Color Image Segmentation Using
spectral clustering

by

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Master of Electrical and Computer Engineering

This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science/ Arts / Doctor of Philosophy.

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Edrees Ramadan Marsel

[Signature]

DEDICATION

To my father

Every success in my life because of your interest and care for me to reach the highest level. I ask God to surround you from her mercy and enter you to Paradise from the widest door.

May Allah have mercy on you and forgive you.

to my mother

The word of thankfulness is few on your right after all your sufferings, and I wish God to grant me a power that I can make you happy.

To my wife

I thank you for standing with me for so long and for your patience.

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ABSTRACT

Color Image segmentation using Spectral clustering

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The spectral clustering has newly arise and has become one of the most common clustering algorithms, and the learning algorithm is considered uncensored. It is easy to apply and can be efficiently solved using standard linear algebra software. Often outweigh the normal clustering algorithms, for example, the K-mean algorithm.

segmentation is a digital image split that is entered into several regions and re-image representation to useful elements and more clearly for analysis. The process of color-based segmentation is greatly influenced by the color of the space. the L*a*b color space is the best representative of the contents of the color image.

In this dissertation, an algorithm was developed to segment the color image using L*a*b color space and then the spectral algorithm was applied to the data to classify it. Description of shape nor representation is an important issue both in the identification and classification of objects.

The resulting color segmentation scheme has been applied to some of the images and empiricism data indicate a well-advanced segmentation algorithm if the coefficients are better configured.

Key words: segmentation clustering, spectral, L*a*b, image, Affinity.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF PICTURES

1. Introduction

In this chapter, we start by defining the basics of the image. image processing, image segmentation, and applications that use image segmentation and definition of image segmentation algorithms. As well as a brief introduction to clustering and classification of clustering.

1.1 Image

The digital image is a digital representation (binary values zero and one) of a material object that can be seen with the eye. The image is inserted into the computer by the digital camera or scanner for storage or modification. The image is a two-dimensional matrix consist of height and width. After converting the real image to the computer, it has a process called Sampling, which, is taking a small sampling of the image of truth.

Each sample square shape is named a pixel and is considered the smallest part of the digital image. Each pixel has only one color depending kind of the image (gray, or colored or other).

1.1.1 Binary Image

It Is an image consisting of a matrix with (m * n) a dimension. And contains only two colors (black color and white color). Where the value of each pixel represents the color black or white. the black color takes the value of 0 and the color of white takes the value of 1. It does not contain any other color in this type of image. These images can be very effective in terms of storage. Images that can be binary representation include text, fingerprints or architectural plans.

1.1.2 Grayscale image

A black-and-white image with grayscale gradients whose intensity or intensity is represented by numbers from 0 to 255 where 0 is the bright white color and 255 is the color of the pixel is dark black and when this image is represented on the computer Represented by equal columns and equal rows of pixels Each pixel has 8 bytes that specify the density or intensity of 0 to 255. Such as medicine images (X-rays), printed images of works.(Gonzalez & Woods, 2002)

1.1.3 Color image

An image is represented by a three-dimensional matrix, MxNx3, whose elements are double or unit8. Each pixel in the image results in combining three compounds to give the right color. The red color consists of a binary matrix (extracted from the three-dimensional matrix), with the color value between the range [0,1] Black 0 and red 1, and between them are red, blue and green. By combining three RGB colors from three three-dimensional arrays we get real colors. (Tarun Kumar, 2010)

1.2 Image processing

Image processing is a way to apply some operations to an image, to get information inside the image or to improve. It is a type of signal processing that inputs the image and the output may be the image or properties/features associated with that image.

Nowadays, interest in image processing has increased and many techniques and algorithms have been developed. It is the fastest growing technology. It is part of a more important field of research within the engineering and computer sciences as well.

There are two methods used to handle images, namely analog and digital for image processing. Analog image processing is used for print copies of printouts and images. Analysts use a different basis of interpretation when using these visual methods. Digital image processing methods help manipulate digital images using computers.

Before starting in image processing process the image is converted into digital format. Digitization includes sample sampling and sample value estimation. After the image is converted into bit information, start processing is performed. This processing technology for image enhancement, image reconstruction, image compression or image segmentation.

1.2.1 Image Enhancement

There are many algorithms to improve images depending on purpose. One of important thing that is purified the image from noise, which is caused by a number of reasons such as the camera's sensitivity or during the transfer and storage of the image. The image is also improved by reducing or blurring the image. Prior to image processing, it is important to correct and redistribute colors and lighting. This is done in a number of ways as needed, such as evenly dividing colors, increasing or decreasing contrast and brightness.

1.2.2 Image compression

image compression is associated with algorithms that reduce the amount of data needed to represent an image in order to decrease its storage size. Image compression is important and necessary since it will be difficult to share images through the Internet and will occupy images large areas of the hard drive. Reducing the files size lets many images to be stored in a specified amount of disk or memory space. It also reduces the time it takes to send or download images online from web pages.

1.2.3 Image Filtering

Filtering is a method used to adjust and improve the image. By using them, for example, we can highlight some of the characteristics of the image as edges or remove some defects such as blurry or blurry. Simply filtering is done by passing a filter (often smaller than the size of the image) onto the image in a certain way and collecting a hit with the image to calculate a given pixel value. Many filters can be designed according to the desired task.

1.2.4 Image Segmentation

Image segmentation has long been known to be a difficult in image processing problem. And there are different approaches have suggested for achieving best results. In computer vision, partitioning is a way of dividing the image into several meaningful regions for applications such as object tracking and understanding. (Ho & Lee, 2003)The purpose of segmentation is to simplify and modify the image demonstration to something more important and easier to investigate.

Image segmentation is usually used to detect different objects and their edges in images. Image segmentation is the procedure for moving a label to each pixel so that the pixel unit with similar labels share firm visual characteristics. As mentioned earlier, there are several segmentation methods. Figure 1. Classification of segmentation algorithms ،such as edge-based, region-based, cluster-based, and split / merge approaches. A brief description of these approaches is provided in the following sections.(Canny, 1986)

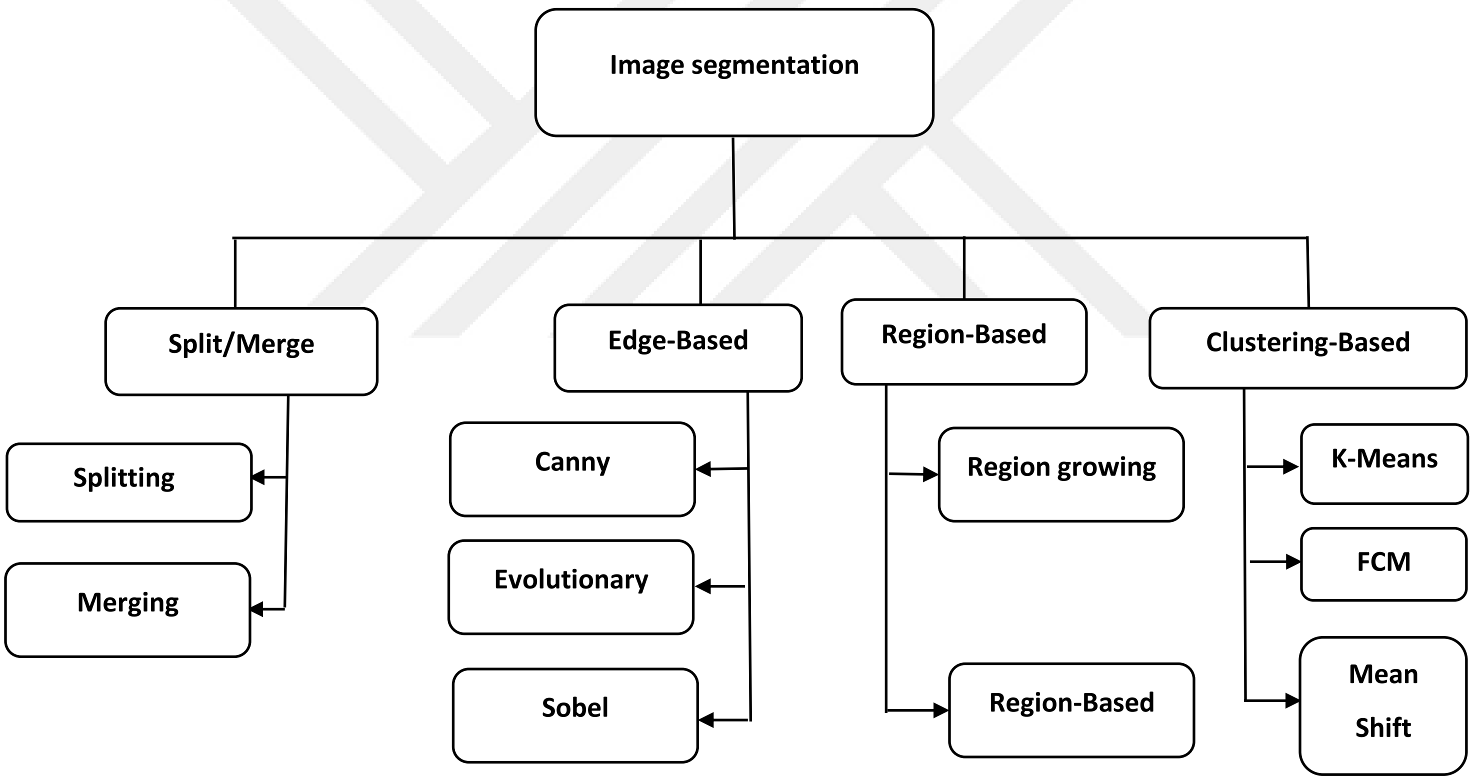


Figure 1: Classification of segmentation

1.2.4.1 Edge-Based Methods

The edge-based image segmentation methods stand on edge detection and are a well-extended field in image processing. Since there is often a sharp change in the intensity of the object boundaries, these boundaries can be considered as edges. However, closed region boundaries to detect the image objects and the detected edges are the boundaries between the objects.

Edge detection techniques have therefore been used as an essential step for other segmentation methods. In this approach, the edges of the image are recognized and then linked to lines that indicate the boundaries of image objects. The edges of the candidates are extracted through the gradient threshold or the Laplacian size. The edges recognized by edge detection algorithms are likely to be intermittent at times. To solve this problem, many evolutionary algorithms have been proposed to detect local thin and well-maintained edges based on optimization of edge configurations (Abood, 2013).

1.2.4.2 Region-Based Methods

In region based methods, the input image is divided into several connected regions by clustering the adjacent pixels to near intensity levels. The objective is to detection of regions that satisfied certain predefined homogeneity criteria. Neighboring regions are further integrated due to their homogeneity or severity of region boundaries. And region based segmentation defined as a technique to set the region directly.

