# Extracted Pixels Similarity Features (EPSF) using Interactive Image Segmentation Techniques

Alhaji Sheku Sankoh
Department of Informatics,
Faculty of Information
Technology, Institut Teknologi
Sepuluh Nopember (ITS)
Surabaya.
Kampus ITS Sukolilo,
Surabaya, Indonesia.

Agus Zainal Arifin
Department of Informatics,
Faculty of Information
Technology, Institut Teknologi
Sepuluh Nopember (ITS)
Surabaya.
Kampus ITS Sukolilo,
Surabaya, Indonesia.

Arya Yudhi Wijaya
Department of Informatics,
Faculty of Information
Technology, Institut Teknologi
Sepuluh Nopember (ITS)
Surabaya.
Kampus ITS Sukolilo,
Surabaya, Indonesia.

## ABSTRACT

Semi-automatic image segmentation methods are among the segmentation methods that are used to achieve high quality segmentation result. These techniques are said to be interactive because their processes required input from their users to distinguish between the foreground and background of the image via color makers. Therefore color and texture features are an important aspect for the improvement of those methods in order to achieve success. The reason is that, the addition of a vast range of color features can guide the region merging process to achieve accurate results.

In this paper, we proposed a new interactive image segmentation method based on extracted pixels similarity features with the aid of color parameters comprising of seven features. These are namely: Red, Green, Blue, Hue, Saturation, Value and Texture Features. In our method, the initial step is to pre-segment the image. The next is the extraction of the color features from the image. Finally our method then merge all the pre-segmented regions of the image background to extract the contour. Our proposed method has successfully been implemented and achieve good quality segmentation results by measuring the similarity between a region and its neighboring regions. In this method, the image regions are acquired by means of a pre-segmentation process via mean-shift. The region merging process was carried out based on the highest similarity between regions. Thus, the regions were merged with their neighboring regions based on the fact that the highest similarity criteria was achieved.

From the various experiments that were performed on the nine test images, it is evident that our proposed method achieved an average of 98.99% from all experiment carried out on the nine test images, when compared with their ground truth. That shows that our proposed method produced better segmentation results than the Graph Cut and the Dimension-free Directional Filter Bank Thresholding and Multistage Adaptive Thresholding respectively. Finally, our proposed method have been proved to be robust enough to segment both color and greyscale images and based on the results produced it can be concluded that our proposed method have achieved good quality segmentation results for both color and greyscale images.

## Keywords
Semi-automatic segmentation, color images, highest similarity, region merging, mean-shift.

## 1. INTRODUCTION
Currently a wide range of image segmentation methods have been developed. They are either automatic or semi-automatic image segmentation methods. Semi-automatic methods are segmentation methods or technique that requires the users to supply an input so that there is an interaction between the user and the segmentation programs. In this research we choose to interact with our segmentation program through the use of color marker. Even though the technique of marking to indicate the object and the background were used in [1], this paper also use it to indicate and preserve the region of interest whilst protecting the contour boundaries.

Many segmentation methods have been in existence. However, it is rare to obtain or discover single segmentation method that will satisfy both color and greyscale images by a distinctprocedure. This is because most segmentation procedure tends to select specific color or greyscale parameters. On the contrary, we tend to select a wide range of features that possesses both color and greyscale images. Even though our focus was on color images, but we introduce a texture feature that is able to satisfy the criteria for the grey scale image segmentation.

In[2], they propose a framework for interactive image segmentation. Their proposed method minimizes a min–max Bayesian criterion that has been successfully used on image segmentation problem and it consists of several steps in order to take into account visual information as well as the given markers, without any requirement of training. They first, partition the image into contiguous and perceptually similar regions (super-pixels). However, the different between their method and our proposed method is that, our method uses mean shift for the pre-segmentation. Furthermore, their method uses clustered base graph cut. Another study in [3], they presented an interactive image segmentation technique with a graph-based method. In their method, they used the watershed as a pre-segmentation / low-level segmentation combined with the graph cut as the next segmentation operation. Other researchers in[4], present an interactive segmentation method for 3D medical images that reconstructs the surface of an object using energy-minimizing, smooth and with implicit functions. In their method, an intuitive segmentation of medical images, variational interpolation can be based on a set of user-drawn, planar contours that can be arbitrarily oriented in 3D space. In [1], another study presents a new region merging based interactive image segmentation method. The users only need to roughly indicate the location and region of the object and background by using strokes, which are called markers. A novel maximal-similarity based

region merging mechanism was proposed to guide the merging process with the help of markers. In [5], they develop an interactive color image segmentation method. Their method makes use of the conception of Markov random fields (MRFs) and D–S evidence theory to obtain segmentation results by considering both likelihood information and priori information under Bayesian framework.

From the above related studies, there are various methods of interactive segmentation for both color and texture images.

In this paper, we propose a new interactive image segmentation method based on extracted pixels similarity features with the aid of color parameters comprising of seven features. These features are namely Red, Green, Blue, Hue, Saturation, Value and Texture Features. Our proposed method requires the user to interaction with the program by providing color marker that indicates the position of the object and the background of the image. Therefore, the main contribution in this paper is the addition and combination of a wide range of features to obtain accurate segmentation result. Our method can accurately segment both color and greyscale images. Its uses a preliminary image region division before the high level segmentation operation of the proposed method, among others: Mean shift, watershed, super-pixels and level sets [1]are familiar pre-segmentation methods. Thus our segmentation results based on the pre-segmentation with mean-shift produced by our method is very good when compared with the grown truth.

