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# Color Image Segmentation by Multilevel Thresholding using a Two Stage Optimization Approach and Fusion

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***Abstract*—In this paper, we propose a new color image segmentation method based on a multilevel thresholding algorithm and data fusion techniques. We have revised the Otsu method for selecting optimal threshold values for both unimodal and bimodal distributions, and tested the performance of the new automatic thresholding method called the TSMO (Two-Stage Multi-level Thresholding) on the color images segmentation. This algorithm is iterative and outperforms Otsu's method by greatly reducing the iterations required for computing the between-class variance in an image. For segmentation, we proceed in two steps. In the first step, we begin by identifying the optimal threshold of the tristimuli (R, G and B). In the second step, segmentation results for the three color components are integrated through the fusion rule, in order to get a final reliable and accurate segmentation result. Experimental segmentation results on medical and textured color images demonstrate the value of combing the thresholding technique and fusion rule for color image segmentation. The obtained results show the robustness of the proposed method.***

*Index Terms*—**Multilevel thresholding, Segmentation, Medical image, fusion, thresholding, Otsu method.**

## I. INTRODUCTION

Image segmentation serves as the key of image analysis and pattern recognition [1] [2]. It is one of the most difficult tasks in image processing, which determines the quality of the final result of analysis [3] [4]. The image segmentation is a process of dividing an image into different regions such that each region is homogeneous, but the union of any two regions is not [4] [5]. More recent research has focused on color image segmentation due to its demanding need [6] [7]. In color image segmentation, color of a pixel is given as three values corresponding to the three component images R (Red), G (Green) and B (Blue). At present, color image segmentation methods are mainly extended from monochrome segmentation approaches by being implemented in different color space. Gray level segmentation methods can be applied directly to each component of a color space, and then the results can be combined in some way to obtain a final segmentation result [4] [8]. Thresholding [9] [10] [11] is widely used in many image processing applications such as (1) medical image applications [12]; (2) automatic visual inspection of defects [13] [14]; (3) optical character recognition [15], and (4) detection of video change [16] [17]. Otsu's method [18] is one of the better ways of image segmentation, where the image contains only two classes. This method selects the threshold value by maximizing the separability of the classes in gray levels. It efficient for thresholding an image with a histogram of bimodal distribution, but they are impractical when extended to multilevel thresholding. To improve the efficiency of Otsu's method, Deng-Yuan Huang et al. [19] have proposed a new fast algorithm called the TSMO method (Two-Stage Multithreshold Otsu method). The TSMO method outperforms Otsu's method by greatly reducing the iterations required for computing the between-class variance in an image. In the past, many authors have addressed the problem of color image segmentation using different methods [20] [21] [22] [23] and, in particular, several researchers have investigated the hybrid methods for color image segmentation [24] [25 [26]. In this context, Lim et al. [27] have proposed a color image segmentation method based on the Thresholding and the Fuzzy C-means techniques (TFCM). The methodology uses a coarse-fine concept to reduce the computational burden required for the FCM algorithm. With the same objective, S. Ben Chaabane et al. [6] have proposed a color cells images segmentation method based on histogram thresholding and Dempster-Shafer evidence theory (TDS). The objective is to rebuild each cell from the three primitive colors (R, G and B) of the original image. From an initial segmentation obtained by using the histogram thresholding, one seeks a segmentation which represents as well as possible the points really forming part of the cells, as also the number of the cells. Also, Zhu et al. [5], have proposed a segmentation method based on Fuzzy c-means algorithm and Dempster-Shafer evidence theory (FCMDS). The membership degree of each pixel coming from the different images to be combined is obtained by applying the FCM algorithm to the gray level of the three component images (R, G and B). Then, the DS combination rule and decision are applied to obtain the final segmentation. The color segmentation method, proposed in this paper, is conceptually different and explores a new strategy. In fact, instead of considering an elaborate and better designed color segmentation method, our technique rather explores the possible alternative of combining automatic thresholding algorithm and data fusion techniques. After the determination of the optimal threshold of each component image, the fusion rule is used to obtain the final segmentation results. The optimal thresholds of each component image are computed using the two-stage Otsu optimization approach [19]. Then, segmentation results for the three color components are

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integrated through a fusion rule in order to get a final reliable and accurate segmentation result. This method is applied to color image segmentation, where we aim at providing help to the doctor for the follow-up of the diseases of the breast cancer. The objective is to rebuild each cell from a series of three component images (R, G and B). From an initial segmentation obtained by using the automatic thresholding technique, one seeks a segmentation which represents as well as possible the cells, in order to give to the doctors a schema of the points really forming part of the cells, as also the number of the cells. Section 2 introduces the proposed method for color image segmentation. The experimental results are discussed in Section 3, and the conclusion is given in Section 4.