The two main constraints to region-based segmentation are as follows:

$$\bigcup_{\boldsymbol{j=1}}^{\boldsymbol{n}} \boldsymbol{R_j} = \boldsymbol{R}$$

where R_j is connected region and j = 1,2, 3, …………, n. that means union of all regions must be the original image R.

$$R_j \cap R_k = \emptyset \, , for \; \mathrm{j} \; = \; 1,2,3, \dots \dots \dots \dots , \mathrm{n}$$

The second constraint means that every pixel should belong to only one specific region .(Ho & Lee, 2003)

1.2.4.3 Split / Merge Approaches

As mentioned in the name, these segmentations approach involves two separate procedures. The first procedure segmented the image into several of regions and then the second procedure, some inappropriate regions are merged into the correct regions. In methods of split/ merge, an input image is segmented into groups of homogeneous regions in advance. Then, similar neighbor's regions are merged for some homogenization features. In merge phase, every inappropriate region needs to be merged with one of their neighbors. As a result, Region Adjacency Graph is proposed to determine neighboring regions. After each merge procedure is repeated, Region Adjacency Graph must be updated to represent the new regions and its neighbors correctly.(Ho & Lee, 2003)

1.2.4.4 Region Growing Procedure

The growing region approach starts with one a pixel, namely a pixel seed. every one of the four seeds (neighbor) pixels is verified with the growing area (or insert) requirement. If the condition is done, the neighbor pixel is added into the region. The four neighbors are then examined from newly added neighbor pixels to be inserted into the area. and this procedure continues so that pixels are not spatially linked to a growing state. The new procedure then starts in the growing area with a closer pixel of the image that is not already a member of the region. The process continues until each pixel is embedded in the image in one of the growing area. For example, in Figure 2, the growing region of the seeds has started in (A), and all pixels of the brain image can be detected after different numbers of duplicates in (f). (Ramesh, Priya, & Arabi, 2014)

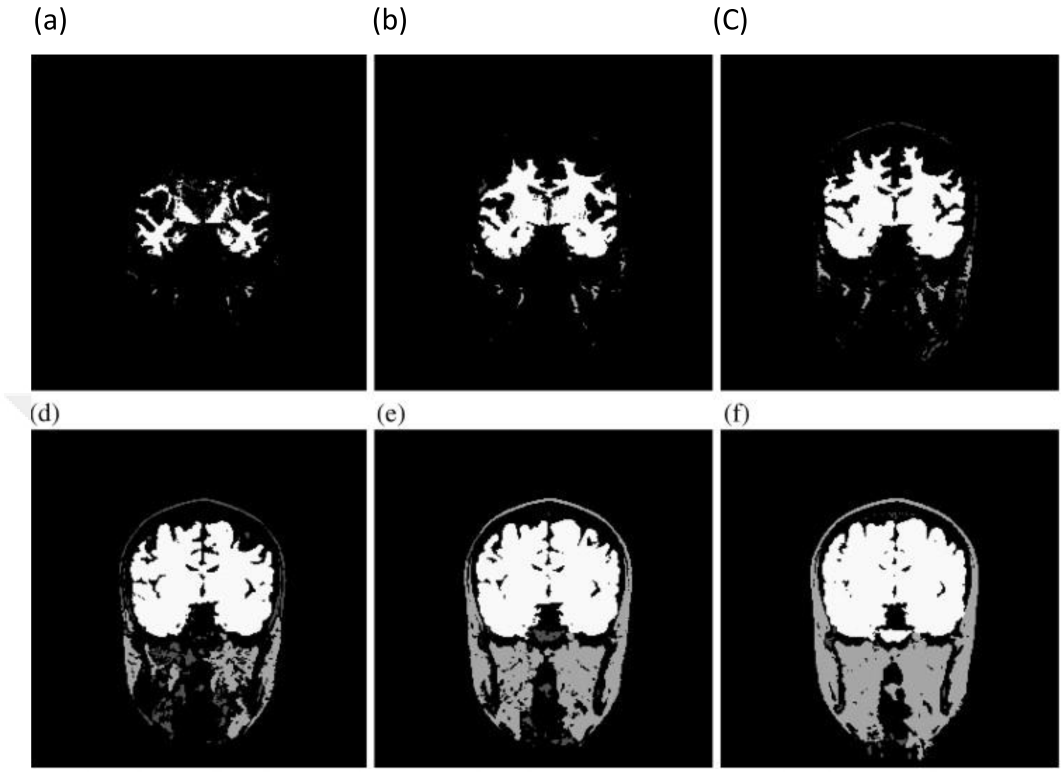


Figure 2. Region Growing for the Brain Image

1.2.4.5 Clustering Based Methods

The term “data mining” appeared in the mid-nineties in the USA which combines statistics and database technology, artificial intelligence and machine learning. There are a lot of tools that are used in data mining, including classification and, Clustering, Association rule learning, Regression and automatic summarization.(Shmueli, Patel, & Bruce, 2007)

Clustering, a process to find and search for specific, meaningful and useful information within a large size of data, and this is done by the process of linking analysis of these data and methods of artificial intelligence to become better efficient in the process of research.(Jackson, 2002)

Clustering is the process of developing data from similar gatherings, which is a branch of data mining. Clustering algorithm divides data sets into several clusters, as the similarities between the points within a certain grouping larger than the similarity between two points within the different two communities. The idea of compiling data simple in nature and very close to the human in his way of thinking where we, whenever we deal with a large amount of data, tend to the vast amount of data to summarize a few of the groups or categories, in order to facilitate the process of analysis.

Does not use only to organize and classify the data, but it uses data compression and build a model arrangement of data clustering algorithms on a large scale. If we can find clusters of data, it is possible to build a model of the problem on the basis of those gatherings.(Geetha & MCA, 2014)

clustering is the process of dividing a specific data set into homogeneous groups based on specific properties so that similar objects are kept in a group while different objects are in different groups. These alone can be considered uncontrolled learning problems. It deals with finding a structure in a set of unnamed data. (Monteiro & Villar, 2014).(Montero & Vilar, 2014)

Clustering is used majorly in the analysis of exploratory data; they have applications automatically in any scientific field dealing with empirical data. There are different techniques for clustering data.

Segmentation by using clustering

In these methods, the entire pixels of an image are sorted in a histogram according to their intensity values. Then, a predefined number of clusters will be defined to split the intensity histogram into several intervals. In this unsupervised region segmentation algorithm, pixels which are located in the same cluster may not be adjacent. Therefore, the number of regions is not the same as in a number of the clusters. There are deafferents kind of clustering-based methods such as k mean method, spectral clustering method and fuzzy c mean method.

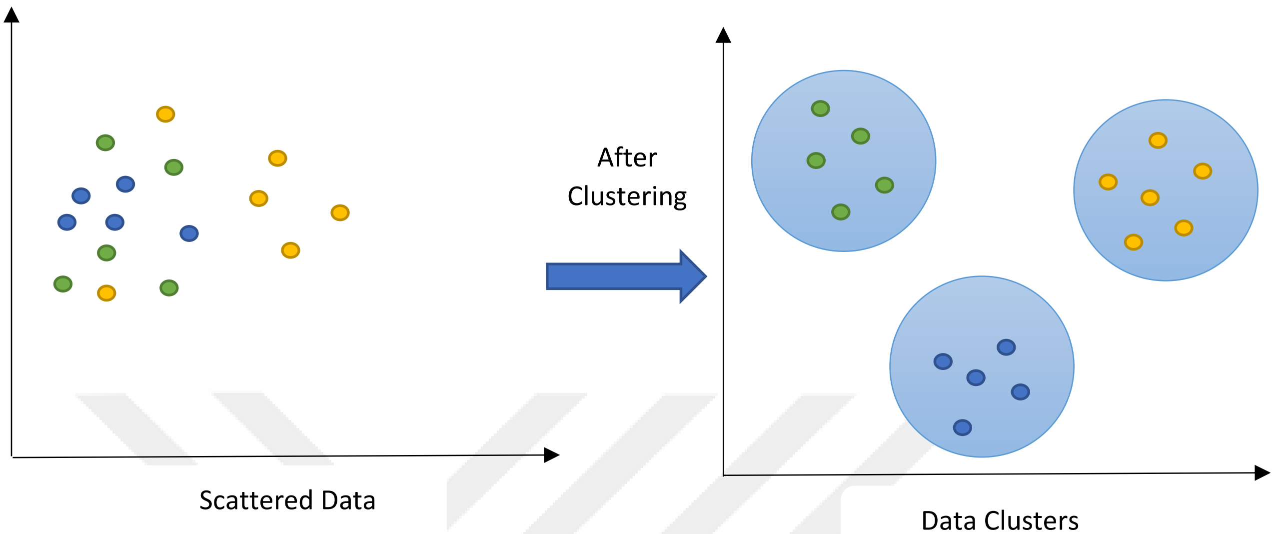


Figure 3. Clustering

Spectral clustering

The spectral cluster can define as an algorithm to place N data sets in the N-dimensional space in several clusters.

Each parameter is determined by its similarity, which means that points in the same group are similar and points in different groups are different from each other.

We start the algorithm by providing data points in the graph similarity format, and then we need to find a division of the graph so that the points within the set are similar and points between different groups differ from each other.

Algorithm

Assume we have a group of n data points $x = \{x_1, x_2, ., ., ., ., x_n\}$ in R^l and want to cluster them into c clusters as following:

1- Compute affinity matrix $A \in R^{n \times n}$ defined using $A = exp\left(\frac{-dist^2(x_i - x_j)}{\sigma^2}\right)$ for $i \neq j$ and $A_{ii} = 0$, where $dist(x_i, x_j)$ is distance between points x_i and x_j. σ Scale parameter and we will discuss more in detail later.

2- Construct degree matrix to be the diagonal matrix which defined using

$$D_{ii= \sum_{i=1}^{n} A_{ij}}$$

3- Compute the normalized Laplacian matrix, which defined using

$$\mathrm{L} = \mathrm{D}^{\frac{-1}{2}} * \mathrm{A} * \mathrm{D}^{\frac{-1}{2}}$$

4- Let e_1 , e_2 ,⋯, e_c be the C eigenvectors conforming to k largest eigenvalues of Laplacian matrix (L) and construct U = [e_1 , e_2 ,⋯, e_c] $\in R^{n \times c}$ via arranging the eigenvectors as columns.

5- Construct matrix Y from U by renormalizing each row of U to norm 1, with

$$\mathrm{T} = \frac{\mathrm{U_{ij}}}{\left(\sum_j \mathrm{U_{ij}^2}\right)^{1/2}}$$

6- Let each row of Y be points in $\mathrm{R^C}$ *and cluster by K=means.*

7- Assign the original point x_i to cluster c if and only if the corresponding row i of the matrix T was allocated to cluster$c$.(Ng, Jordan, & Weiss, 2002)

Advantage and disadvantage of spectral clustering in General

• It is simple algorithm, which can be implemented in an effective form using standard algebra methods. It does not matter the size of the data sets.

• Do not put strong assumptions about the statistics or shape of the clusters, it can solve very general problems as tangled spirals.

• It considers the geometric information for local data.

The algorithm can be a very powerful tool if we apply it carefully. But there are some disadvantages that we must take in consider:

• We have to look at many parameters such as choosing a good similarity graph or a convenient number of combinations. We must choose them carefully to get good results.

• If we want to use these methods with the purpose of classification, we need to re-configure the algorithm every time we have a new point in our data set.

1.2.5 Application of image segmentation

1.2.5.1 Object detection

it can be considered the process of detecting the object from the operations of the task because of detection of objects in the real world, for example, human faces, cars or buildings in pictures or videos. Object detection methods often use extracted features and learning algorithms to recognize instances of an object category. It is generally used in applications such as image recovery, safety, monitoring, supervision, and automated vehicle parking systems. (Gossain & Gill, 2014)

1.2.5.2 Face detection

The human face plays a dominant role in the field of human recognition among the available biometric identifiers such as fingerprint, hand geometry, iris, keystroke, signature and voice due to its high acceptability, universality, collectability and foolproof. each biometric has its strengths and weakness but the choice depends upon the application. (Ajit Danti, 2012)

face detection aims to at locating, aligning and delimiting faces in images containing a single face in frontal position. it is determined facial features only and ignores all other objects, such as like buildings, cars, and bodies.

We can consider face detection as a custom case to detect the object class. Facial detection algorithms were initially focused on detecting frontal human faces, while modern algorithms were trying to solve the most difficult problem of multiple face detection.(Singla, Sharma, & LEI, 2014).

