CIE LAB Color Space and K-means Clustering Algorithm for Segmenting Remote Sensing Images

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Abstract:

Remote sensing images contain several types of geological phenomena such as mountains, valleys, rivers, and faults, which require a considerable effort to accurately identify them from digital satellite imagery and use them in topographic mapping. There exists big importance of the automatic segmentation methods of the remotely sensed color images. Segmenting stage is considered as an initial stage in processing and analysis, topographic and land use mapping effectively and accurately, and any mistake at this stage has significant impacts on the rest of the subsequent stages of image processing such as extraction, classification and interpretation.

Keywords: CIELAB Color Space, Segmentation, Clustering, Remote Sensing.

فضاء الالوان CIELAB وخوارزمية العناقيد K-means لتقطيع صور الاستشعار عن بعد

الملخص:

تحتوي صور الاستشعار عن بعد على عدة أنواع من الظواهر الجيولوجية والاغطية الارضية مثل الجبال والوديان والأنهار والتي تتطلب بذل جهد كبير لتحديدها بدقة من صور الأقمار الصناعية الرقمية واستخدامها في رسم الخرائط الطبوغرافية وخرائط استخدامات الارض. ولهذا توجد أهمية كبيرة لطرق التجزئة والتقسيم التلقائية لهذه الصور الملونة. وتعتبر مرحلة التقسيم بمثابة مرحلة أولية في المعالجة والتحليل، ورسم الخرائط بفعالية ودقة، وأي خطأ في هذه المرحلة له انعكاسات مهمة على بقية المراحل التالية من معالجة الصور مثل الاستخراج والتصنيف والتفسير.

الكلمات المفتاحية: فضاء الالوان (L* a* b*)، التجزئة، التجميع، الاستشعار عن بعد.

1. Introduction

Remote sensing imagery faced a paradigm shift in the decade after the year 1999 due to the different progress in multispectral and spatial resolution. This led to research on new classification algorithms for high and very high resolution remote sensing images, because traditional pixel based analysis was proved to be insufficient due to its incapability to handle the internal variability of complex scenes. In computer vision, image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels). The goal of segmentation is to simplify and change the representation of an image into something that is more meaningful and easier to analyze [1][2]. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics. The process of image segmentation is one of the important stages in digital image processing. Any error at this stage will have a significant impact on the rest of the visual processing stages, such as feature extraction, classification and interpretation. This means that the methods of image segmentation are subject to the hypothesis that the output of the process of segmenting must be different areas and contains the inner part of each region on points of homogenous intensity. Developments of image segmentation algorithms for remote sensing imageries have been drastically increased after the availability of high resolution imagery. The methods of processing image segmentation are closely related to the unsupervised classification of images, called clustering methods. A number of questions must be answered when designing a segmentation algorithm to illustrate the difference and the similarity between the issues of segmentation and clustering issues [3]. For example: what is the concept of similarity, which is used to assemble visual points to be divided into distinct areas, and the other question of how many areas are available in the image.

There are a large number of image segmentation methods, as these methods vary according to the type of each image and according to the type of application, three main types of these methods are: methods that depend on finding threshold and clustering, Edge Detection based methods, and methods that depend on the composition of regions growing.

The choice of the segmenting method depends on the quality of the image used and on the target application, so that the threshold method was used in this research for two reasons: Firstly, the number of classes is determined in advance in the classification process while the number of classes in the segmentation process remains unknown and not specified at the beginning, and need to use a mechanism to find the number of classes from the data used. Secondly, the Entities used in the classification process represent small images cutting off from the original image while the resulting entities used in the segmentation process represent the light points of the visual component.

The simplest way of image segmentation is when the image is composed of two distinct areas, that is, the picture contains a dark area with a light background, as in the case of an image that contains text written in black on a white paper, or vice versa. For example, the written text can be isolated from bright background points by creating a threshold for the image pixel. Image pixels that have an intensity value greater than the threshold (t) return to the dark zone and other pixels return to the bright background. The important question is how to find the value of the threshold. The most common way to find a threshold is to create a histogram of the image pixel values. Peak and valley values of the histogram were picked up. Then the threshold values based on them were chosen. These values represent the upper limit of the change in grayscale values. There are segmentation methods that depend on the process of processing the whole image (Global methods) and there are other methods in which the work depends on the segmenting of the image into smaller parts and the treatment of each part on its own (Local methods) [4].

