels) by support vector machine (SVM) algorithm. Different dataset was created. First dataset was a composite of bands of original images only, second dataset was a composite of different outputs of anisotropic diffusion neural network algorithm only and third dataset contains band of original image and each output of anisotropic diffusion neural network algorithm and the last had bands of original image together with all outputs of anisotropic diffusion neural network algorithm. SVM classification algorithm was used to classify all datasets separately with the same training site input. Classification accuracy was performing through Kappa coefficient of agreement. Results show that the highest kappa coefficient of agreement in classifying the Landsat 8 image is with level 2 of the ADNNA pluse original image bands with approximately 86% compare to other datasets (original images, all 5 level ADNNA outputs, other levels pluse original images). It is concluded that ADNNA outputs can improve classification results effectively.

1. Introduction

Image classification is one of the most important methods to Interpretation of satellite images and change detection of land use (Ehsani and Shakeryari, 2018). researchers have tried to develop methods and advanced classification techniques to improve the accuracy of classification, these including artificial neural networks, fuzzy logic and intelligent systems (Lu and Weng, 2007). The main advantage of artificial neural networks compared to other methods is that it requires less training data for accurate analysis (Bui, et al. 2012). A better classification result is obtained using the edge preservation filter based on the anisotropic diffusion equation before classification, compared to other methods such as the Gaussian filter or the original images without smoothing with low-pass linear filters (Yuan and He, 2008). This algorithm performs multilevel segmentation of an image at many scales using a multiresolution texture representation. Each level uses anisotropic diffusion to segment a multispectral image at successively lower resolutions. Texture and statistical similarities between and within levels guides the diffusion process. The restriction of coarse-to-fine segmentation is removed, and one operates at all levels simultaneously. In this manner the labeling process can choose the scale or scales at which useful segments exist (Fernandesl and Jernigan, 1992). Since the anisotropic neural network algorithm does not perform classification, no training data is required for this algorithm and it also does not produce any thematic map (Perona and Malik, 1990). This algorithm has a more

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Cite this study

Asl, B. T. Zeaieanfirouzabadi, P., & Sabour, S. M. T. (2023). Improving the accuracy of classification of multispectral Images using an anisotropic diffusion neural network algorithm (ADNNA) and machine learning SVM algorithm. Intercontinental Geoinformation Days (IGD), 6, 57-60, Baku, Azerbaijan

acceptable result in classifying satellite images with high resolution than fuzzy clustering algorithms (Fernandesl and Jernigan, 1992).

The main goal of this work is to investigate the effect of anisotropic diffusion neural network algorithm on classification accuracy. To do this, different dataset was created. First dataset was a composite of bands of original images only, second dataset was a composite of different outputs of anisotropic diffusion neural network algorithm only and third dataset contains band of original image and each output of anisotropic diffusion neural network algorithm and the last has bands of original image together with all outputs of anisotropic diffusion neural network algorithm. SVM classification algorithm was used to classify all datasets separately with the same training site input. Classification accuracy was performing through Kappa coefficient of agreement.

2. Research background

The anisotropic diffusion algorithm was first introduced by Prona and Malik (1990), which is an adaptive smoothing method. This method is attractive due to its preservation of edge localization and the ability to control feature scale. The principal of a diffusion-based smoothing method is to allow diffusion where the local gradient magnitude is low, and prevent diffusion at the intensity edges, where the gradient magnitude is relatively high. Therefore, anisotropic diffusion allows intra-region smoothing without inter-region smoothing (Perona and Malik, 1990).

In 2003 Daryaei (2003) used the anisotropic diffusion algorithm and multi-scale wavelet transform for change detection. this study was to reveal urban/agriculture changes using multi-scale analysis by using multi-resolution/multi-temporal image data in Esfahan city in Iran.

In 2007, Noberga et al. (2007) compared the classification accuracy of 3 different image types, an original LiDAR image, an image filtered with a low-pass kernel filter, and an image filtered with an anisotropic diffusion filter, both Anisotropic diffusion filter and filter with low-pass kernel are used to remove noise from images. They found that anisotropic diffusion method with the best result among others.