This is the detection of faces that rotate either along the pivot of the face to the observer (in the rotating plane) or rotated along the vertical pivot, left and right (outside the rotating plane), or both. The newer algorithms take into account differences in image or video through factors as facial appearance, fret, and lighting. (Gaur & Sagar, 2014)

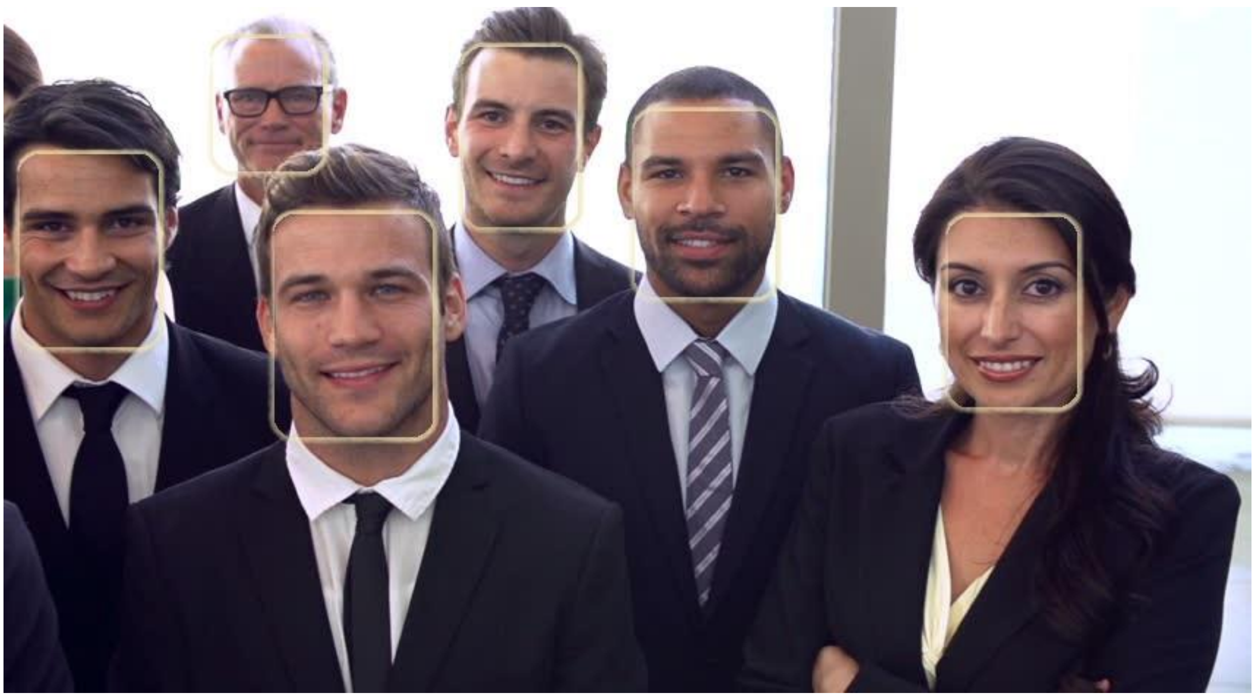


Figure 4. Face detection

1.2.5.3 Face Recognition

Facial recognition is facial recognition technology. It is possible to identify a person through his face and build upon them many applications. It can be possible to call all data relating to the person from the database via a computer program.

The importance of knowing the exact face of face-based applications such as credit card authentication, passport identification, Internet security, criminal databases, etc. With the increasing need for surveillance and security-related applications in access control, law enforcement and information safety due to criminal activities, the face recognition has grown dramatically and widely from pattern recognition and image analysis. The difference between facial detection and recognition is that in detection we want to determine any face in the image, but in recognition, we want to know the face owner.

1.2.5.4 Remote sensing

Remote sensing is simply getting small or wide information signals from an object or phenomenon, through the use of various types real-time sensors that are wireless in nature, or Direct or indirect connection with the target (as aircraft, spacecraft, satellites or ships). we can be considered Practically; Remote Sensing is collecting different data signals using a set of devices to gather information on a particular object or region. parolee monitor using ultrasonic, magnetic detection system (MRI), positron emission tomography (PET), X-ray (X-ray) and space probes are all examples of remote sensing. (Dewangan, 2016)

1.2.5.5 Signature Recognition

Signature Recognition is a data validation tool by signing a sample that is compared with database records. Signatures are of a special nature because they are usually unreadable.

The purpose of recognition of the signature is recognition of the author. The scope of automatic signature verification is divided into two parts, online signature, and offline signature.

The offline technique recognizes the person whether he/she is genuine or forged. The signatures are taken as an image form, which is captured by any camera or a digital scanner.

The parameter is extracted with the help of surf feature extraction. The feature extraction is the key to develop the offline signature recognition system.(Kaur & Kaur)

Signature Recognition - Signature verification and recognition are a valuable application, which is to determine if a signature belongs to a given signer based on the image of the signature and a few sample images of the original signatures of the signer. Handwritten signatures are inaccurate in nature as their angles are not always sharp, the lines are not quite straight, the curves are not necessarily smooth.

Moreover, lines can be drawn in different sizes and direction contrast handwriting which is often assumed to be written on a straight-line baseline. Therefore, the handwritten signature recognition system must take into account all these factors. (Dewangan, 2016)

1.2.5.6 Machine vision

The machine vision system allows the computer primarily to recognize and evaluate images. It is like the voice recognition technology but uses images instead.

The system vision device usually consists of digital cameras, image processing equipment, and software. The front camera picks up images from the environment or from a center object and then sends them to the processing system. Depend on the design or requirement and need of the machine vision system, the images that are captured or processed are stored accordingly.

Automated Vision System is a type of technology that enables a computing device to examine, evaluate and determine static or animated images and guide the robot in the industry.

It is a field in computer vision which is just like a surveillance camera but provides automatic image capture, evaluation, and processing capabilities.(Li & Zhang, 2016)

Chapter 2

In this chapter, we will explain in detail about RGB image color and L*a*b color space and later about the method of conversion from RGB image color to L*a*b color space. In second section, explain about spectral clustering algorithm in detail and was mentioned in the first chapter in brief.

2.1 Color space

we can define as create and visualization color. as human beings, we have determined the color of its characteristic of brightness, hue, and colorfulness. A computer may describe a color using the amount of red, green and blue phosphorus emissions required to match the color. Printing may produce a certain color in terms of reflection and absorption of celestial, purple, yellow and black inks on the printing paper. Thus, the color is usually determined using three coordinates, or parameters. These parameters describe the color position inside the color space used. They do not tell us what color is, it depends on what color space is used.(Ford & Roberts, 1998)

And, we can describe as a collection of codes for each color. Every pixel in an image has a color that is depicted in the color space, and this color space used to pixel labeling. There are different approaches to describe all colors, so there are additionally unique color spaces. We will focus on (RGB and LAB) of color spaces that related with our thesis.

2.1.1 RGB color Space

The concept of RGB (an acronym from Red, Green, and Blue) space is derived to represent color images with their fundamental colors: red, green, and blue. The aim of the RGB color is to stick to the principle of human vision and represent colors as a simple sum of any quantities from 0 to 1 (or from 0 to 255) of the fundamental colors. . (Gonzalez & Woods, 2002) As such it can be represented as an ordinary cube where three of the vertices along the axes represent the primary colors.

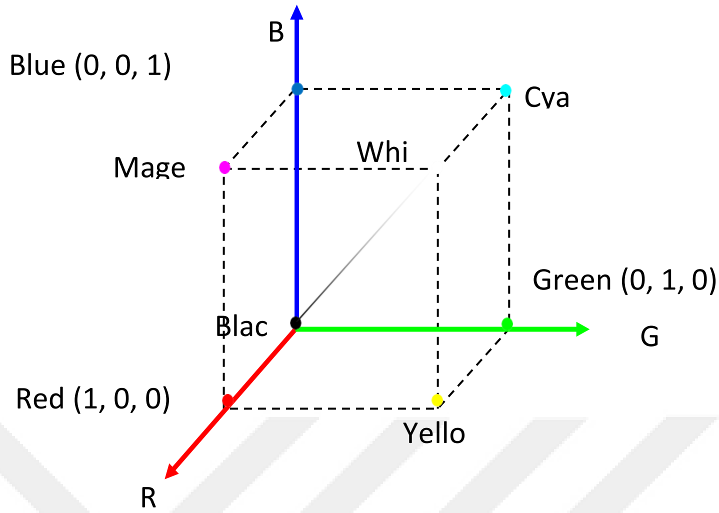


Figure 5. the RGB color space

As it can be seen in Figure 5, any point inside or on the surface of the cube represents a color with the amount of primary color components with corresponding values on the respective axes.

The vertices (0, 0, 0) and (1, 1, 1) are special because they match to white (when the three basic colors mixed up together in full amount) and black (absence of any of the three basic colors). The diagonal of the cube between the vertex (0, 0, and 0) and vertex (1, 1, and 1) represents the gray line (scale). A point on the gray line means its components (R, G, and B) have equal values, i.e. a gray scale image can be represented on the RGB space with all its primary color values equal.

The RGB representation only describes the chromatic values of the primary colors and their additive combinations; however, this is not the only visual effect any color has. There are more meaningful color features that have to be considered, like: how green is a color? Is it bright green or dark green? Two green colors can have identical primary chromatic content but difference in their intensity or luminance. Such features cannot be represented with their RGB values; they require a different color space one of them being the L*a*b color space.(Gonzalez & Woods, 2002)

2.1.2 LAB color space

LAB color is a 3-axes system. It is contained of The L axis is vertical to the ab* axes and identifies the darkness or lightness of the color. The axis value for the L axis ranging from 0 to 100, where 0 is “dark” and 100 is “light”. The other horizontal axes are now represented by a* and b*. These are in right angles on each other, crossing each other in the center, which is neutral (gray, black or white). They are based on the principal that a color cannot be both red and green, or blue and yellow. The (a*) axis is green at one extremity (represented by -a), and red at the other (+a). The b* axis has blue at one end (-b), and yellow (+b) at the other. The Centre of each axis is 0. A value of 0, or very low numbers of both a* and b* will describe a neutral or near neutral. a * represents greenness to redness with values of -128 to +127; and b * represents blueness to yellowness also with values from -128 to +127 .(Timar, Teusdea, Bara, & Purcarea, 2011) as it can be seen in Figure 6:

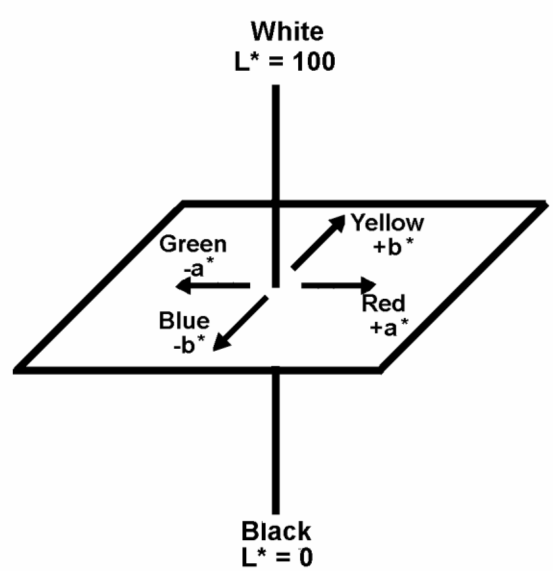


Figure 6. The L*a*b color Space

2.2 Conversion between RGB and Lab color space

Conversion between RGB and Lab color space in studying color perception, it was one of the first specific mathematical defined color spaces was XYZ color space, created by International Commission of Lighting (CIE) In 1931. (Agudo, Pardo, Sánchez, Pérez, & Suero, 2014)

CIE XYZ may be thought of as derived parameters from CIE RGB color space, the red, green, blue colors. CIE LAB color space is based directly on the CIE XYZ color space as an attempt to linearize the perceptibility of color differences. The non-linear relations for L*, a*, and b* are intended to mimic the logarithmic response of the eye. In order to convert an image from RGB color space to CIE LAB color space (or vice versa), the CIE XYZ color space is used as an intermediate color space at transformation phases from one color space into other .(Hanbury & Serra, 2001)

It is during conversion from RGB to XYZ that the characteristics of the image capture or display device and the illumination conditions are considered. The conversion formulas between CIE XYZ and RGB color spaces are as follows:

$$\begin{vmatrix} \boldsymbol{X} \\ \boldsymbol{Y} \\ \boldsymbol{Z} \end{vmatrix} = \begin{vmatrix} \boldsymbol{X_r} & \boldsymbol{X_g} & \boldsymbol{X_b} \\ \boldsymbol{Y_r} & \boldsymbol{Y_g} & \boldsymbol{Y_b} \\ \boldsymbol{Z_r} & \boldsymbol{Z_g} & \boldsymbol{Z_b} \end{vmatrix} * \begin{vmatrix} \boldsymbol{R} \\ \boldsymbol{G} \\ \boldsymbol{B} \end{vmatrix}$$

Where

X, Y, Z are the desired CIE tri-stimulus values, R, G, B are the displayed RGB values obtained from the transfer functions and the 3x3 matrix is the measured CIE tri-stimulus values. And X_r , Y_r , Z_r are the measured CIE tri-stimulus values for the red channel at maximum emission. (Ford & Roberts, 1998)

To convert from XYZ to RGB use the inverse form of the matrix given in equation:

$$\begin{vmatrix} \boldsymbol{R} \\ \boldsymbol{G} \\ \boldsymbol{B} \end{vmatrix} = \begin{vmatrix} \boldsymbol{X_r} & \boldsymbol{X_g} & \boldsymbol{X_b} \\ \boldsymbol{Y_r} & \boldsymbol{Y_g} & \boldsymbol{Y_b} \\ \boldsymbol{Z_r} & \boldsymbol{Z_g} & \boldsymbol{Z_b} \end{vmatrix}^{(-1)} * \begin{vmatrix} \boldsymbol{X} \\ \boldsymbol{Y} \\ \boldsymbol{Z} \end{vmatrix}$$