## II. THE PROPOSED METHOD

For color images with RGB representation, the color of a pixel is a mixture of the three primitive colors red, green, and blue. By applying a segmentation technique to the red, green or blue color features, in this case, a region can be recognized in one of the three components but is not identified by the other components. This shows the high correlation among the R, G, and B components [4] [6] [8]. By high correlation, we mean that if the intensity changes, all the three components will change accordingly. In this context, color image segmentation using data fusion techniques appears to be an interesting method. The segmentation method, proposed in this paper, is conceptually different and explores a new strategy. In fact, instead of considering an elaborate segmentation procedure, our technique rather explores the possibility of combining several approaches. This method is an hybrid image segmentation technique which integrates the results of the automatic thresholding algorithm and data fusion technique, in which the thresholding technique is used to select the optimal threshold in each image to be combined. In this work, we are interested in color image segmentation of cells in the breast images. The problem is to separate cells from the background. The initial segmentation maps which will then be fused together are simply given, in our application, by the automatic thresholding technique [19], applied on the three primitive colors (R, G and B). Then the combination rule is used to obtain the final segmentation results. This technique allows obtaining an optimal segmented image, superior to versus existing techniques [5] [6] [27].

### *A. Recursive Otsu Method*

Histogram thresholding is one of the widely used techniques for monochrome image segmentation. Otsu's method is one of the better ways of image segmentation, which selects a global threshold value by maximizing the separability of the classes in gray levels. This method is efficient for thresholding a histogram with bimodal distribution, but it is inefficient if there is a large class number M required in an image due to the fact that it involves a large number of repetitious computations of the zero- and first-order cumulative moments of the gray-level histogram. A comprehensive survey of image thresholding methods is provided in [9] [10]. To significantly improve the deficiencies in Otsu's method with regard to selecting the multi-level threshold, we use an algorithm called the Two-stage Multithreshold Otsu's method (TSMO). A general concept of the TSMO method is given in Ref. [19]. The idea of this method is quite simple and straightforward: to greatly reduce the iterations required for calculating the zeroth and first-order moments of a class. In the first stage of the TSMO method, the histogram of an image with $L$ gray levels is divided into $M_z$ groups which contain $N_z$ gray levels. Let $\Omega$ denote the groups of the total image space; then $\Omega = \{\Omega_j \mid j = 0,1,\ldots, M_z - 1\}$, where j represents the group number. Hence, each group contains a certain range of gray levels as follows: $\Omega_0$ contains a range of gray levels $\{0,1,\ldots, N_z - 1\}$, $\Omega_1$ with gray levels $\{N_z, N_Z + 1,\ldots, 2N_Z - 1\},\ldots,$ $\Omega_q$ with gray levels $\{qN_z, qN_z + 1,\ldots,(q+1)N_z - 1\},\ldots,$ and the last group $\Omega_{M_z - 1}$ with gray levels $\{(M_z - 1)N_z, (M_z - 1)N_z + 1,\ldots, M_z N_z - 1\}$.

The number of cumulative pixels (the zeroth- order cumulative moment), in the $q^{th}$ group denoted by $g\Omega_q$ can be calculated as:

$$g_{\Omega_q} = \sum_{i=q\times N_z}^{(q+1)\times N_z - 1} f_i \tag{1}$$

where $f_i$ represents the number of pixels with gray level $i$. Since each group contains $N_z$ gray levels, the corresponding gray level value for each group can be considered as a mean value for those $N_z$ gray levels. Therefore, the corresponding gray level value or mean intensity (the first-order cumulative moment), in the $q^{th}$ group denoted by $i_{\Omega q}$ can be calculated as:

$$\begin{aligned} i_{\Omega q} &= \sum_{i=q\times N_z}^{(q+1)\times N_z - 1} i f_i \Bigg/ \sum_{i=q\times N_z}^{(q+1)\times N_z - 1} f_i \\ &= \frac{1}{g_{\Omega q}} \sum_{i=q\times N_z}^{(q+1)\times N_z - 1} i f_i \end{aligned} \tag{2}$$