In the field of space visualization, multispectral image is used, in which case a spectral band can be configured for each spectral band, such that, each of the image pixels used represents a vector with one value, and for one band. A histogram can be configured for all multi-spectral images (each spectral band is a feature used in the segmentation process), such that each image pixel used represents a vector with a number of values equal to the number of spectral bands.

The number of features needed in the process of segmenting depends on the complexity of the image and the details or information it contains. The features used may be outputs of digital filters or certain digital processing processes. For example, texture image, or it may be a function of calculating the value and direction of the slope [5], or the brightness at each point is analyzed to the three main colors (red, green, blue) in a color image, and then each point in the image will represent a three-dimensional vector in the multidimensional space. The clustering process is the aggregation of points in the multichannel image space to form clusters that express of the image information [6].

The image size used in industrial applications at the very least is (256 * 256 pixels). Therefore, the number of pixels involved in the segmenting process will be large and thus the processing time will be relatively large as well. To minimize the processing time, the image size is minimized in a particular way. For example, every four rows account only a fourth row of them and same as for the columns, and the rest of the pixels are placed in the cluster, which is closer to the exact pixel.

The goal of this research is to study the use of the k-means clustering algorithm for the purpose of segmentation and using colored space images in remote sensing applications to obtain accurate information in topographic mapping and land use maps.

The present study included three basic topics after the introduction. In the second part, the algorithm of cluster formation will be clarified and defined. In the third section, the color approximation algorithm will be discussed. The fourth topic will explain the steps and methodology of the work to conclude the study with the results and conclusions.

2. K-means clustering algorithm

The k-means clustering algorithm is one of the most widely used as a clustering algorithm and is based on the concept of clusters that have minimal inter-class dispersion. For example, in this algorithm, the number of classes is determined at the beginning, let's be (K) for example. The algorithm attempts to classify the image data into (k) of clusters. This algorithm requires determining the value of the center of each class from the beginning. The initial values of the classes' centers are determined either by random values or by bringing values from other sources such as field survey, which in turn are more accurate. The algorithm calculates Euclidean distance between each pixel in the feature space and the center of each class. The pixel is represented as a vector in the multidimensional space, and let's be x, and is the center of each class μk. The pixel is placed in the feature space within the class how is closest to the specific pixel, as in Euclidean Distance equation (1)[7]:

$$E.\ D. = \left\| x_{ij} - \mu_k \right\|^2 \ldots\ldots\ldots\ldots(1)$$

The algorithm calculates the Euclidean distance for each image pixel with the class centers, so that the image at the end is divided into a group of different classes. After the classes are configured, the algorithm calculates the class centers again. In order to test the new values, the difference between all the new values of the class centers and all the previous values of the classes center is calculated so that if the difference is less or equal to the value of the specified threshold, the algorithm stops and ends. If the difference is not less or equal, the class centers are re-configured again until the stopped condition is applied. It is possible to develop a k-means algorithm by calculating the number of pixels in each class to merge classes that contain a small number of pixels whose positions are close; or each class is separated into two classes if it contains a large number of pixels [7]. This technique is closely related to the unsupervised image classification.

3. Color approximation algorithm (CIELAB Color Space)

Different color spaces were used to distinguish colors in digital images, different image segmentation methods for color image analysis, and the effect of color space selection on the quality of results provided by segmentation methods. A color space is a geometric representation of colors in a space and allows the determination of colors by three components that essentially determine their numerical values for a particular color [8]. In this research the CIELAB Color Space algorithm has been adopted as a universal standard for describing and approximating colors, with a space called L*a*b*. The color space (L * a * b *) consists of three layers: Luminosity layer L *, and chromaticity layer a *, which determines where the color is located on the red-green axis in the RGB color cube; and chromaticity layer b * which determines where the color is located on the axis blue-yellow in the color cube. All color information falls into (layer a *, layer b *). The difference between colors can be measured using the Euclidean distance [5]. The color space (L*a*b*) that the algorithm represents is a homogeneous space. The Euclidean distance between any two points in the color space (L*a*b*) is related to the perceptual perception of the human mind to recognize the difference between any two colors. This color space property has made it an important space and has great use of color analysis techniques as well as its widespread use in digital image processing applications. This color space was used in color clustering applications with great success. The difference between the colors in the space (L * a * b *) was also used to express the similarity of the colors and therefore the use of this principle in the formation of color clusters [9].