The conversion formula from the XYZ color space to the LAB color space is as follows:

For X/X_n , Y/Y_n and Z/Z_n all greater than 0.008856, then

$$\boldsymbol{L* = 116 \sqrt[3]{\frac{Y}{Y_n}} - 16}$$

$$\boldsymbol{a* = 500\left(\sqrt[3]{\frac{x}{x_n}} - \sqrt[3]{\frac{Y}{Y_n}}\right)}$$

$$\boldsymbol{b* = 200\left(\sqrt[3]{\frac{Y}{Y_n}} - \sqrt[3]{\frac{Z}{Z_n}}\right)}$$

And For X/X_n , Y/Y_n and Z/Z_n is equal to or lower than 0.008856, then

$$\boldsymbol{L* = 903.3 \left(\frac{Y}{Y_n}\right)}$$

$$\boldsymbol{a* = 500 \left[f\left(\frac{X}{X_n}\right) - f\left(\frac{Y}{Y_n}\right) \right]}$$

$$\boldsymbol{b* = 200 \left[f\left(\frac{Y}{Y_n}\right) - f\left(\frac{Z}{Z_n}\right) \right]}$$

Where

$L*, a*, b*$ are the coordinates of Lab color space. X, Y, Z are tristimulus values of the test object color stimulus considered. X_n, Y_n, Z_n are tristimulus values of specified white object color stimulus. (Kuru, 2014)

2.3 Spectral clustering algorithm

Assume we have a group of n data points $x = \{x_1, x_2, ., ., ., x_n\}$ in R^l and want to cluster them into c clusters. Therefore, we should take processing steps as follows:

Calculate affinity matrix (Similarity matrix). It consists of similarity measures between data points. If number of data points is '*n*', the size of similarity matrix is '*n* x *n*'. The elements of similarity matrix is given by equation:

$$W = [A_{ij} : i \in [1: n \,, j \ \in [1, n]]$$

Where, A_{ij} is the similarity between points x_i, x_j defined as in equation:

$$A = exp\left(\frac{-dist^2(x_i - x_j)}{\sigma^2}\right)$$

for $i \neq j$ and $A_{ii} = 0$, where $dist(x_i, x_j)$ is distance between points x_i and x_j. σ Scale parameter. The choosing value of σ is commonly done manually.

We get different results every time after the execution and this depends on σ when using a new value for σ the results change. So, we cannot ignore the value of σ. the relationship between c and clusters number is that σ have smaller value and that means every data have the smaller effect on the around areas. A_{ij} shows to the sum of like functions who takes n data sets as the center. The clustering result will produce many of clusters.

The most extreme case is that each data set is grouped in a row, which is useless. On the obverse, when σ pick a larger value, every data object has a greater impact on all regions. A_{ij} show to the sum of the function composed by n datasets, changing slowly with a large range. In the most extremist case, all the points are collected into one cluster. thus, to obtain clustering result as clear as possible, it referees to/or should embody the distributed features of fundamental data. Choosing a good value for this parameter is critical to the success of the algorithm.

How to Choose parameters of the affinity matrix is still an open question and field of active research. (Qin, 2014)

Calculate degree matrix

Construct the degree matrix **D**. degree matrix is computed from the affinity matrix (A) first by count the degree matrix. The degree matrix is computed with all pixel, as the aggregate of all similarity values connected to the pixel it given as:

$$\boldsymbol{D_i} = \sum_{i=1}^{n} \boldsymbol{A_{ij}}$$

D is the degree of a vertex (in our search here is pixel), i and **A** the similarity or weight value between pixel i with pixel j. The diagonal matrix is then constructed by taking $d_{ii} = d_i$ and Zero otherwise.

The degree matrix of the similarity graph is the diagonal matrix with the degrees on the diagonal.

$$d = \begin{pmatrix} d_1 & 0 & 0 & 0 \\ 0 & d_2 & 0 & 0 \\ & & . & \\ 0 & 0 & 0 & d_n \end{pmatrix}$$

Figure 7. Degree Matrix

Construct Laplacian matrix

Calculation of the Laplacian matrix normalized 'L'. by using the diagonal matrix and the affinity matrix, a normalized, symmetric Laplacian matrix is constructed using the formula in equation

$$\boldsymbol{L} = \boldsymbol{D}^{\frac{-1}{2}} * \boldsymbol{A} * \boldsymbol{D}^{\frac{-1}{2}}$$

Extract the Eigen values and Eigen vectors

Calculates Eigen values λ_i and corresponding Eigen vectors x_i from Laplacian matrix. In previous step we generated a symmetric Laplacian matrix, then all Eigen values are real valued.
Then, we organize the eigenvalues in decreasing order $(\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq . \geq . \geq \lambda_n)$.

Then select K largest eigen vectors, assume the value of k=5 than we select 6 eigen vectors. the K largest eigenvectors are relevant for grouping K clusters and it is important to first identify and remove those irrelevant / uninformative eigenvectors before performing clustering.

construct Y matrix by normalizing each element of neigvec matrix using the formula in equation:

$$Y_{ij} = \frac{s_{ij}}{\left(\sum_j s_{ij}^2\right)^{1/2}}$$

Finally, apply a K-mean algorithm to a Y matrix. to clusters them into groups.

Chapter 3

3. THE PROPOSED APPROACH AND ITS IMPLEMENTATION

In this chapter, we will display the steps to execute the proposed algorithm, which is to segment the image using spectral clustering. The algorithm is divided into three phases are as follows:
The first stage is Initialization Data Which is, converting the color image to L*a*b color space, we will list in detail.
The second stage is related to the application of algorithm to the data obtained from the first stage.
The third and final stage is to display the results obtained after applying the algorithm (segment image). Figure 8 illustrates flowchart of proposed approach.

Algorithm Description

The first step of our segmentation approach, the RGB image is taken as an input image. Then, Next, Spatial-color compactness function is calculated for the L*a*b image. After that, the spatial color compactness function is applied to spectral clustering. The final image is divided into regions. Pre-processing the phase includes the following steps:

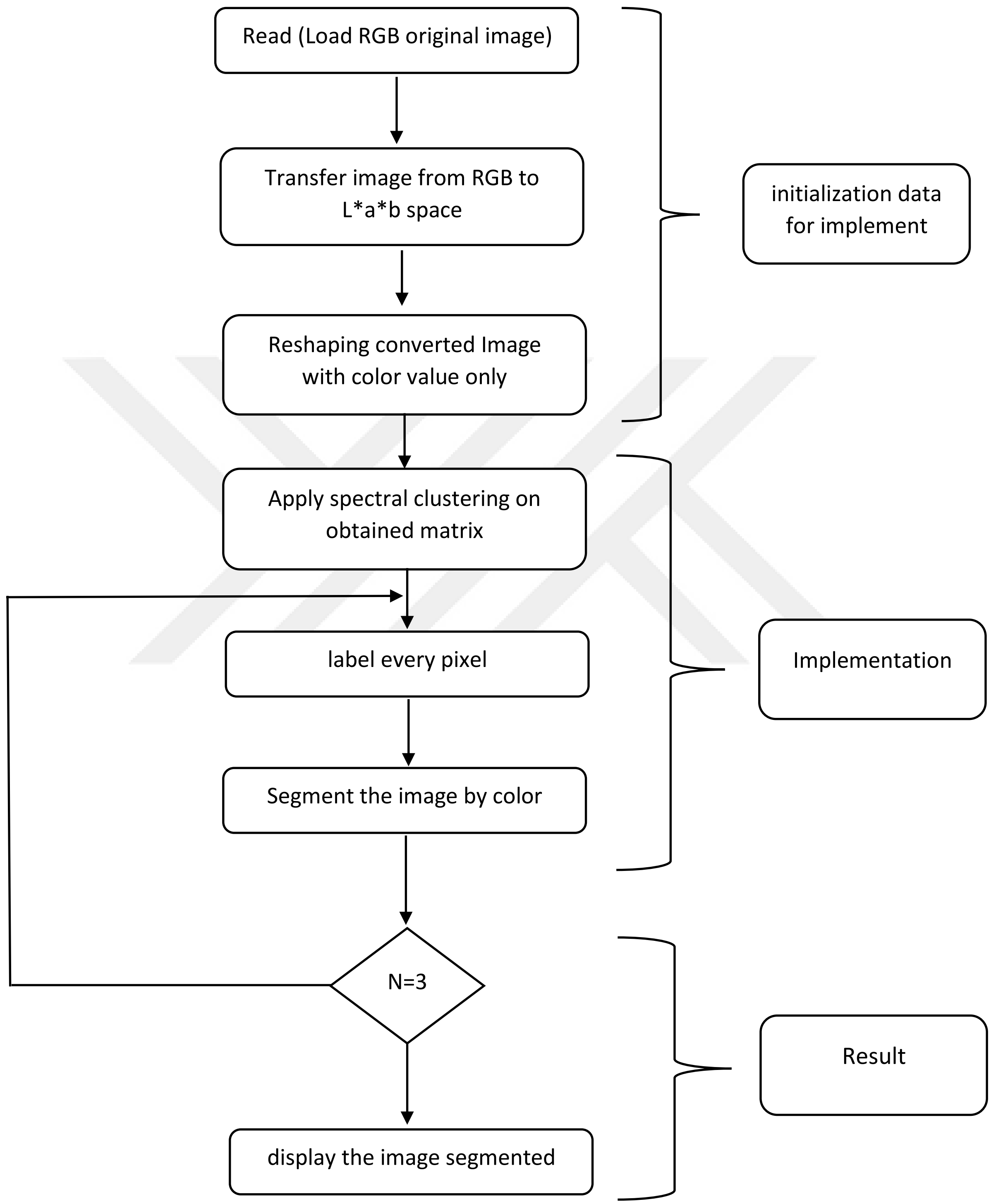


Figure 8. Flowchart of proposed approach

3.1 Initialization data

3.1.1 The first Step: Read Image

Reading the image and write it out into the matrix “image Matrix”. If the input image is grayscale, the matrix has dimensionality [R × M]. For the color image is a 3 channel, and the dimensionality of the matrix is [R × C × 3]. R is the height of the image while C is the width.

3.1.2 The second Step: Convert image from RGB color space to L*a*b color space

The previously acquired image is obtained. Start the reprocessing by converting RGB Image to L * a * b Color Space. That means if we ignore the brightness (Luminance) of the original image. Then, we can easily find out a color blue, pink and white color which is called as L*a*b color space. The L*a*b* color space consists of layer L* lightness (Luminance), layer a* and b* (which are chromatic components). All color information is stored in layers a * and b *. This requires making a color form so that the RGB colored image is transferred to L*a*b* space function is makefrom (), the formatting is applied later the image obtained.

3.1.3 The Third Step: reshape the columns and rows

All images were read in a three-dimensional format. decorrelation stretch has been performed to enhance color separation. The color space was turned into Lab. the matrix values were changed to double, and the matrix was represented to combine the columns and rows into a single column. suppose, an image has the dimensions of 160x200x3 becomes 32,000x2. The rows accord to point, and the columns accord to variables for input into spectral clustering. The rows match the points, and the columns match to the variables for input into spectral clustering. Since all wanted color information available in the (a and b) space, then, these objectives are pixels with 'a * b ' values. [1]

Figure 9, indicates the differences between the original input image, RGB image and converted L*a*b color space image.

(a)

(b)

(C)

(d)

Figure 9. (a and b) Original Input Image; (c and d) converted L*a*b image.

3.2 Implementation

3.2.1 Applying Spectral clustering

The data generated by the parameters considered in the previous step is stored in the matrix (ab). This matrix (ab) is used as input data to spectral clustering technique. The creation of the similarity graph (or affinity matrix) is the basic phase in the spectral cluster which determines the efficiency of the clustering technique.

then, Construct affinity matrix using Gaussian kernel function as defined in equation:

$$A = exp\left(\frac{-dist^2(p_i - p_j)}{\sigma^2}\right)$$

where: dist $(p_i - p_j)$) is the measurement of the distance between pixels and σ as discussed previously scale parameter.