Hence, Otsu's method can be applied to find the optimal threshold $j^*$ by maximizing the between-class variance $(\sigma_B^2)$ with the sets of $i_\Omega$ and $g_\Omega$. The optimal threshold $j^*$ which is also regarded as the number of the group into which the maximum variance of the between-class, i.e., $(\sigma_B^2)_{\max}$, falls with the corresponding group $\Omega_{j^*}$ is defined as:

$$j^* = \arg\max_{0 \le j \le M_z - 1} \{\sigma_B^2(j)\} \tag{3}$$

If an image can be divided into two classes, $C_1$ and $C_2$, by $\Omega_{j^*}$, where class $C_1$ consists the group from $\Omega_0$ to $\Omega_{j^*}$,

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and class $C_2$ contains the other groups with $\Omega_{j^*+1}\ to\ \Omega_{M_z-1}$, then the numbers of the cumulative pixels and the means for the two classes, respectively, are given by:

$$w_1(j^*) = \sum_{j=0}^{j^*} g_{\Omega j} \tag{4}$$

$$w_2(j^*) = \sum_{j=j^*+1}^{M_z-1} g_{\Omega j} \tag{5}$$

and

$$\mu_1 = \frac{S_1}{w_1} \tag{6}$$

$$\mu_2 = \frac{S_2}{w_2} \tag{7}$$

where $S_1$ and $S_2$ are the first-order cumulative moments for classes $C_1$ and $C_2$, respectively

$$S_1 = \sum_{j=0}^{j^*} i_{\Omega j} g_{\Omega j} \tag{8}$$

$$S_2 = \sum_{j=j^*+1}^{M_z-1} i_{\Omega j} g_{\Omega j} \tag{9}$$

Thus, the maximum variance of the between-class $(\sigma_B)^2{}_{\max}$, can be easily found using the modified version of Otsu's method proposed by Liao et al. [28]. In the case of bi-level thresholding $(M = 2)$, the maximum variance of the between-class is defined as:

$$\begin{aligned}(\sigma_B)^2_{\max} &= \sum_{k=1}^{M} w_k \mu_k^2 = w_1\mu_1^2 + w_2\mu_2^2 \\ &= \frac{S_1^2}{w_1} + \frac{S_2^2}{w_2} \\ &= \frac{S_1^2}{w_1} + \frac{(S_T - S_1)^2}{N - w_1}\end{aligned} \tag{10}$$

where M is the class number in an image, $S_T$ is the sum of $S_1$ and $S_2$, and $N$ is the total number of pixels in an image. That is

$$\begin{aligned} S_T &= S_1 + S_2 \\ N &= w_1 + w_2 \end{aligned} \tag{11}$$

In the second stage of the TSMO method, since $\Omega_{j^*}$ contains the gray levels with $(j^*)N_z$ to $(j^*+1)N_z - 1$ in which $(\sigma'_B)^2_{\max}(j^*)$ occurs has already been found in the first stage, Otsu's method can be applied again to group $\Omega_{j^*}$ in a similar fashion to found the optimal threshold $T$. Hence

$$T = \arg_{(j^*)N_z \le t \le (j^*+1)N_z-1} \max\{(\sigma'_B)^2(t)\} \tag{12}$$

### B. Fusion of the Segmentation Map

The optimal threshold T is automatically determined by the two-stage Otsu optimization approach, as described in section 2.1. Given an optimal threshold, e.g. $T_R$, , the $R_s$ function classifies the pixels on the Red component into two opposite classes: objects versus background , as:

$$R_s(x,y) = \begin{cases} 1 & \text{interrest object} \quad if\ R(x,y) \ge T_R \\ 0 & \text{background} \quad if\ R(x,y) < T_R \end{cases} \tag{13}$$

In fact, the pixel $(x, y)$ is classified as an interest object (the cells in the biomedical image) if its gray level pixel $R(x, y)$ is higher than the optimal threshold determined automatically by the two stage Otsu's thresholding technique, in which case is set to 1. Otherwise, it is classified as a background pixel and is set to 0.