## 2. COLOR SPACES
In this paper, our research consist of three color spaces comprising of seven features. These seven features were used to measure the highest similarity between a region and its neighboring regions. The color spaces used in this research are explained in the sub-sections below. Below is a representation of the color features used in this research.
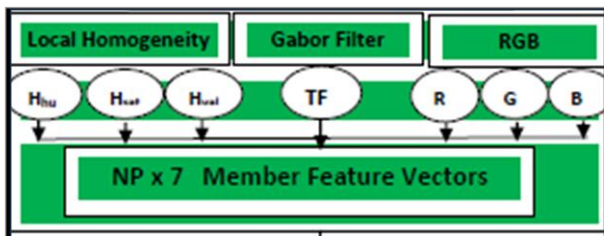


**Figure 1 Color spaces used**

### 2.1 RGB Color Space
The measurement of colors in the RGB color space does not represent the color difference on a uniform scale. Normal color space has a uniform scale of perception, if the distance difference between two colors in a color space is approximate or equal to the distance that captured the color difference in the human eye [6]. Therefore, it is not possible to evaluate the exact similarity between two colors using distance or difference in color on the RGB color space alone. Based on this reason, we decided to combine RGB with other color spaces to obtain efficient results in our proposed method. Figure 1 shows a representation of the RGB.

### 2.2 HSV Color Space
The HSV color space is often used by those who are selecting colors from a color wheel or palette, because it corresponds better to how people experience color than the RGB color space does [7]. The functions rgb2hsv and hsv2rgb convert images between the RGB and HSV color spaces.
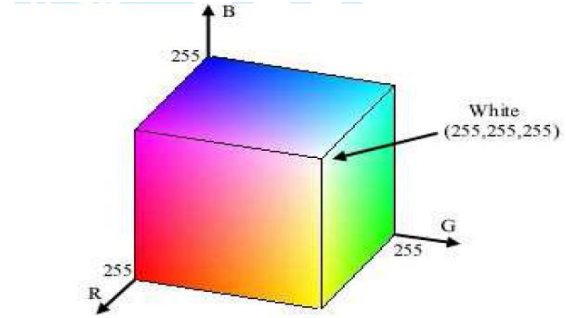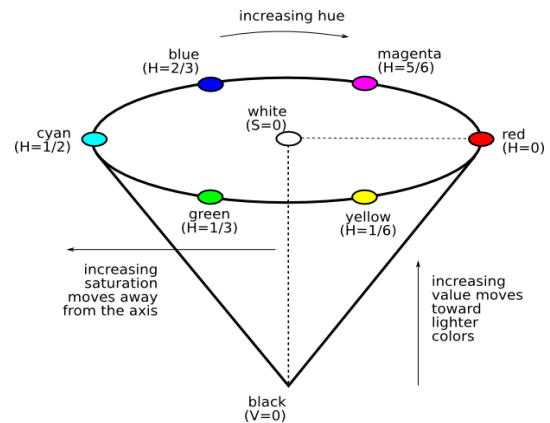


**Figure 2 RGB Color Space**



**Figure 3 HSV Color Space**

$$H = \cos^{-1} \beta ,\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots,(1)$$

$$\beta = \left( \frac{\frac{1}{2}[(R-G)+(R-B)]}{\sqrt{(R-G)^2+(R-B)(G-B)}} \right)$$

$$S = 1 - \frac{3}{R+G+B}[\min(R,G,B)]\cdots\cdots\cdots(2)$$

$$V = \frac{1}{3}(R+G+B) \cdots\cdots\cdots\cdots\cdots(3)$$

### 2.3 Gabor Filter
Gabor filter used to analyze characteristics of the texture of an image based on scale and orientation parameters [8]. 2D Gabor filter can be expressed as space sinusoid of frequency, scale and orientation modulated with a 2D Gaussian function g(x,y), following this: g(x, y).

$$(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left\{ 1 - \frac{1}{2}\left[ \left(\frac{x}{\sigma_x}\right)^2 + \left(\frac{y}{\sigma_y}\right)^2 \right] \right\} [\cos(W_x) + 2\pi j \sin(W_x)]$$

$$\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

With $j = \sqrt{-1}$ and *W* is the frequency of the modulated sinusoidal wave.

#### 2.3.1 Gabor wavelet
The Gabor wavelet texture feature extraction is a calculation using the Gabor filter based on its wavelet. The goal of the Gabor wavelet is to analyze the frequency of the image by means of the process of dilation and rotation parameters of different scale and orientation, thus giving rise to a character or special features in the image that has been convoluted with the Gabor wavelet. The formula of the Gabor wavelet at scale

(m) and orientation (n) is obtained from the dilation and rotation on its function can be expressed as follows:

$$g_{mn}(x, y) = a^{-m} g(x', y')$$ …………..…(5)

With:

$$x' = a^{-m}(x \cos \theta + y \sin \theta)$$ …………..(6)

$$y' = a^{-m}(-x \sin \theta + y \cos \theta)$$ …………..(7)

Where (x, y) is the function of the Gabor filter that is used by the process of dilatation and rotation, with a scalar (m) and orientation (n). And a-m = the scalar factor (a>1), and the θ=nπ/k, k is the amount of the total rotation.