Although our selection of σ parameter was manual by choosing a range between (0.5 - 4) and applying an algorithm. But this is a way to choose the value of σ was by experiment and replication (right and wrong) because the different implementation of the data (distances between pixels) sometimes leads to not get the desired results. Using a new value for σ parameter is tedious and it takes too long to get results.

next we calculate degree matrix for every pixel as the sum of all similarity values connected to the pixel using equation:

$$D_i = \sum_{i=1}^{n} A_{ij}$$

Then calculate Laplacian matrix using the diagonal matrix and the affinity matrix using equation:

$$\boldsymbol{L} = \boldsymbol{D}^{\frac{-1}{2}} * \boldsymbol{A} * \boldsymbol{D}^{\frac{-1}{2}}$$

Now calculate the value of the Laplacian matrix in the previous step. We have to decomposition Laplacian matrix for getting on Eigen values and Eigen vectors.

After obtaining the values of Eigenvalue and Eigenvector. The next step is to specify a value k-largest that is between (3, 5).

We have tried a value greater than 5 and the results were not good compared to the results when the value was selected between (3 and 5).

Constructing the normalized matrix Y from the obtained neigvec matrix to find every element of this matrix using the equation:

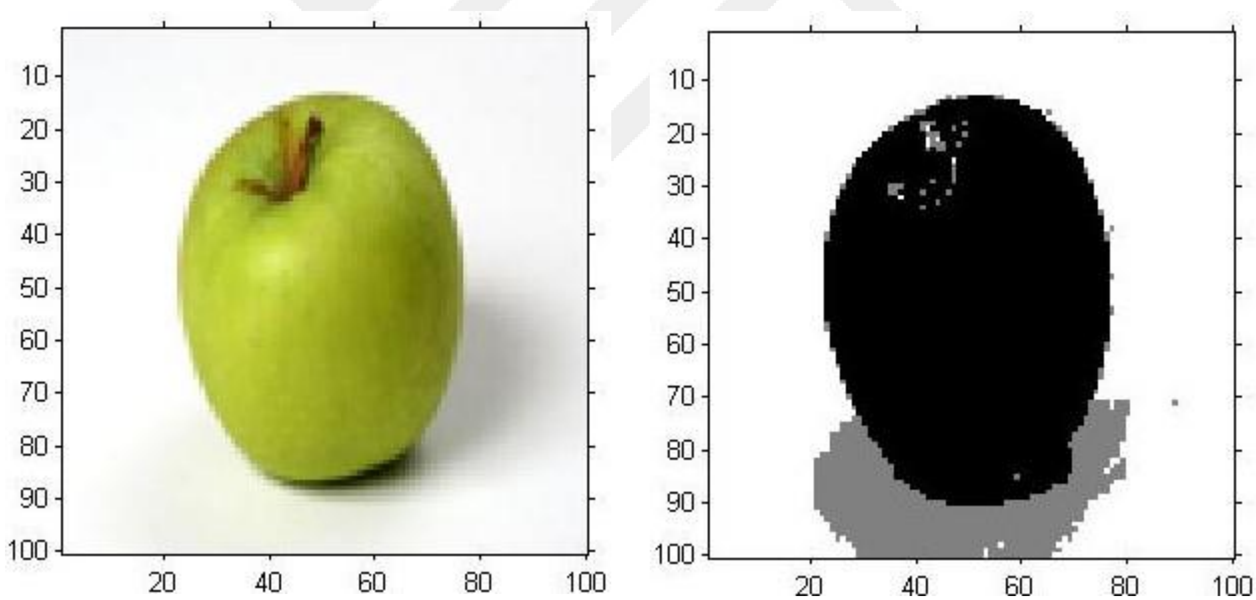
$$Y_{ij} = \frac{s_{ij}}{\left(\sum_j s_{ij}^2\right)^{1/2}}$$

The last step for the spectral algorithm is the application of the k-means algorithm on the Y matrix and as a result of obtaining an index for each pixel within the Y matrix. Then move on to the next step which is label pixel.

3.2 .2 Labeling pixel

After obtaining the results from k-mean, and specifying each pixel to which the group belongs. Now next step labeling each pixel. Labeled image is better intermediate representations for regions that can be used for additional processing. The idea is to assign a unique symmetry (integer number) to each detected region and create an image in which all pixels of a given region has a unique value. Almost connected component operators produce this type of output.

A labeled image can be used as a type of mask to specify the pixels of a region in some operations that calculate region characteristics, such as the area or length. And from the labeled image can compute boundaries for Region.

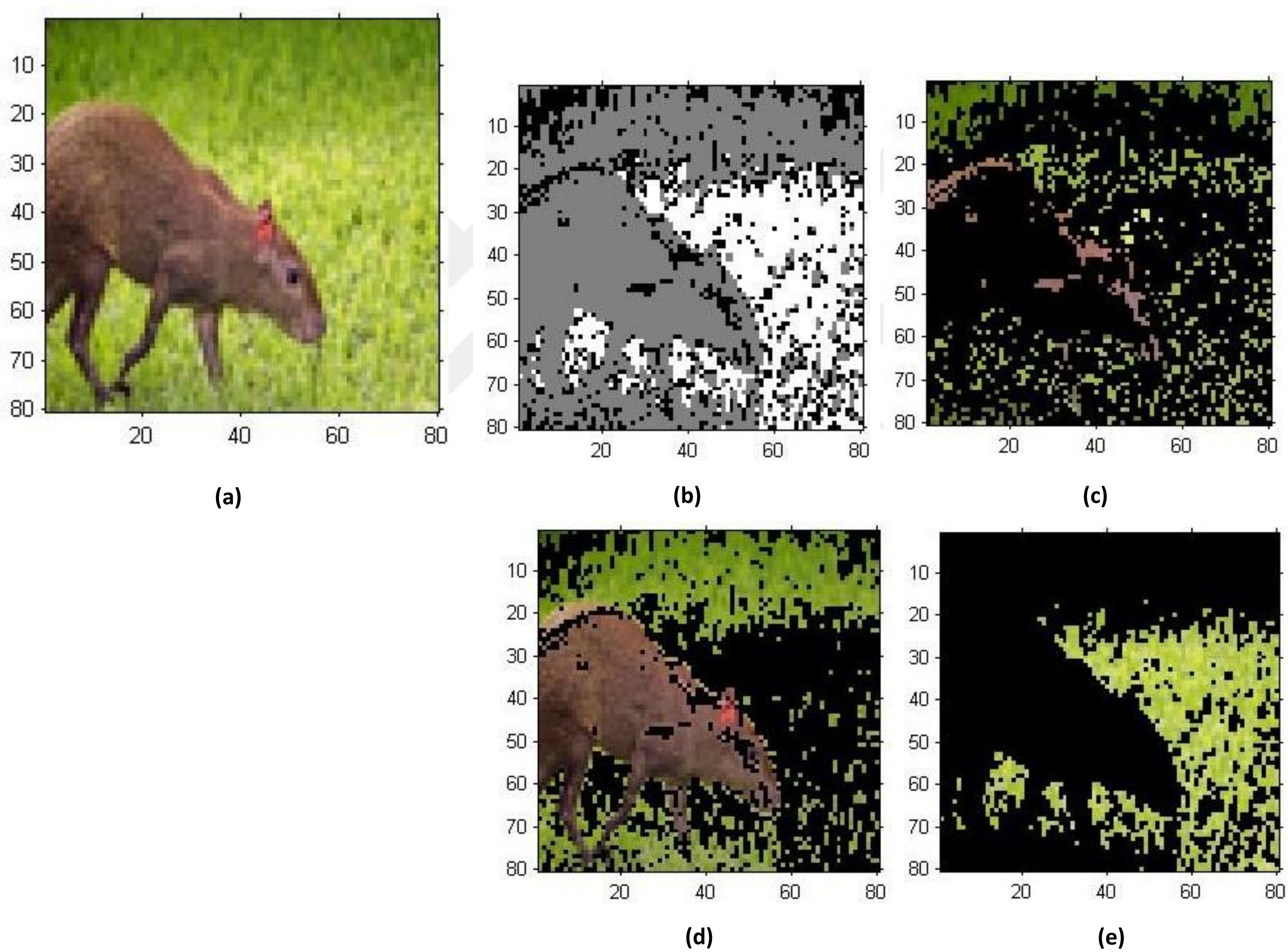


(a) (b)

Figure 10. ***(a) Original Image (b) labeled image***

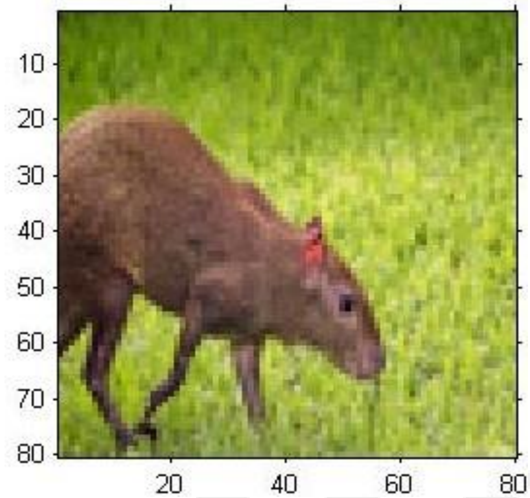
3.3 Experiments and Results

The algorithm was applied to many images. Experiments have been conducted on many different types of images. All the results on the color image without converting the formula and with the change k-mean to (3,4,5) were close and did not result in any segmentation of the objects in the image. However, the best results were obtained from (L*a*b) color space.

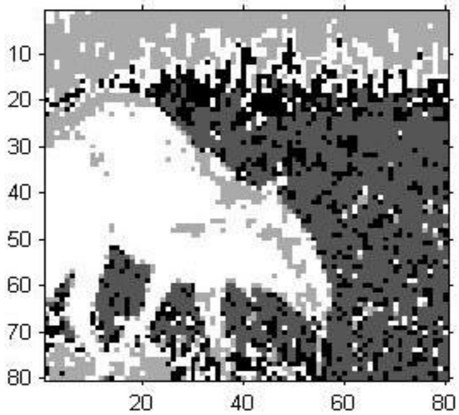


(a) **(b)** **(c)** **(d)** **(e)**

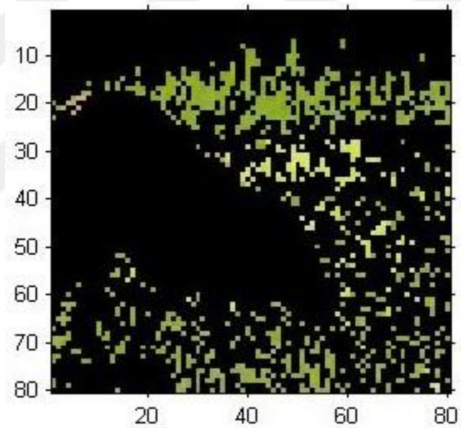
Figure 11. (a) Original Image (b) labeled image Using cluster index (c) Segmented Image (d) Segmented Image (e) segmented Image. The spectral clustering algorithm has been applied to the color image (RGB) without changing to any other space and these results at kmean=3



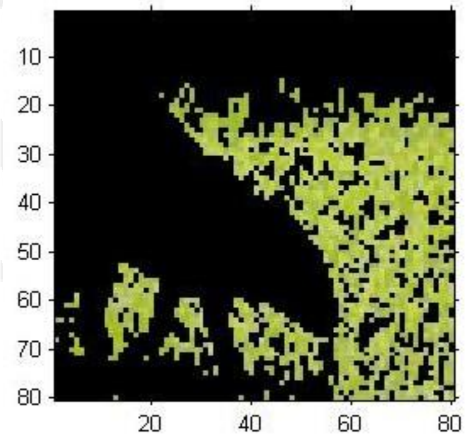
(a)



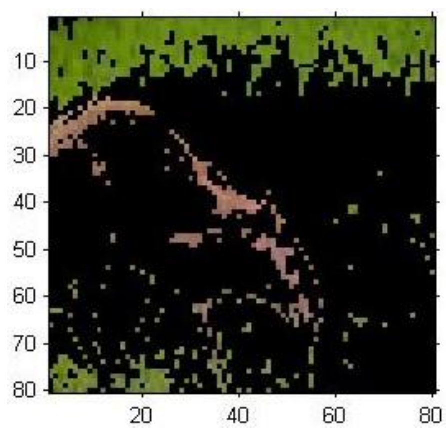
(b)



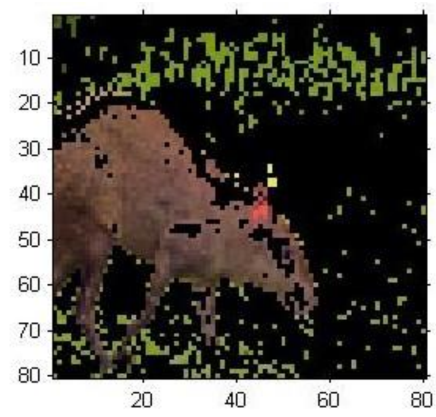
(c)



(d)



(e)



(f)

Figure 12. (a) Original Image (b) labeled image Using cluster index (c) Segmented Image (d) Segmented Image (e) segmented Image (f) Segmented Image. The spectral clustering algorithm has been applied to the color image (RGB) without changing to any other space and these results at kmean=4.