The mathematical formula that expresses of the difference in color is used in the calculations of color similarities and in the composition of the function that determines each color to any cluster can go [6]. To convert from color space (RGB) to color space (L*a*b*) the following mathematical expressions are used (Eq. 2,3, and 4):

X=0.412453R+0.357580G+0.180423B (2)
Y=0.212G71R+0.715160G+0.0721G9B(3)
Z=0.019334R+0.119193G+0.950227B (4)

Depending on the previous mathematical expressions, color conversion (L*a*b*) is defined as follows (Eq. 5,6,7 and 8):

$L^*=ll6f(Y/Y_n)-16$ (5)
$a^*=500[f(X/X_n)-f(Y/KJI)$ (6)
$b^*=200[f(Y/Y_n)-f(Z/Z_n)]$ (7)

Whereas

$$f(q)=\begin{cases} q^{1/3} & \text{if } q>0.008856 \\ 7.787q+16/116 & \text{otherwise} \end{cases} \quad (8)$$

Whereas

q: belong to X / X_n, Y / Y_n, Z / Z_n

The values (X_n, Y_n, Z_n) represent reference white color as defined by the CIE standard, where RGB values are as follows (Eq. 9):

R=G=B=100 (9)

4. Methodology

The multi-spectral image used in the research covers part of Nineveh province near the city of Mosul in northern Iraq. This was captured by the Thematic Mapper sensor (TM sensor) on the satellite called (LANDSAT5). The image dimensions used have 512 rows and 512 columns. The spectral bands used for the research are visible spectrum bands which are (1,2 and 3) and infrared spectrum packets which are (4,5 and 7). Matlab program was used for image processing. The proposed work algorithm for the research was carried out in stages as in the Fig. 1.

Fig. 2 represents the original visual image, which is displayed in a false color composite (FCC) form, and is composed from the integration of the three bands of Landsat TM5 (2, 4 and 5) in an RGB color space respectively.

The first step of the action involves converting the colored image in Fig. 2 from the RGB color space to the (L* a* b*) color space by using the equations 5,6 and 7 (statement in the third paragraph of this paper).

It can be seen from Fig 2, that there are three main colors. The three colors are black, green and dark orange. The color space (L* a* b*) can be used to quantify the visual differences between colors.

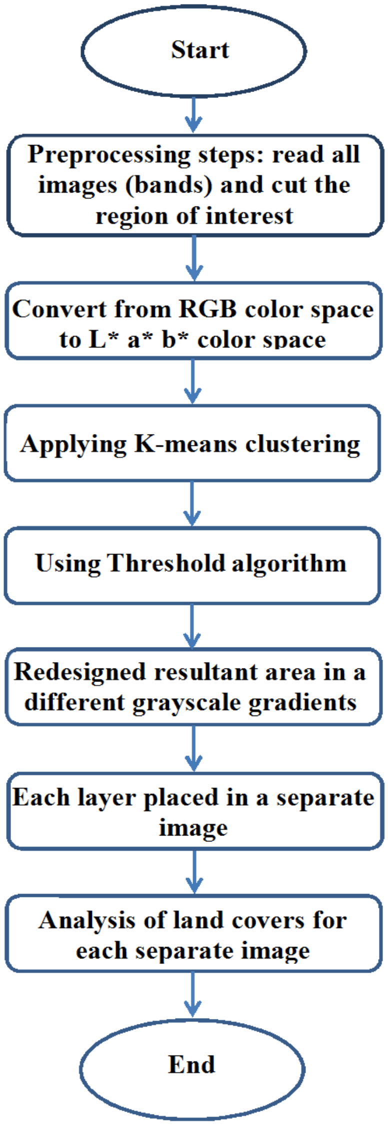

Fig. 1: Outline of the proposed work algorithm

Fig. 2: A FCC satellite imagery representing a section of the Tigris River near Mosul city.