Therefore, an analogous segmentation procedure is further performed on the components G and B, as:

$$G_s(x,y) = \begin{cases} 1 & \text{interrest object} \quad if\ G(x,y) \ge T_G \\ 0 & \text{background} \quad if\ G(x,y) < T_G \end{cases} \tag{14}$$

$$B_s(x,y) = \begin{cases} 1 & \text{interrest object} \quad if\ B(x,y) \ge T_B \\ 0 & \text{background} \quad if\ B(x,y) < T_B \end{cases} \tag{15}$$

where $G(x, y)$ and $B(x, y)$ indicate the gray level of the Green and Blue pixel at $(x, y)$ and $T_G$ and $T_B$ indicate the respective optimal thresholds. These optimal thresholds are also determined automatically by the two-stage Otsu optimization approach described in Section 2.1.

Once the segmentation results for the three components (R, G and B) are formed, their joint edge is calculated according to the following formula:

$$S(x,y) = \begin{cases} 1 & \text{interrest object} \quad if\ R_s(x,y) = 1 \cup \\ & G_s(x,y) = 1 \cup B_s(x,y) = 1 \\ 0 & \text{background} \quad otherwise \end{cases} \tag{16}$$

Pixel $(x, y)$ is classified as an object if it is so classified by at least one of its three color components, in which case $S(x, y)$ is set to 1. Otherwise, it is classified as a background pixel and $S(x, y)$ is set to 0. The major steps of the proposed segmentation method are depicted in the flowchart shown in Fig. 1.

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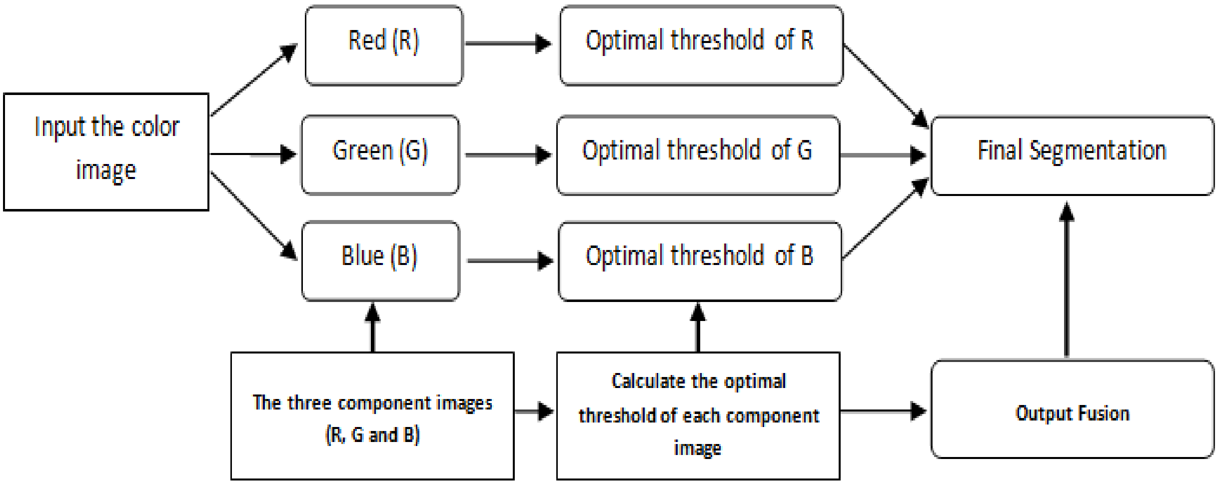


**Fig 1. Flowchart of the proposed method.**

## III. EXPERIMENTAL RESULTS AND DISCUSSION

To evaluate the efficiency and accuracy of the proposed method, the results are compared versus existing methods, as described earlier. The efficiency evaluations for these different methods are carried out on the Matlab software 7.1.

For the accuracy evaluations, the segmentation sensitivity $(Sen\%)$ method is used to determine the number of correctly classified pixels. The evaluated color cells images with 100 test images and synthetic images with 70 test images were used; some sample images are shown in Figure 2.

The images originally are stored in RGB format. Each of the primitive color (red, green and blue) takes 8 bits and has the intensity range from 0 to 255.