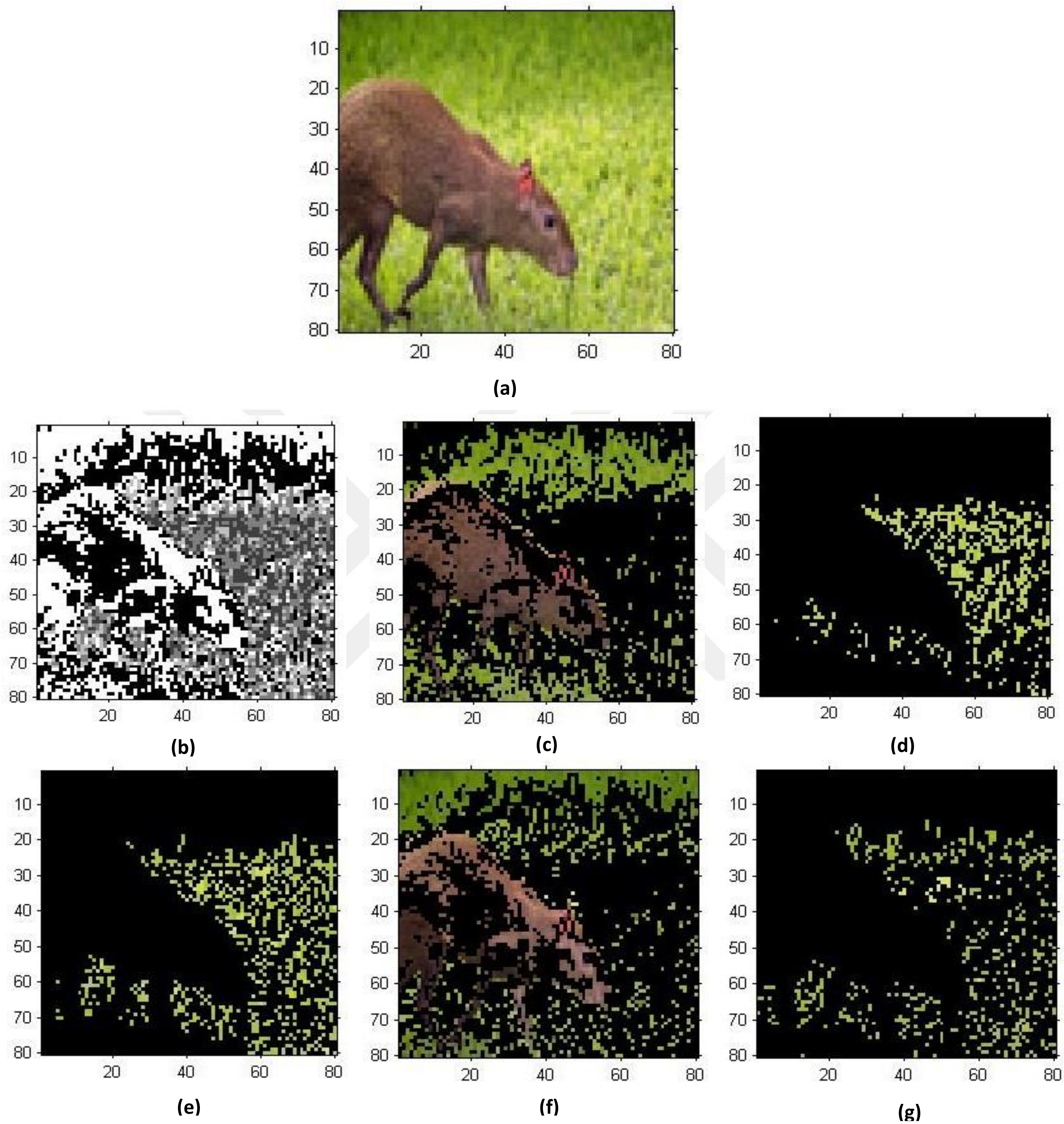


Figure 13. ***(a) Original Image (b) labeled image Using cluster index (c) Segmented Image (d) Segmented Image (e) segmented Image (f) Segmented Image (g) Segmented Image. The spectral clustering algorithm has been applied to the color image (RGB) without changing to any other space and these results at kmean=5.***

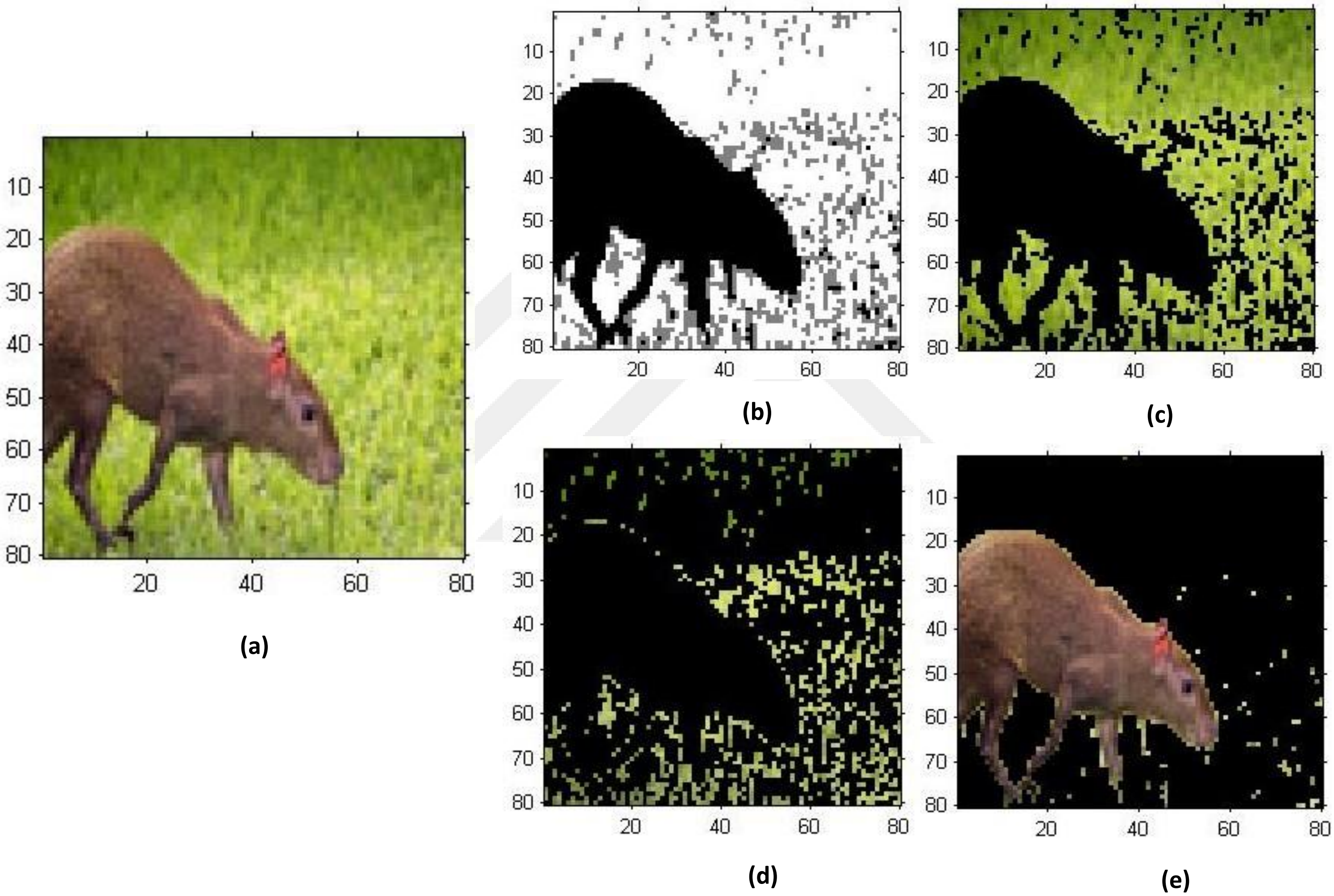


Figure 14. ***(a) Original Image (b) labeled image Using cluster index (c) Segmented Image (d) Segmented Image (e) segmented Image. The spectral clustering algorithm has been applied to the color image (RGB) after changing to (L*a*b) space and these results at kmean=3.***

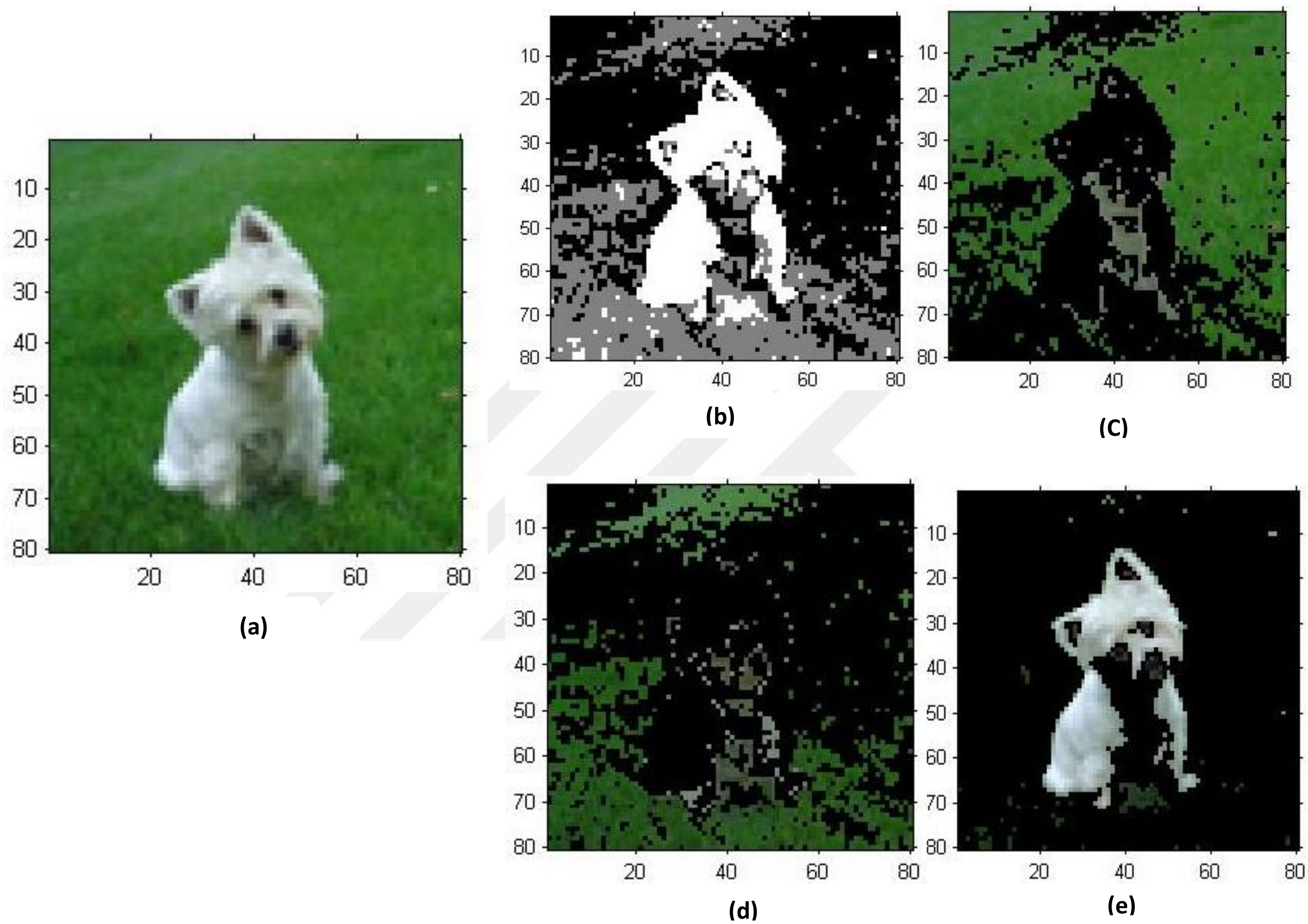


Figure 15. ***(a) Original Image (b) labeled image Using cluster index (c) Segmented Image (d) Segmented Image (e) segmented Image. The spectral clustering algorithm has been applied to the color image (RGB) without changing to any other space and these results at kmean =3.***