3. Anisotropic diffusion neural network framework

Anisotropic Diffusion Neural Network is a five-level network where the lowest l having one node per pixel in the full resolution image, and successive levels are connected to each other in the manner of a quad tree. Each node at the lowest level is connected to the output, the highest frequency of the texture map, at the same location, and the nodes of successive levels are connected to the lower frequencies of the texture maps (Fernandesl and Jernigan, 1992).

Perona and Malik pursued 3 basic goals to present the 5-level neural network of the space scale of the anisotropic diffusion equation:

1. No artificial details should be created from smaller scales to larger scales.
2. At each level, the boundaries of each region should be preserved and correspond to meaningful boundaries in the same image resolution.
3. Anisotropic diffusion allows intra-regional smoothing to occur without inter-regional smoothing [6].

The general formula of anisotropic diffusion neural network is given in equation (Perona and Malik, 1990 (1):

$$I_t = div(c(x.y.t)\nabla I) = c(x.y.t)\Delta I + \nabla c \cdot \nabla I \qquad (1)$$

In the above equation, the diffusion coefficient is assumed to be constant and independent of the location. Perona and Malik believed that by modifying the anisotropic diffusion formula they could achieve the goals stated in the previous section, they explained how a suitable choice of c(x,y,t) can satisfy the criteria 2 and 3 listed in the section He estimated the previous one.

Div is the divergence operator, Δ and ∇ represent the gradient and Laplacian operators, respectively, according to the distance variables. In the relation of I_t = cΔI, if c (x,y,t) is constant, the isotropic heat diffusion equation is obtained. Suppose we know the locations of the boundaries of the region in the time scale and we want to perform smoothing throughout the ranges instead of smoothing at the edge and borders; This result can be reached by placing the diffusion coefficient c=1 inside each region and c=0 at the borders (Perona and Malik, 1990).

According to Equation (2) each network level is an implementation of anisotropic diffusion equation discretized using 4-neighbour connections on a square lattice as suggested by Perona and Malik (1990).

$$I_{i.j}^{t+1} = I_{i.j}^{t} + \lambda[c_N \cdot \nabla_N I + c_S \cdot \nabla_S I + c_E \cdot \nabla_E I + C_W \cdot \nabla_w I]_{i.j}^{I} \qquad (2)$$

where (4) CN, CS, CE and CW are the direction coefficients in the north, south, east and west direction respectively at time t, and λ is an update rate between [0,1.4]. Prona and Malik use conductivity coefficients that are proportional to the local illumination gradient in the direction shown (Fernandesl and Jernigan, 1992).

Other conductivity coefficients have been proposed, but none of them deal with multispectral images and all of them only depend on gradient information from the same scale (Fernandesl and Jernigan, 1992).

The followings are the advantages of this method:

1- Unlike other low-pass linear filters, the image smoothed using the anisotropic diffusion neural network will be displayed on several scale levels, in contrast to the common simultaneous filtering methods, which are only performed on one scale level (Yuan and He, 2008).
2- This algorithm processes all input spectral channels at the same time, but other filters process each spectral channel independently Richmond, (2008).
3- Anisotropic Diffusion Neural Network Algorithm simultaneously uses both local spectral and texture information to determine the amount of accumulation in a certain level. Spectral information is extracted from the input multispectral image and texture information is extracted from texture-context maps. Most filters are

invariant to spectral or texture information Richmond, (2008).

4. Materials and Methods

In this research, level 2 Landsat 8 satellite images acquired on March 11, 2022 have been used. This image is corrected for atmospheric and radiometric distortions (U.S. Geological Survey).