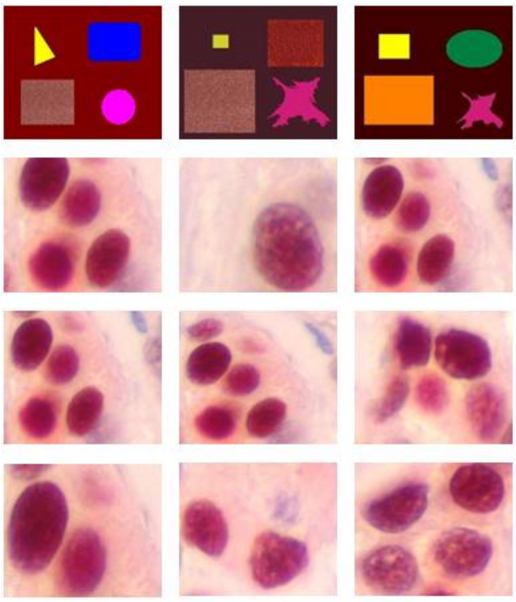

**Fig 2. Data set used in the experiment. Twelve were selected for a comparison study. The patterns are numbered from 1 through 12, starting at the upper left-hand corner.**

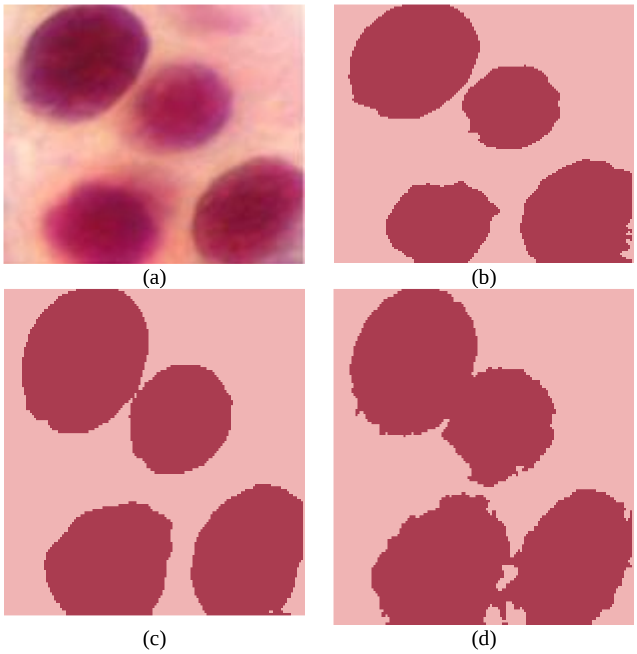


**Fig 3. Segmentation results on a complex medical image (2 classes, various cells). (a) Original image (256x256x256) color medical image with RGB description, (b) Red resulting image by TSMO method, (c) Green resulting image by TSMO method, (d) Blue resulting image by TSMO method. The select thresholds are 197; 108 and 125, respectively.**

Figure 3 shows a medical image provided by a cancer hospital. Figures 3(b), (c) and (d) show the final segmentation results obtained from the TSOM applied to Red, Green and Blue components, respectively. The selected thresholds are 197; 108 and 125, respectively. Comparing Figures 3(b), 3(c), and 3(d), one can see that the different cells of the image are much better segmented in (b) than those in (c) and (d). Also, the first resulting image contains some missing features in one of the cells, which do not exist in the other resulting images. This shows the lack of information when using only one information source and may be explained by the high degree of correlation among of the three components of the RGB color space. Hence, it demonstrates the necessity of the merging process. For purpose of comparison, we apply the proposed approach and some existing approaches to the same-color image segmentation. The latter methods include those of Lim et al. [27], Ben Chaabane et al. [6] and Zhu et al. [5].