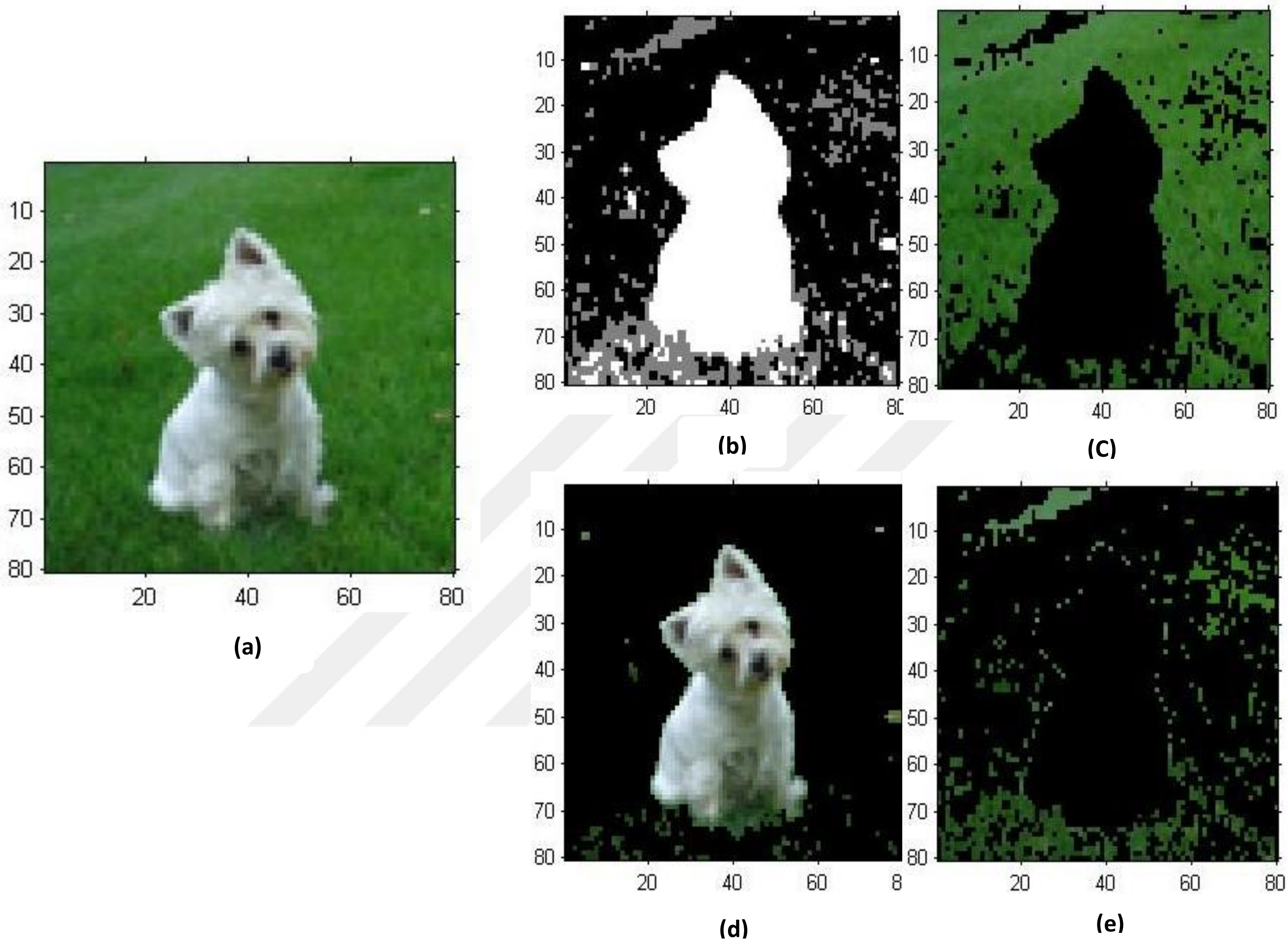


Figure 16. (a) Original Image (b) labeled image Using cluster index (c) Segmented Image (d) Segmented Image (e) segmented Image.

*The spectral clustering algorithm has been applied to the color image (RGB) after changing to (L*a*b) space and these results at kmean=3.*

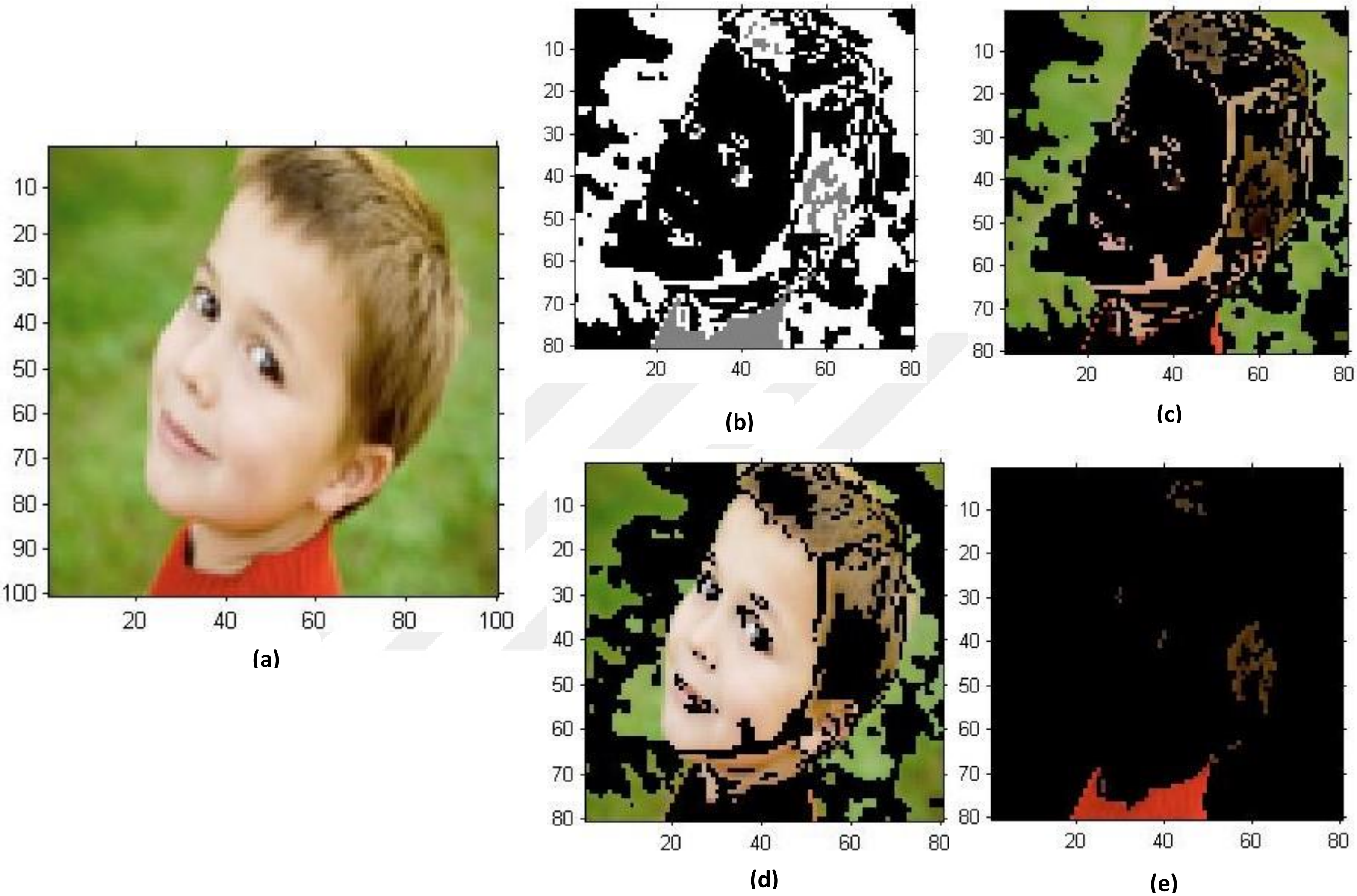


Figure 17. ***(a) Original Image (b) labeled image Using cluster index (c) Segmented Image (d) Segmented Image (e) segmented Image. The spectral clustering algorithm has been applied to the color image (RGB) without changing to any other space and these results at kmean =3.***

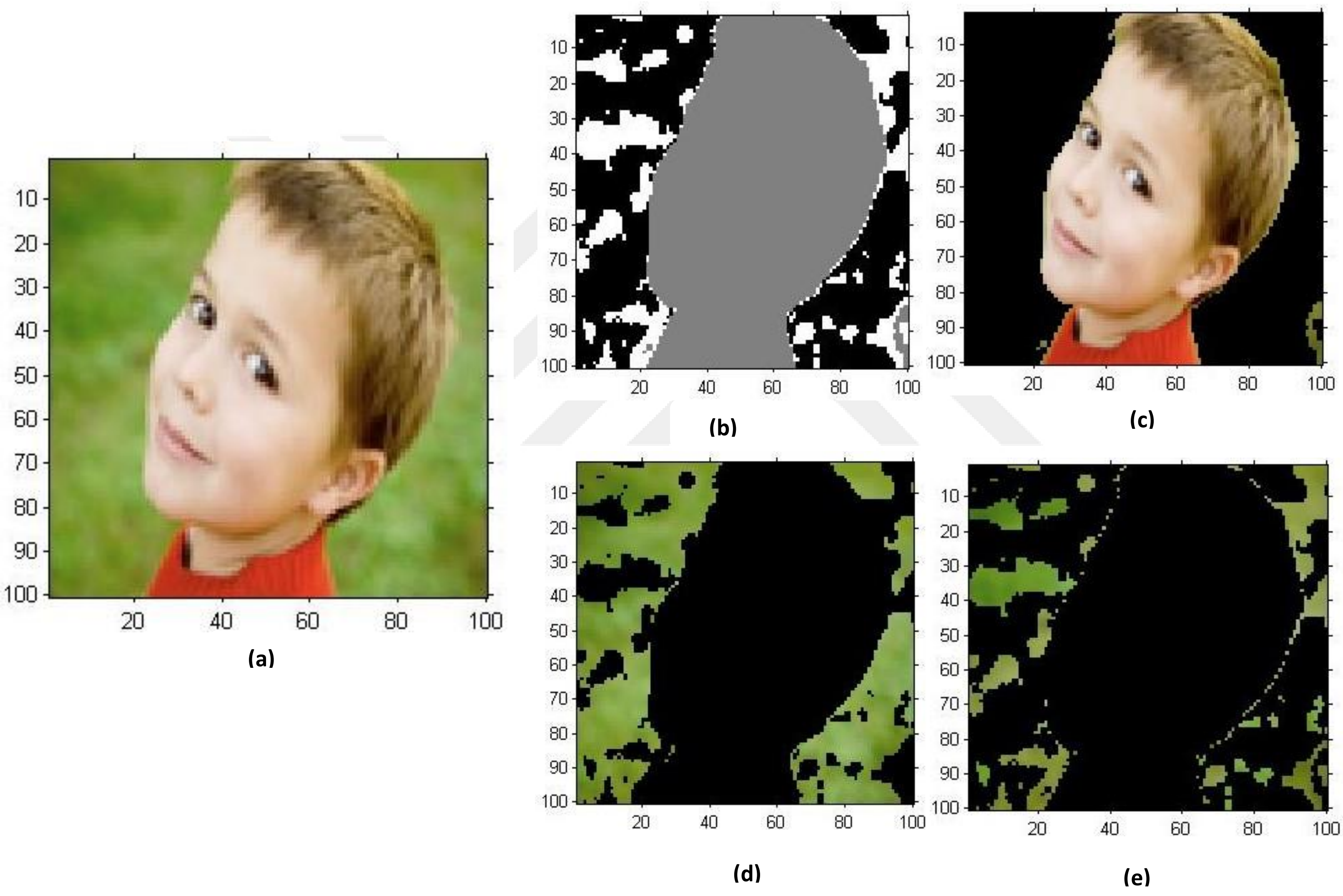


Figure 18. ***(a) Original Image (b) labeled image Using cluster index (c) Segmented Image (d) Segmented Image (e) segmented Image.***

The spectral clustering algorithm has been applied to the color image (RGB) after changing to (L*a*b) space and these results at kmean=3.