The second step involves color classification by applying the K-means clustering algorithm to the information in layers (a* and b*).

After performing the second step, a segmented image will be produced; and it can be seen three distinct regions representing three types of land cover types separated from each other and can be separated using the human eye. Each distinct area has been redesigned in a different color representing one of the grayscale gradients as shown in Fig. 3.

Fig. 3: Resultant image after applying the K-means clustering algorithm.

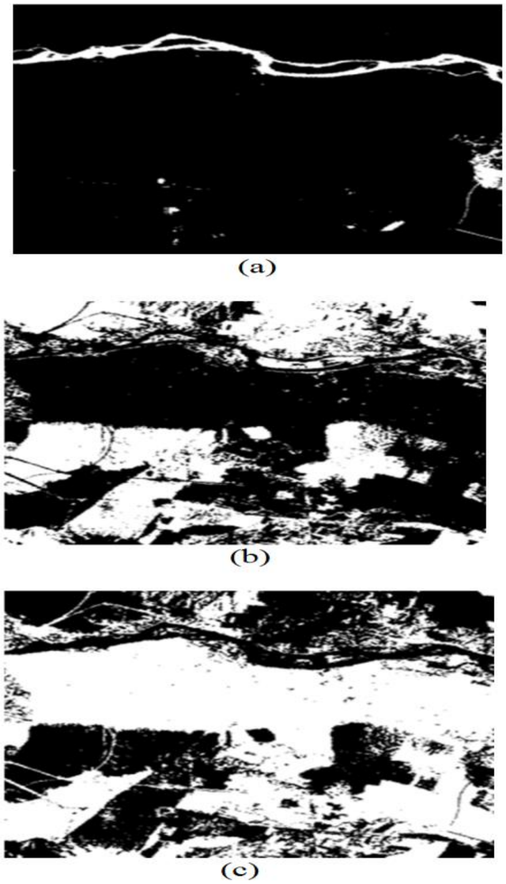

Fig. 4: Classification results according to the proposed algorithm. (a) Tigris River, (b) Agricultural land, (c) Barren land.

A threshold algorithm was used after obtaining the segmented image to separate the three distinct regions in Fig. 3 into three layers. Each layer was then placed in a separate image. The use of threshold algorithm results in three different images, as in Fig. 4, each image with one cover type where the white color indicates where the earth cover is located. Fig. 4a, represents cover 1 which is the track of the Tigris River, Fig. 4b represents cover 2, which is agricultural land, and Fig. 4c represents cover 3 which is barren land. The use of the threshold method is very easy in the subsequent operations of the classification process, and it is also possible to make any accurate or quick surface measurements on any of these items because the binary system was used, that was only two values for all satellite data.

5. **Conclusions**

Through this research, a Color Approximation algorithm (CIELAB Color Space) in conjunction with a K-means clustering algorithm is used for remote sensing image segmentation. Mosul city satellite images are used as a prototype to verify the action steps and algorithms.

Experimental results using Matlab program and Landsat Satellite images show the efficiency of color space (L* a* b*) in the calculation of the quantitative assessment of the differences between colors; and thus getting on the accurate segmentation of remotely sensed images. In more detail the following conclusions were reached:

1. Color space efficiency (CIELAB) in the calculation of the quantitative assessment of color differences.
2. All color information is located in layers (a*, b*) in the color space (L* a* b*). Therefore, the cluster configuration algorithm is applied only using these two layers.
3. The great importance of the automated color-segmentation algorithm that accomplishes work more accurately than the algorithms that require human intervention.
4. The selection of segmentation approach in remote sensing applications depends on what quality of segmentation and what scale of information is required.

For future work, the development of automated change detection and updating map procedures can be drawn-out to other types of land cover and object classes.

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