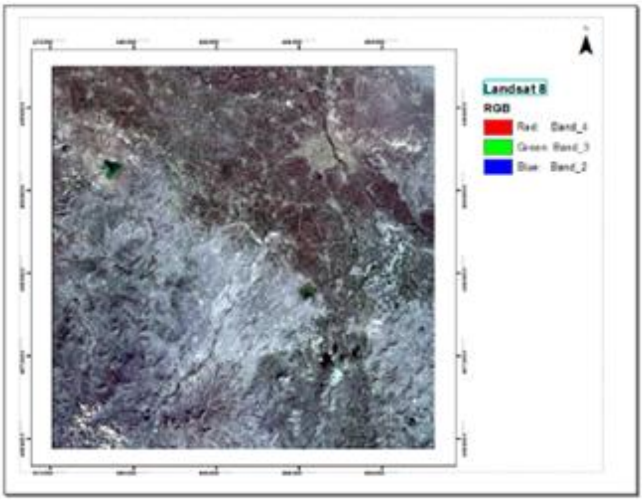

Figure 1. Landsat 8 false color composite (U.S. Geological Survey)

4.1. Study area

Satellite image is pcovering Miandoab region of West Azerbaijan province, Iran which is located at a distance of 164 km far from Urmia and in the south of the province (Figure 2). The approximate area of this region is 2,694 Km2 and it is located at the longitude of 46 degrees and 6 minutes east of the Greenwich Meridian and within 36 degrees and 58 minutes north of the equator in the middle of the plains leading to Lake Urmia with a height of 1,314 meters above sea level. This area has been chosen due to the presence of different land use land cover including vegetation, barren lands and pastures (soil), as well as numerous waterbodies.

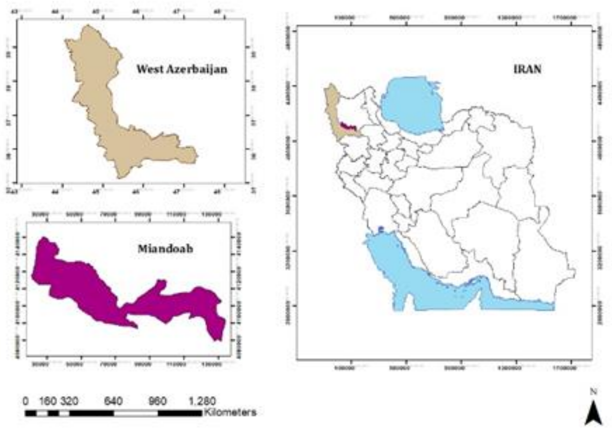

Figure 2. The geographical location of Miandoab region in West Azarbaijan province of Iran

4.2. Methodology

In this study, OLI data was used for classification. A multi-level segmentation algorithm, which is an anisotropic diffusion neural network implementation, was evaluated to generate multi-spectral/multi-scale images using spectral and texture information (wavelet transform method). Since the neural network algorithm does not perform classification and is like a filter, the SVM algorithm was used on all output levels of the neural network for classification. In this study, to evaluate and compare the multi-level network design, the original image was also classified with SVM. Finally, the accuracy of the classification, which is measured by the Kappa coefficient of agreement, was extracted from the independent data set and evaluated for validation. As it can be seen, the output of the classification network algorithm does not separate complications. In this study, multi-resolution data was used for unsupervised classification of Miandoab city, West Azarbaijan province. Anisotropic diffusion neural network, which is a multilevel segmentation algorithm, was used to generate multispectral images using spectral and texture information. From bands 2, 3, 4, 5 and 6, the Landsat 8 image was extracted as the main multi-spectral image, and from band 7, the texture map was extracted by using wavelet transformation.

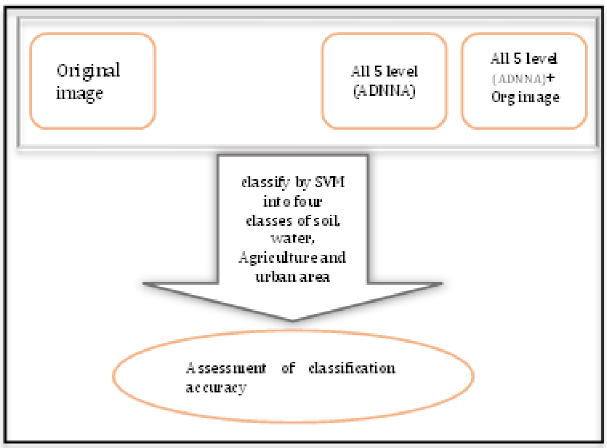

Figure 3. The flowchart of methodology

Finally, the output of the anisotropic propagation neural network was obtained in 5 levels.