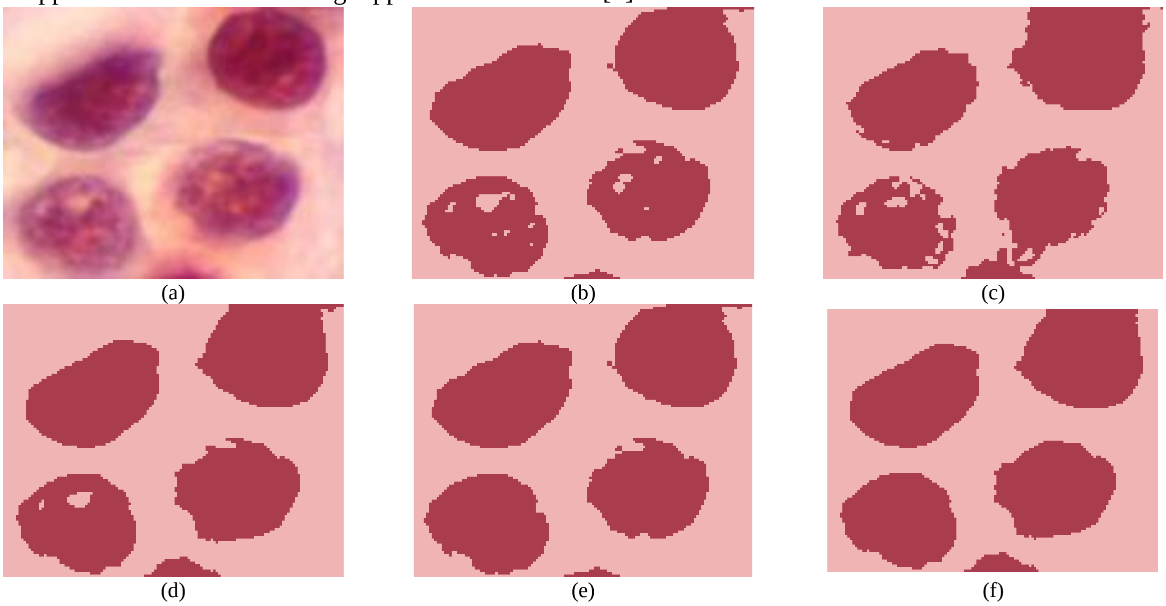


**Fig 4. Comparison of the proposed segmentation method with other existing methods on a medical image, (a) original image with RGB representation, (b) segmentation based on TFCM method, (c) segmentation based on TDS method, (d) segmentation based on FCMDS method, (e) segmentation based on the proposed method, and (f) reference segmented image.**

**Table 1. Segmentation sensitivity From TFCM, TDS, FCMDS and the proposed method for the Data set Shown in Fig 2.**

| | TFCM | TDS | FCMDS | TSMO AND FUSION (PROPOSED METHOD) |
|---|---|---|---|---|
| | SENSITIVITY SEGMENTATION (%) | | | |
| **Image 1** | 0.9454 | 0.9549 | 0.9643 | 0.9785 |
| **Image 2** | 0.9300 | 0.9393 | 0.9486 | 0.9626 |
| **Image 3** | 0.9371 | 0.9465 | 0.9558 | 0.9699 |
| **Image 4** | 0.8819 | 0.8907 | 0.8995 | 0.9128 |
| **Image 5** | 0.9039 | 0.9129 | 0.9220 | 0.9355 |
| **Image 6** | 0.9138 | 0.9229 | 0.9321 | 0.9458 |
| **Image 7** | 0.8850 | 0.8939 | 0.9027 | 0.9160 |
| **Image 8** | 0.9110 | 0.9201 | 0.9292 | 0.9429 |
| **Image 9** | 0.9088 | 0.9179 | 0.9270 | 0.9406 |
| **Image 10** | 0.9224 | 0.9316 | 0.9408 | 0.9547 |
| **Image 11** | 0.9040 | 0.9130 | 0.9221 | 0.9356 |
| **Image 12** | 0.8671 | 0.8758 | 0.8844 | 0.8974 |

The segmentation results obtained by TFCM [27], TDS [6] and FCMDS [5] methods are shown in Figs. 4(b), (c) and (d), respectively. Fig. 4(e) shows the segmentation based on TSOM and Fusion (proposed method) and Fig. 4(f) represent the reference segmented image. In fact, the cells are exactly and homogeneously segmented in Fig. 4(e), which is not the case in Fig. 4(b), (c) and (d). To evaluate the performance of the proposed segmentation algorithm, its accuracy was recorded. Regarding the accuracy, Tables 1 lists the segmentation sensitivity of the different methods for the data set used in the experiment.

The segmentation sensitivity [29] [30], is determined as follows:

$$Sens(\%) = \frac{N_{pcc}}{N \times M} \times 100 \tag{17}$$

with: $Sen(\%)$ , $N_{pcc}$ , $N \times M$ denote respectively the segmentation sensitivity (%), the number of correctly classified pixels and the dimension of the image.

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Also, to evaluate the performance of the proposed color-segmentation method, we tested many color synthetic images.

Fig. 5(a) gives the original synthetic image, Fig. 5(b) represent the $N \times M$ synthetic image where a *"salt and pepper"* noise of $D$ density was added. This affects approximately $(D \times N \times M)$ pixels.