### 2.3.2 Convolution of the image

Convolution Gabor wavelet image using an image processing operation that multiplies an image with a Gabor wavelet. On the concept of using a convolution operator (*) as a sign of the convolution process between the input of the image *I(x, y)* with Gabor wavelet $g_{mn}(x, y)$. Convolution results with Gabor wavelet image using operator (*), namely:

$$W_{mn}(x, y) = I(x, y) * g_{mn}(x, y)$$ …………...,(8)

In order for the operator (*) can be replaced with carrier multiplication *(x)*, then Y(x, y) and $g_{mn}(x, y)$ is inserted into the frequency domain by transforming the Fourier transformation by using the I(x, y) and $g_{mn}(x, y)$, resulting in the following equation (Gonzalez, RC and Woods, RE, 2008):

$$W_{mn}(u, v) = \hat{I}(u, v) * \hat{g}_{mn}(u, v)$$ …………....,(9)

With:

I(x, y) = the input image,

$g_{mn}(x\ y)$ = Gabor wavelet,

I(u, v) = image result that has been transformed by Fourier transformation.

$g_{mn}(u, v)$ = Gabor wavelet result which has been transformed with Fourier transform.

Gabor filter output is a complex number, while the output on the $W_{mn}(x, y)$ is also a complex number. Therefore, the output of the $W_{mn}(x, y)$ must absolutely be a face magnitude to be real numbers and using the following equation:

$$W_{mn}(x, y) = \frac{}{\sqrt{Re^2\{I(u,v) \times g_{mn}(u,v)\} + Im^2\{I(u,v) \times g_{mn}(u,v)\}}}$$ ….,(10)

## 3. REGION MERGING BASED ON HIGH SIMILARITY MEASUREMENT

Initial segmentation using mean-shift is the first step that assists the division of the image into several small regions that have similarities with their neighboring regions. For the purpose of this research work, we choose to use the mean-shift method using the EDISON system [9] (mean-shift software) for low-level segmentation operation. From this step a high-level operation can then be carried out by the merging process through the proposed method. Figure 1 shows the segmentation result from the EDISON mean-shift software system.

From the low-level segmentation results with the EDISON system, the image is then inputted into the proposed EPSF system to segment the image by separating the foreground from its background. This system also follows a stepwise operation. The system first of all requires the user to choose an image if the default image is not the required one.

Following the selected image, the user then give color markers to the selected image to indicate the object (foreground) and the background. Using Green to indicate the object and Blue to indicate the background.

## 3.1 SimilarityMeasurement for each Region

After conducting initial mean shift with the EDISON system pre-segmentation, we will get a lot of small regions separating the image [10]. The initial step of our method used in this paper is that, the system uses color descriptors for the representation of color features on the object regions obtained from the pre-segmentation. Thus, a region can be represented by several descriptors, among others, color, edge, texture, shape and size [11] of the region are known descriptors. Their purpose is that each descriptor represents the same region, namely the color histogram.

After representing the region with a color descriptor, the process then continues to calculating the similarity between a region and it neighboring regions. During the similarity calculation of the various regions using Euclidean distance, the process is continues and it's iterative till all the background is merged and left the object unmerged. The object is then extracted from the background. The Euclidean distance is used because it is another very simple and efficient measure of representing the similarity of regions by distance measurement[12][13]. Assuming that R and Q are the two regions. The similarity between the two regions is then calculated as shown in the equation below.

$$p(R, Q) = \sqrt{\sum_{u=1}^{8208}((Hist_R^u) - (Hist_Q^u))^2}$$ ……..…(11)

Wherein $Hist_R$ and $Hist_Q$ are the normalized histograms of R and Q, and u is the $u^{th}$ element of each region. At the end, the lower the value of the Euclidean distance between the regions *R* and *Q*, the higher similarity among all of the neighboring region. Figure 4 shows an example of a region *Q* and its neighboring regions *R*.

## 3.2 Marking the Object and Background

In interactive image segmentation methods, the help of users to specify the object and background is needed [14]. Users can enter their interactive input by drawing color markers that shows line to indicate the object or the background (Green = Object and Blue = Background).

The area that the green marker strokes marks the object is called the object marker area. Similarly, the pixels within that region are called the object pixels. Also the area that the blue marker strokes marks the background is called the background marker area[3][15]. The pixels within that region are called background pixels. Therefore the areas that are left untouched from both of the two colors, are called non-marker areas or regions [1]. Throughout this paper each of the images used must indicate a target object and its background.
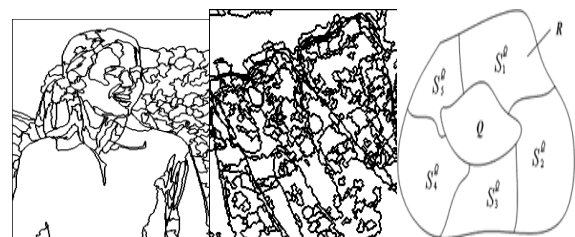


**Figure 4 Pre-segmented image and Region representation**

# 4. HIGHEST SIMILARITY RULE-BASED MERGING

After marking the object and the background, the next step in our method is done by identifying the areas of non-marker with the aid of a marker object and background [16][17]. Because the marker area covers only a small portion of the object and the background, and local non-marker must be identified and prevented from not merging with the background region. Then it can be used to identify the highest similarity based on our EPSF method. The assumed area Q located adjacent to the area of R and denoted by:

$$\rho(R, Q) = \max_{i=1,2,\dots q} \rho(Q, S_i^Q) \quad \dots\dots\dots\dots..(12)$$

From the equation above, the process of amalgamation or merging is done if has the highest similarity. The merging rule-gat san simple but this is the basis of the method to achieve such credit in this paper.