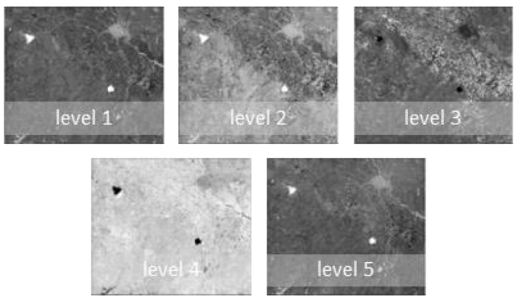

Figure 4. 5-level classification output of anisotropic diffusion neural network algorithm on Landsat 8 image using spectral and texture information

Since the neural network algorithm does not perform classification and has an approach similar to image filters, to compare the output of the algorithm, each level was combined with 2 bands from the original image (band 4 and 7) And all 5 levels combined with the original image and also combined all 5 level together and SVM (Support Vector Machine) algorithm was used to classify the image into four classes of soil, water, Agriculture and urban area.

As a result, the multi-level network algorithm using texture analysis on the Landsat 8 image, the output of level 2 of the network with a classification kappa of 0.86 is more accurate than the rest of the levels (Table 1). If the primary image has 512x512 pixels, the output of the first level of the network is the size of the primary image, the second level is 256x256, and the subsequent levels are smaller in the same way and are multiplied by the power of 2 (here the first level is 2048x2048). According to the Figure 3, the first level of the images has a lot of noise (spots) and the details were lost in the third scale and later, as a result, the most suitable level for classifying the output image is the second level.

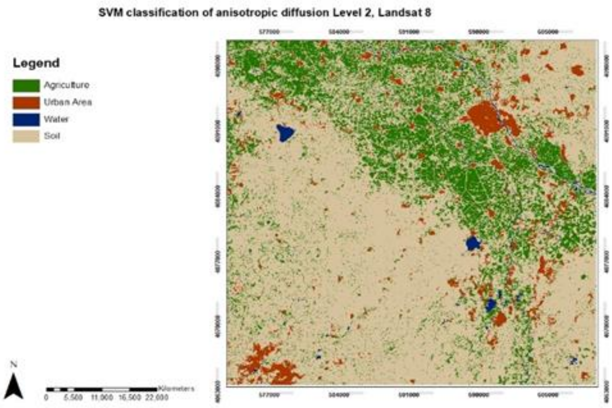

Figure 5. SVM Classification of anisotropic diffusion Level 2 on Landsat 8 image (the best accuracy)

Table 1. Classification kappa

	Level 1+ ORG Image	Level 2+ ORG Image	Level 3+ ORG Image	Level 4+ ORG Image
Kappa	0.84	0.86	0.8	0.76
	Level 5+ ORG Image	All 5 Level+ ORG Image	All 5 Level	Org Image
Kappa	0.63	0.69	0.73	0.67

5. Conclusion

Classification of remote sensing images for interpretation and preparation of thematic maps is one of the most important issues of remote sensing science. Due to the importance of classification in extracting information from multispectral satellite images in remote sensing, this research tried to use the anisotropic diffusion neural network algorithm to classify the basic pixels of multispectral images such as Landsat 8. Increase accuracy Anisotropic Diffusion Neural Network algorithm is described as a multi-level scheme where each level uses the anisotropic diffusion equation to classify a multi-spectral image in successively lower spatial resolution. Texture and statistical similarities between and within each level guide the diffusion process. Since the anisotropic neural network algorithm does not perform classification, no training set is required for this algorithm and it also does not produce any topic map. In this study, we classified the result of the network algorithm with the use of texture information by support vector machine classification and compared each level, all level together, stacked all levels and original image and also original image singly. The level of two network algorithms in classification of support vector machine in Landsat 8 image with Kappa of 0.86 is more accurate than the SVM classification of original image with kappa of 0.67and also original image + All levels with kappa of 0.69. The poor result of clarification of all 5 level and all 5 level + original image was not unexpected due to a lot of noise (spots) in level 1 and the details were lost in the third scale and later.

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