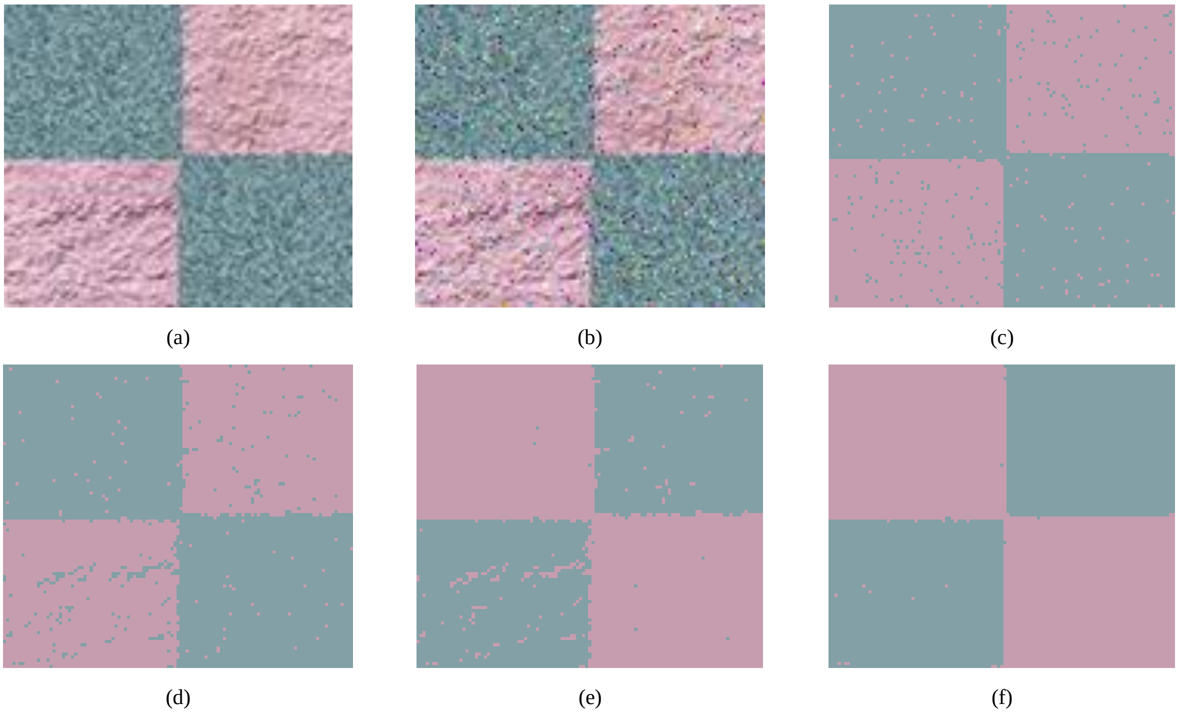


**Fig 5. Comparison of the proposed segmentation method with other existing methods on a medical image, (a) original image with RGB representation, (b) color synthetic image disturbed with a "salt and pepper" noise, (c) segmentation based on TFCM method, (d) segmentation based on TDS method, (e) segmentation based on FCMDS method, and (f) segmentation based on the proposed method.**

Figs. 5(c), (d), and (e) show the segmentation results obtained by TFCM, TDS and FCMDS methods, respectively. Fig. 5(f) shows the segmentation based on proposed method. Comparing Figs. 5(c), (d), (e), and (f), we observe that the two regions are correctly segmented in Fig. 5(f), showing the complementary information provided by three primitive colors and the efficacity of the TSMO method for determining the multi-level thresholds of an image. The performance of the proposed method is quite acceptable. It can be seen from Table 1 that 13.26% 10.64% and 10.55% of pixels were incorrectly segmented for the TFCM, TDS and FCMDS methods, respectively, but only 03.13% are incorrectly segmented pixels by our proposed method. Comparing Figs. 5(c),(d), and (e) with (f), we can see that the image resulting from the proposed method is much clearer than the one resulting from the TFCM, TDS and FCMDS based methods.

## IV. CONCLUSION

In this paper, we have proposed a new method to color image segmentation based on multi-level thresholding technique and data fusion. In the first phase, uniform regions are identified in each primitive color via a thresholding operation. Then, the combination rule is applied to fuse the three primitive colors. Instead of considering an elaborate and better designed segmentation model of biomedical and textured images, our technique rather explores the possible alternative of combining two segmentation techniques in order to get a good consistency segmentation results. The results obtained demonstrated the significant improved performance in segmentation. The proposed method can be useful for color image segmentation.

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