## 4.1 The Region Merging Process

Having obtained the highest similarity for each region. The process of merging is then carried out to extract the foreground from it background. For the merging process of this method, there are two stages that will be executed. During the first stage, the merging process will be executed on the background with all its other neighboring areas $B \in M_B$. For each region, will set up a collection area adjacent to B and is denoted by $\overline{S}_B = \{A_i\}_{i=1,2,\dots,r}$ Then for every $A_i$ and $A_i$ not a member $M_B$ ($A_i \notin M_B$), it will set up a collection of the area, which is expressed by the notation $\overline{S}_{A_i} = \{S_j^{A_i}\}_{j=1,2,\dots k}$. Certainly $B \in S_{A_i}$, will then calculate the similarity between $A_i$ and each of it element in $\overline{S}_{A_i}$. After doing the calculation, if the highest similarity rule shows that $A_i$ and $B$ has the greatest similarity, in the merging area then $S_j^{A_i}$ is denoted by:

$$\rho(A_i, B) = \max_{i=1,2,\dots q} \rho(A_i, S_j^{A_i}) \quad \dots\dots\dots\dots\dots.(13)$$

Thus the area of $A_i$ and $B$ will be merged into a single region. The new region will be labeled in the same region specifically the region $B$. However, if it does not meet the highest similarity rules, then $A_i$ and $B$ will not be merged.

The above procedure will be repeated several times in a recurrence manner until the procedure reach a halt, when all the background area or region $M_B$ have been completely merged. Once all the background area has been merged, in stage one. The procedure will then stop in the first stage of the merging process and hence indicate completion. However, not all parts of the background can sometimes entirely merge all the regions at the first stage. Because some of the object regions possessing higher similarity than the other areas or regions. Also some of the object regions are entrenched into some parts of the background.

To resolve the remaining problems from the first stage, the segmentation process will continue to the second stage. In such a situation the whole non-marker region that was left on the background area, will be merged [1]. Non-marker region that was left on the object and the background is therefore assumed to be $P \in N$. Eventually, the areas adjacent to P is as summed as $\overline{S}_P = \{H_i\}_{i=1,2,\dots P}$. Then for every $H_i$ which is not part of the background region ($H_i \notin M_B$) and $H_i$ which is not part of the object region ($H_i \notin Mo$), the set area is assumed to be $\overline{S}_{H_i} = \{S_j^{H_i}\}_{j=1,2,\dots P}$. There is also a region P confined in $\overline{S}_{H_i}$, then the similarity between P and each of the elements in $\overline{S}_{H_i}$ will be calculated, if the highest similarity rule is signified.

$$\rho(P, H_i) = \max_{i=1,2,\dots q} \rho(H_i, S_j^{H_i}) \quad \dots\dots\dots\dots\dots\dots(14)$$

Then $P$ and $H_i$ will be merged into a single region. However, if it does not meet the above merging rule then the process will go back and start from stage 1 and continue to stage 2 as describe by the procedure in this algorithm. It well run continuously until there is no longer a non-marker area N that can be merged. As such, these two stages (Stage 1 and Stage 2) will run continuously till there is no more area to merge.

Finally the results will shows two remaining areas that will be labeled as object and background. From this result, the program will now be able to easily extract the contour of an object from its background area.
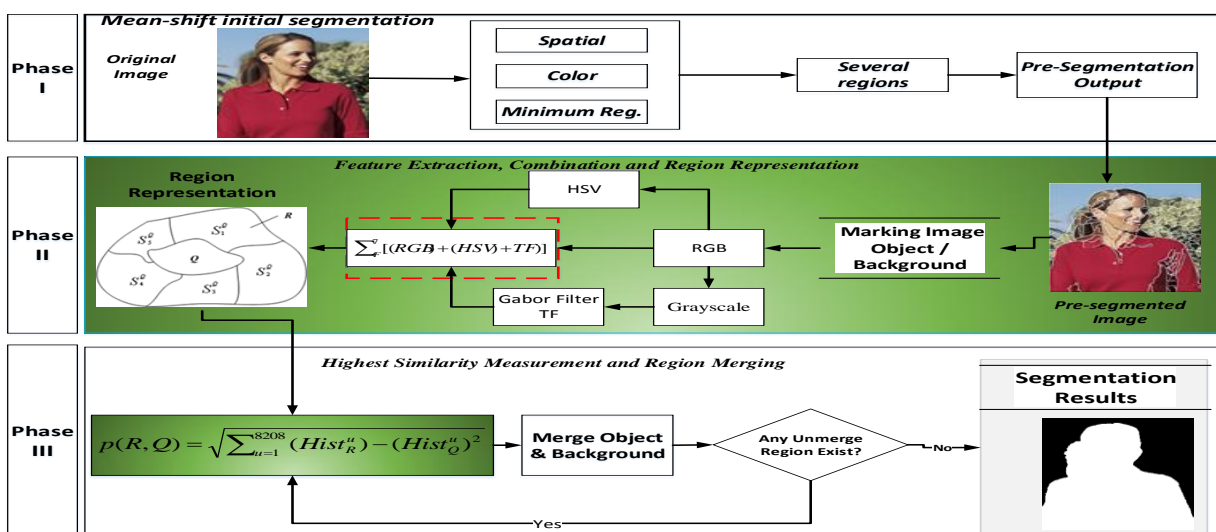