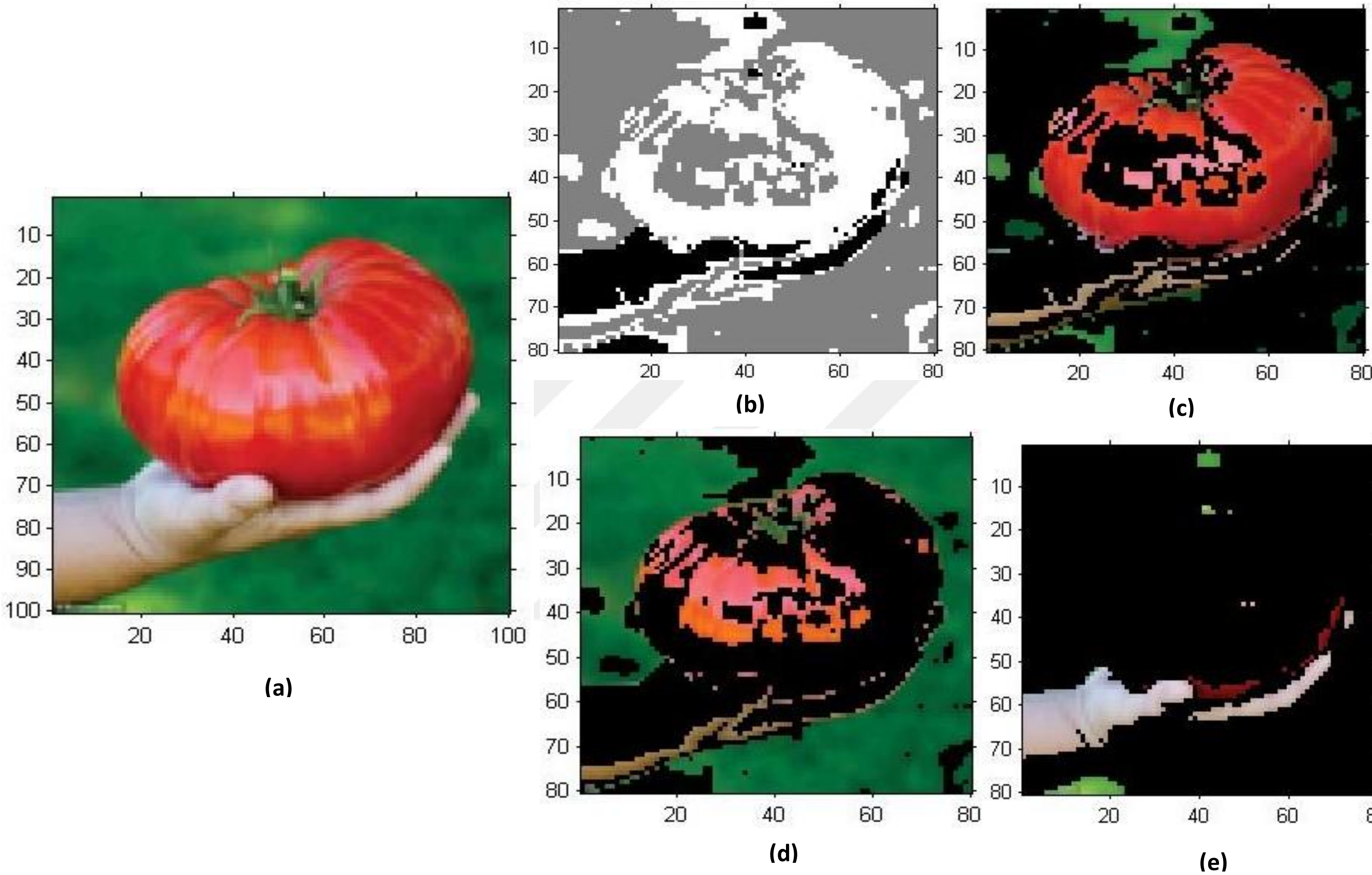


Figure 19. ***(a) Original Image (b) labeled image Using cluster index (c) Segmented Image (d) Segmented Image (e) segmented Image. The spectral clustering algorithm has been applied to the color image (RGB) without changing to any other space and these results at kmean =3.***

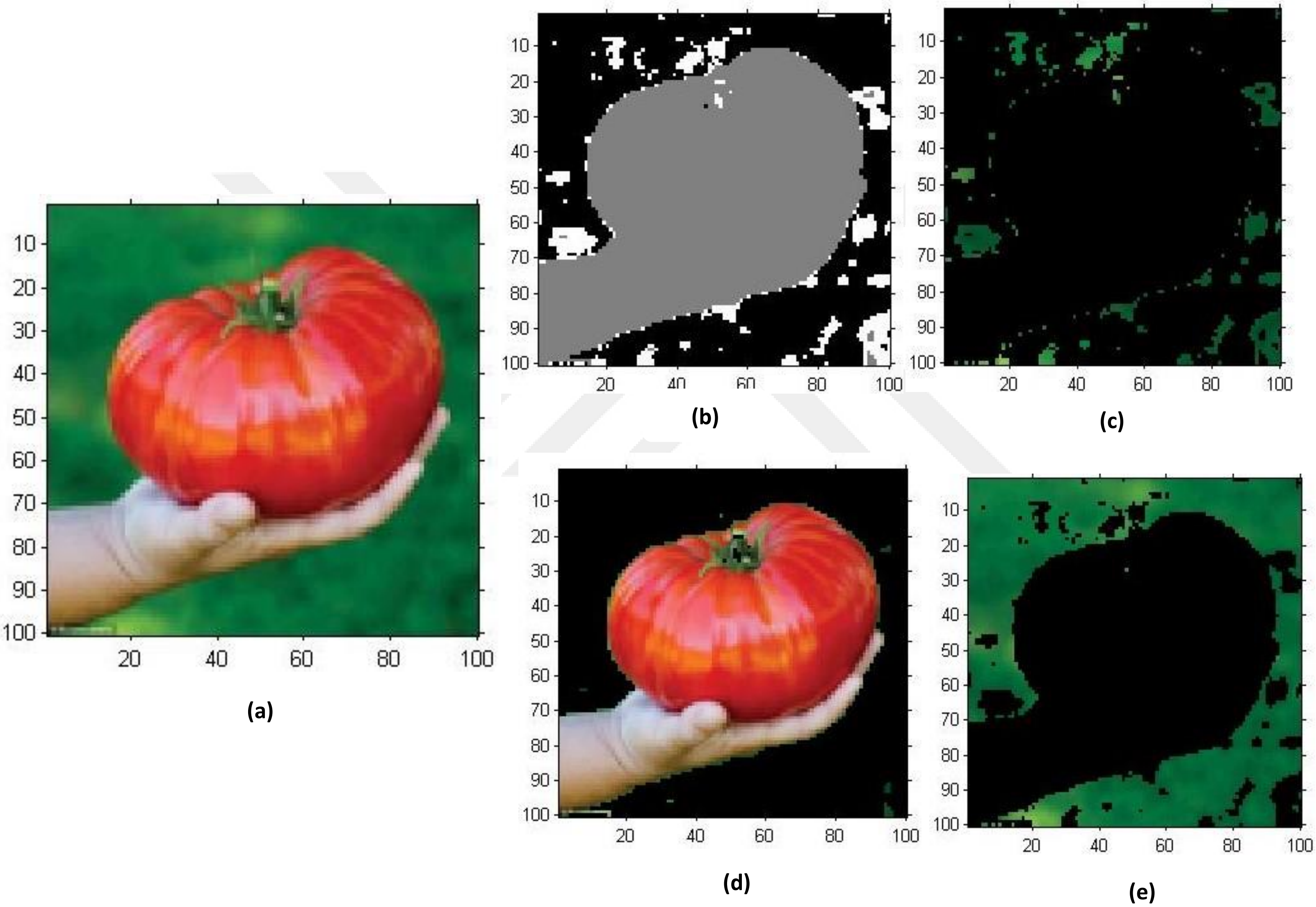


Figure 20. (a) Original Image (b) labeled image Using cluster index (c) Segmented Image (d) Segmented Image (e) segmented Image.

The spectral clustering algorithm has been applied to the color image (RGB) after changing to (L*a*b) space and these results at kmean=3.

4. Conclusion and future work

4.1 Conclusion

clustering considered as the most common techniques used in many applications such as pattern recognition, machine learning, statistics, image processing, and data mining.

Spectral clusters are becoming increasingly widely used because they are a simple method of cluster analysis and often outperform traditional assembly algorithms such as K-Mines.

Spectral clusters, in brief, it uses the eigenvalues of the data similarity matrix to reduce the dimensions before clustering in lower dimensions and then we find a partition of the graph so that the points within the set are similar and the points between the different sets are different to each other.

In this thesis, we have developed Region image segmentation approach with a Spectral clustering algorithm. So that the color image (RGB) is converted to (Lab) color space and then apply spectral clustering algorithm This algorithm has been executed in MATLAB. The algorithm is efficient to extract regions and works correctly for all kinds of color images, the experimental results obtained from this satisfactory algorithm, giving better sets and better-segmented image.

4.2 Future work

There are many directions for future research that we think would be interesting to follow as an extension of the results presented:

• First: Improve the algorithm by developing the method of selecting Sigma parameters. Where selecting the appropriate value for sigma improves the process of a calculating Affinity matrix.

• Second: Comparison of the proposed algorithm with other clustering algorithms related to image Segmentation so that the algorithm's efficiency can be measured.

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Appendix

Matlab Program used for implement proposed method:

```
% ======================================================
% Color image segmene using spectral clustering
% =====================================================
%1. Loading color image
I = imread('1.jpg');
%2. Convert color image RGB to L*a*b space color
cform = makeform('srgb2lab');
%3. Applying L*a*b  color to  RGB image
Lab = applyform (I,cform);
%4. Convert to double
ab = double(Lab(:,:,2:3));
%5. Obtaining columns and rows from Converted image
Rows = size (ab, 1);
Cols = size (ab, 2);
%6. Reshaping to combining column and rows
ab = reshape(ab, Row * Cols,2);
%7. Choosing sigma parameter
  Sigma = 2;
```

```
%8. Computed affinity matrix

For i=1: size (ab, 1);

   For j=1: size (ab, 1);

       AF(i,j) = exp((-sqrt((ab(i,1) - ab(j,1))^2)/(2*sigma^2)));

   End;

End;

%9. Computed degree matrix

  For j=1: size (AF, 1);

      D (i,i) = sum(AF(i,:));

   End;

Figure, imshow (AF, [])

%10. Construct the Laplacian matrix...

For i=1: size (AF, 1)

   For j=1: size (AF, 2)

       A(i,j) = AF(i,j) / (sqrt(D(i,i)) * sqrt(D(j,j)));

   End

End


%11. Eigen value decomposition

[VE, VA]=eig (A);
```

```
 %12. Select K largest Eigen vectors

k = 3;

nVE = VE(:,(size(VE,1)-(k-1)): size(VE,1));

 %13. Construct the normalized matrix

For i=1: size (nVE, 1)

       S=sqrt (sum (nVE (i, :). ^2));

       S1=nVE(i,:)./ S;

End

 %@@@@@.  Kmeans clustering

Y=nVE/S1;

%15. Clustering   Y using K-mean

nClustering= 3;

% repeat the clustering to avoid local minima, number of repeating 3 times

[cluster_idx cluster_center] = kmeans(Y,nClustering,'distance','sqEuclidean', ...
'Replicates',3);

 %16. Label each pixel in RGB image using Result from k-mean

Pixel label = reshape (cluster_idx,Rows,Cols);

Figure, imshow (pixel label, []), title (' label ');
```

```
%17. Construct image that segment by color

Segmented images = cell (1, 3);

rgb_LbL = repmat (pixel label, [1 1 3]);

For C = 1: nClustering

   RGBColor = I;

   RGBColor (rgb_LbL ~= C) = 0;

   Segmented images {C} = RGBColor;

End

%18. Displaying different images that has segmented

Figure, imshow (segmented images {1}), title ('frist cluster ');
Figure, imshow (segmented images {2}), title ('scond cluster ');
Figure, imshow (segmented images {3}), title ('thrid cluster ');
```