**Fig 5Flowchart method of EPSF**

# 5. THE SYSTEM LAYOUT AND METHODOLOGY

The figure below outline the various steps used in the execution of our proposed interactive segmentation method.The Figure 5 above shows a flowchart of our proposed interactive segmentation algorithm based on the highest similarity merging technique. From the chat, one can see that our input image is the pre-segmentation results of the mean shift segmentation software. To have a solid understanding on the mean shift operation, please see [10] The image is then read by the system and allowed by the user to give input to the system in order to direct the algorithm which portion of the image is a foreground or background. After the indication of the various regions, the user then click on a button shown on our program interface to command the algorithm to execute the segmentation process. The process then check the similarity of the various small regions of the background and the foreground that were produced as a results of the pre-segmentation with the EDISON SYSTEM. Each of the regions will only merge with its adjacent region if it meets the merging criteria.

## 5.1 The Designed Algorithm

Within our method, there are steps that are embedded in the highlighted phases above which reflected on our algorithm below shown in figure 3. Those steps are the ones we follow to achieve the completion of the program that led to our segmentation results. The method therefore outlines significant distinction of the mean-shift, feature extraction & combination and the highest similarity measurement.

It further shows the main connection to the color spaces of the RGB, HSV, and Gabor Filter. While the inclusion of the Gabor wavelet transformation method is required to assist the extraction of the image texture information. The highest similarities of combined features to merge the regions were also carryout within our method. Figure 6 below shows the algorithm.
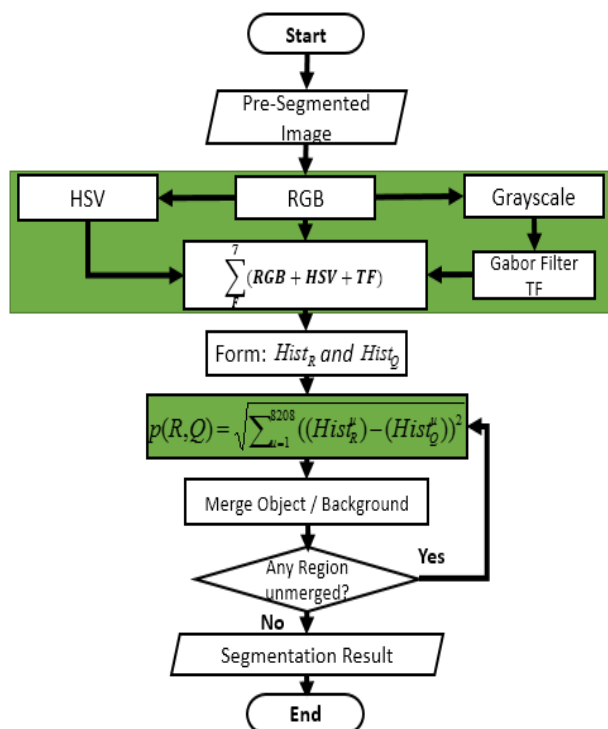


**Figure 6Algorithm of the EPSF method**

## 5.2 Experiments and Evaluations

The implementation of our proposed method is tested using various types of color images and mandible grayscale images. The color images are acquired from the Berkeley Segmentation Dataset (BSDS) [17] and a previous referenced source in[3], while the gray scale images form the IGS Laboratory of ITS Informatics department. Some of the images from the above mention repository and reference websites were used to evaluate our method as shown in Figure 6 below. Our experimental results is compared with other method by measuring the pixels of the foreground of the ground truth and the pixels of the foreground of our results using the misclassification error formula used by [18].

To evaluate the performance of our proposed method using a misclassification error, black and white image that were produced as a results of our segmentation method were compared with the segmentation results of other methods for the all color images used in this paper. For the case of the grayscale images acquired from the IGS Laboratory of ITS Informatics, we use a manually created ground truth by Photoshop software to measure the accuracy of our proposed method with another method that uses the same ground truth in its evaluation process. The misclassification error formula used in our method can measure the deviation (misclassified) pixels between our segmentation results and the Photoshop ground truth of the greyscale images. Therefore the lesser the percentage of the error when compared with the ground truth, the better the segmentation results.

$$ME = 1 - \frac{|B_O \bigcap B_T| + |F_O \bigcap F_T|}{|B_O| + |F_O|} \dots\dots\dots\dots(15)$$

Wherein the background and foreground pixels of our segmentation results (black and white image) are denoted by $B_O$ and $F_O$ while $B_T$ and $F_T$ for the background and foreground pixels (black and white image) of the ground truth image, respectively. The result of measurement is shown in terms of percent (%). The lesser the value from result measurement (close to 0%), the better the results. It is also important to highlight the fact that with better output, the accuracy of the segmented image become more similar to the ground truth.

In our experimental process, we uses two types of image. That is both color images and grayscale images. These two types of images are further divided in to two groups (I & II). The group one (I) contain nine (9) test images. That is, five color images and three color images. Whilst the group two (II) images contain forty five (45) images. That is, the test image, the ground truth, the segmentation result by our proposed method and the segmentation results of the compared method. In this paper, the six (6) color image in group one (I) are images obtained from [19] and[3]. Whilst the remaining three grayscale images are images obtained from the IGS laboratory of ITS Informatics department.

All the color images in group one (I) comes along with their ground truth from the source repository. While the grayscale image ground truth were obtained through Photoshop software. Note: all test images and their ground truth has equal dimensions. Therefore the ground truth and result that are used to measure the misclassified pixels has equal dimensions.

The group two (II) image are a set of images that contains the test, pre-segmented, segmentation results both our method and the compared method and the ground truth images.

As said earlier on, the test images were obtained from different sources in order to make a fair evaluation on our proposed method. Based on deviation difference of the segmentation results and the grown truth. Therefore conclusion are going to be drawn based on comparing the various methods used to segment those images and the deviation detected with the grown truth. Dental panoramic radiograph gray scale images used in this experiment consist of 200 x 200 pixels. Figure 4 below shows the images group (II).



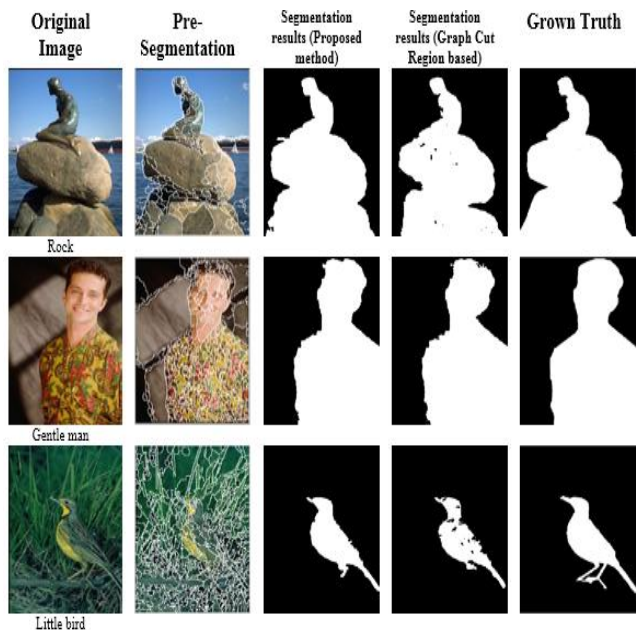**Figure 7 Group one (I) Test Images of equal dimensions**



**Figure 8 Group two (IIa) Original Images, Pre-Seg, Image, EPSF Result and Ground Truth of equal dimensions**
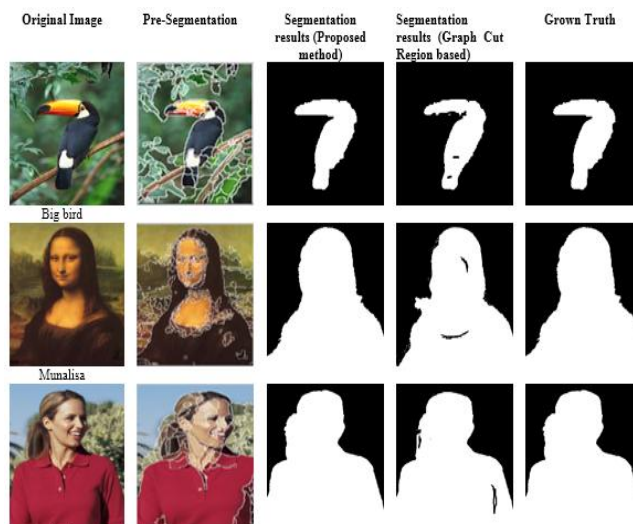


**Figure 9 Group two (IIb) Original Images, Pre-Seg, Image, EPSF Result and Ground Truth of equal dimensions**
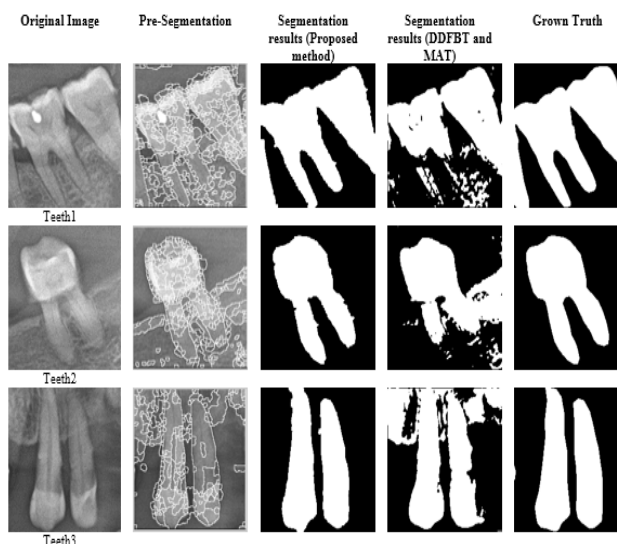


**Figure 10 Group two (IIc) Original Images, Pre-Seg, Image, EPSF Result and Ground Truth of equal dimensions**

From the above color images and dental panoramic greyscale images, it can be seen that all of the images have been pre-process with EDISON Mean-Shift System and then used our proposed method to segment each of the images. The experimental results has shown clear evidence to proof that our interactive segmentation method is very efficient and can segment various types of color images including grayscale or texture images. Furthermore, the marking strokes applied to each region of interest is a key towards the quality of the segmentation result. In this experiment, there are forty five (45) images shown in group two (II) which includes the nine test images shown in group (I).

Dental panoramic radiograph images used as test images in our method, were also used to compare the accuracy of our method with another method used in [19]. However, the results from our method has indicatively shown better accuracy compared with the previous method in [19]. The same case applied to the color images, we used our results to compare with[8]. The two tables below show the differences between out method and the previous methods.

**Table 1: Analysis of color images by comparing the proposed method with the Graph cut method**

| Image Name | Image Size | Proposed Method | | Graph Cut Method | |
|---|---|---|---|---|---|
| | | % Error with GT | % Accuracy with GT | % Error with GT | % Accuracy with GT |
| Rock | 232x350 | 1.68 | 98.32 | 3.84 | 96.16 |
| Gentle Man | 232x350 | 1.42 | 98.58 | 2.02 | 97.98 |
| Little bird | 232x350 | 2.02 | 97.98 | 2.88 | 97.12 |
| Big bird | 163x192 | 0.00 | 100.0 | 0.71 | 99.29 |
| Mona Lisa | 376x425 | 0.00 | 100.0 | 3.23 | 96.77 |
| Lady | 277x366 | 0.00 | 100.0 | 1.51 | 98.49 |

**Table 2: Analysis of grayscale images by comparing the proposed method with the Dimension-free Directional Filter Bank Thresholding and Multistage Adaptive Thresholding (DDFBT & MAT) method**

| Image Name | Image Size | Proposed Method | | DDFBT and MAT Method | |
|---|---|---|---|---|---|
| | | % Error with GT | % Accuracy with GT | % Error with GT | % Accuracy with GT |
| Teeth1 | 200x200 | 1.92 | 98.08 | 14.53 | 85.47 |
| Teeth2 | 200x200 | 0.86 | 99.14 | 16.63 | 83.37 |
| Teeth3 | 200x200 | 1.13 | 98.87 | 18.64 | 81.37 |

Experimental results with the six different kinds of color images and three gray scale images are shown in the above two tables. Within this scenario, our interactive image segmentation method using nine kind of color and texture images were segmented to show the results of each of the images segmentation experiment. These images has a number of characteristics in their regions and each of them are different. These nine kind of color and texture image were obtained from the different sources mention above. The purpose of this experiment was to determine the accuracy of the system with various images suing our proposed semi-automatic method and other methods.

The results of each segmentation experiment are compared with the ground truth of each of the images. However, the same ground truth is also used to compare with the other segmentation results of some other previous segmentation methods. From the segmentation results above, it is evidence that our proposed method shows better results compare to other segmentation methods.

From the results of the experiments performed on the nine color and texture image, it is indeed indicative that our proposed interactive method of image segmentation using the highest similarity to compare the various image regions, can properly segment the images and extract the foreground from it background.

# 6. CONCLUION

The Interactive image segmentation method used in this research, obtained accurate segmentation results from various kind of test images. The merging process was successfully carried out and the image contour regions were preserved accurately. The method used a pre-segmentation process to initially segment the image as a way of preparing it for the high level segmentation process.In addition, the seven member features used in this method were extracted and combined to distinctly merge the image regions in an accurate form. These member features are the main hub to make a correct and impartial representation for all the pre-segmented regions of the image. Thus it makes the segmentation process very flexible for all regions to be merged easily. Furthermore, the images used in this experiment are divided in to two groups. The first (I) group consist of only test images and the second (II) group consist of both the test and the experimental images, which is further divided in to three sets of image groups (that is, Color images with two sets(IIa and IIb) and the Grayscale images with one set). From experimental results of the color images in group two (setsIIa and IIb), we can observe that the images are evaluated by comparing our proposed method with that of the graph cut method using the same ground truth. The ground and each of the test images are compared with the experimental results using a misclassification error. The deviation between the ground truth and the segmentation results are considered as the misclassified error. Therefore, the smaller the error, the better the results.

The other experiment is carried out with the grayscale images (set IIc). In that experiment, we compared our proposed method with another method called Dimension-free Directional Filter Bank Thresholding and Multistage Adaptive Thresholding (DDFBT & MAT) used. The results of our proposed method was compared with the DDFBT & MAT using the same grown truth, by utilizing the misclassification error formula as well. The result shows that our proposed method produced better results.

It is important to indicate here that the accuracy of the results from our proposed method is highly dependent on the pre-segmentation results and the accuracy of the marking procedure. Therefore the user must ensure that the foreground and the background are indicated in a very proper manner, so that the algorithm of the merging process will be conducted accordingly. Looking at all the experiments of the nine different imaged and their evaluation scenario mentioned above, we can hereby conclude that the proposed (EPSF) interactive image segmentation method produced better segmentation results compared to the other methods.

Finally, the proposed algorithm of this method can be improve by reducing the segmentation time via updating the algorithm. Moreover, it is necessary to study the influence of interactive image segmentation techniques with regards to certain color characteristic which can further improve the similarity measurement of the various region.

# 7. ACKNOWLEDGMENTS

# 8. REFERENCES

[1] J. Ning, L. Zhang, D. Zhang, and C. Wu, "Interactive image segmentation by maximal similarity based region merging," Interact. Imaging Vis., vol. 43, no. 2, pp. 445–456, Feb. 2010.

[2] Costas Panagiotakis, HarrisPapadakis, EliasGrinias, and NikosKomodakis, "Interactive image segmentation based on synthetic graph coordinates," ScoenceDirect, vol. Volume 46, no. Issue 11, p. Pages 2940–2952, 2013.

[3] Pedro F. Felzenszwalb and Daniel P. Huttenlocher, "Efficient Graph-Based Image Segmentation," Int. J.

Comput. Vis., vol. Vol. 59, no. No. 2, p. pp 167–181, Sep. 2004.

[4] Frank Heckel, Olaf Konrad, Horst Karl Hahn, and Heinz-OttoPeitgen, "Interactive 3D medical image segmentation with energy-minimizing implicit functions," Virtual Real. Braz. Comput. Biol. Med. 3D Media ContentCultural Herit., vol. 35, no. 2, pp. 275–287, Apr. 2011.

[5] B. Chen, Q. Zou, and Y. Li, "A new image segmentation model with local statistical characters based on variance minimization," Appl. Math. Model., vol. 39, no. 12, pp. 3227–3235, Jun. 2015.

[6] Ming Zhang, Ling Zhangb, and H.D. Cheng, "A neutrosophic approach to image segmentation based on watershed method," Spec. Sect. Stat. Signal Array Process., vol. 90, no. 5, pp. 1510–1517, May 2010.

[7] Gururaj P Surampalli, Dayanand J, and Dhananjay M, "An Analysis of Skin Pixel Detection using Different Skin Color Extraction Techniques," Int. J. Comput. Appl. 0975 - 8887, vol. 54, Sep. 2012.

[8] Dunn D and Higgins WE., "Optimal Gabor filters for texture segmentation," IEEE Trans. Image Process., vol. 4, no. Issue 7, pp. 947 – 964, Year 1995.

[9] Meer, P and Georgescu, B., "Edge detection with embedded confidence," Pattern Anal. Mach. Intell. IEEE Trans., vol. 23, no. 12, pp. 1351 – 1365, Aug. 2002.

[10] Doring Comaniciun and Peter Meer, "Mean Shift: A Robust Approach Towards Feature Space Analysis.," IEEE, vol. 24, no. 5, pp. 603 – 619, May 2002.

[11] Birchfield, S., "Elliptical head tracking using intensity gradients and color histograms," IEEE Conf. Comput. Vis. Pattern Recognit., pp. 232 – 237, Jun. 1998.

[12] Liwei Wang, Yan Zhang, and Jufu Feng, "On the Euclidean Distance of Images," IEEE Trans. Pattern Anal. Mach. Intell., vol. 27, no. 8, pp. 1334 – 1339, Aug. 2005.

[13] Donald G Bailey, "An Efficient Euclidean Distance Transform," 10th Int. Workshop IWCIA 2004, vol. 3322, no. 2, pp. 394–408, Dec. 2004.

[14] Qiong Yang, Xiaoou Tang, Chao Wang, and Zhongfu Ye, "Progressive Cut: An Image Cutout Algorithm that Models User Intentions," Multimed. IEEE, vol. 14, no. 3, pp. 56–66, Sep. 2007.

[15] C. Panagiotakis, H. Papadakis, E. Grinias, N. Komodakis, P. Fragopoulou, and G. Tziritas, "Interactive image segmentation based on synthetic graph coordinates," Pattern Recognit., vol. 46, no. 11, pp. 2940–2952, Nov. 2013.

[16] T. N. A. Nguyen, J. Cai, J. Zheng, and J. Li, "Interactive object segmentation from multi-view images," J. Vis. Commun. Image Represent., vol. 24, no. 4, pp. 477–485, May 2013.

[17] University of California and Berkeley Segmentation Dataset (BSDS), "Berkeley Segmentation Dataset and Benchmark," Comput. Vission Group, vol. BSDS500, no. 1, Jan. 2013.

[18] Agus, Z A. and Akira A, "Image segmentation by histogram thresholding using hierarchical cluster analysis," Pattern Recognit. Lett., vol. 27, no. 13, pp. 1515–1521, Oct. 2006.

[19] Rarasmaya Indraswari, Agus Zainal Arifin, Dini Adni Navastara, and Nasar Jawas, "Teeth Segmentation on Dental Panoramic Radiograph using Dimension-free Directional Filter Bank Thresholding and Multistage Adaptive Thresholding," Inf. Commun. Technol. Syst. ICTS 2015 Int. Conf., pp. 49 – 54, Sep. 2015.