Impact of Using Different Color Spaces on the Image Segmentation

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Abstract. Image segmentation is considered one of the most difficult challenges in image processing. Recently many advanced applications have emerged in this field. Color images provide more information and more reliable in segmentation than grayscale images. In this paper, the color spaces RGB, YCbCr, XYZ, and HSV are compared using four different methods of image segmentation. These methods are k-means, Fuzzy C-means, Region growing, and Graph Cut. The main objective of image segmentation is to simplify and change the image to something more meaningful and easier to analyze. In this study, we used single-color space components. In addition to this, we vote between the three components of every color space in the segmented image to get the best image segmentation result. Different RGB color images from Berkeley databases are used. The accuracy of the image segmentation is measured using the peak signal-to-noise ratio (PSNR) and mean square error (MSE). The experimental results show that the voting between color components achieved good segmentation accuracy.

Keywords: Color image segmentation · Color spaces · K-mean · Fuzzy C-mean · Region growing

1 Introduction

Image Segmentation is an important task in image processing, that dividing an image into parts, objects, or different regions based on pixels. Each set of pixels in a region has similar properties such as color, intensity or texture, etc. [1, 2].

Image segmentation continues to be widely used in advanced applications in many fields like machine vision, face recognition, traffic control systems, medical imaging, and others [3]. The image represents a finite set of digital values called pixels. Images may be grayscale or color images. So, image segmentation may be either gray scale image segmentation or color image segmentation. Color images as provide more information and enhance the processing of analysis images than grayscale images [4].

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The pixel's of digital color images can be represented in different color space models for different color image segmentation techniques [5]. A color space represents visual information that describes the color spectrum as a multidimensional model which most color spaces have three dimensions and the basic digital color image is given in RGB coordinate [4, 6].

Image segmentation has an important influence on image analysis and understanding [7]. There are different methodologies for the image segmentation process, these methodologies can be organized into different groups: Histogram, Thresholding, Clustering, Region-based, Edge-based, Model-based, Fuzzing approaches, and Neural Network-based [7, 8].

In this paper, different image segmentation methods are used to study the impact of changing the color space models on image segmentation accuracy. K-means, FCM, Region Growing, and Graph Cut methods are used in this paper. In experimentl results, we used the RGB, YCbCr, XYZ, HSV color spaces. The image segmentation methods apply to the single color component of the RGB, YCbCr, XYZ, HSV color spaces. We also vote on the segmented image of the three components of every color space. The performance is measured using the peak signal-to-noise ratio (PSNR) and mean square error (MSE).

The rest of the paper is organized as follows. Section 2 presents the related work. Section 3 describes the color spaces used in our experiments. Section 4 describes the image segmentation methods. Section 5 shows the experimental results. Section 6 concludes the results of the paper.

2 Related Work

It is an important and interesting problem to understand and analyze the image for color image segmentation, but not found the specific color space can be best for every image segmentation problem [9]. In this section, we survey several image segmentation methods based on different color spaces. In recent years, a lot of researchers received attention to image segmentation and the relation between color spaces and segmentation.

Jurio et al. [10] presented a comparative study between different color spaces in cluster-based image segmentation. The comparison carried out between four color spaces HSV, YUV, CMY, and RGB. The authors concluded that CMY is the best color space for most cases. Burney et al. [11] analyzed the algorithm of k-means clustering for image segmentation methods. This study proposed how to work on the k-means cluster algorithm for some color spaces (RGB and LAB). This work concluded that the LAB color space achieved better than RGB color space. Khattab et al. [12] presented a comparative study using different color spaces to evaluate the performance of color image segmentation using the automatic Grab Cut method. The author used RGB, HSV, XYZ, CMY, and YUV color spaces. The experiments result show that RGB color space is the best color.

Mythili et al. [13] k-means clustering and Effective robust Kernclized fuzzy C-means(ERKFCM) for color image segmentation based on different color spaces such as RGB,HSV,YIQ,and XYZ by using the PSNR and MSE to evaluate the performance that gave the combine segmentation of various color spaces give more accurate segment of signal color.

Shih et al. [14] presented an efficient segmentation algorithm for the color image using automati seed region growing. The authors firstly convert input RGB color space to YCbCr color. Second, automatically select initial seeds. Third, the color image is segmented into regions. Finally, region merged This method carried out good results used k-means clustering and Effective Robust Kernelized fuzzy C-means (ERKFCM) for color image segmentation based on different color spaces such as RGB, HSV, YIQ, and XYZ. The authors used the PSNR and MSE to evaluate the performance. The experiments result show that combined segmentation of various color spaces archived more accurate segment than using signal color space.than existing algorithms in the paper.

Wang et al. [15] applied a comparison of different color spaces for image segmentation using Graph Cut. The tested colors, RGB, HSV, L*U*V, and L*a*b show that the color space L*a*b archived higher or similar quality as all other methods, but RGB worse than segmentation-based on any other tested color space.

Busin et al. [16] analyzed the use of color spaces and image segmentation. They described the choice of color space significantly depending on the kind of image to be segmented and the segmentation method. The evaluation was used for the selection that was based on spectral color analysis.

3 Color Spaces

A color space is an abstract mathematical model describing the way colors can be represented as tuples numbers (e.g. triples in RGB or quadruples in CMYK). However, there are a lot of different color spaces, each with its properties, advantages, limitations, and areas of application [10, 17].

In this study, we are comparing four color spaces in image segmentation are RGB (Red, Green, Blue), HSV (Hue, Saturation, Value), YCbCr (Luminance (Y), Chrominance (Cb, Cr)), and XYZ (Luminance (Y), Chromaticity coordinates (X, Z)).

3.1 RGB

The RGB color space is all possible colors that can be made from three colorants red, green, and blue. The RGB model considers the most natural space and is commonly used in image processing, computer graphics, and multimedia systems. So, all color spaces can be derived from the RGB information, so that we are going to use this color space as in [9].

3.2 HSV

The HSV (Hue, Saturation, Value) color space is very close to the RGB color space in which humans create and perceive colors in the sense of color. HSV color space attempts to characterize colors according to their hue (H), light objects in saturation (S), and intensity (value, or lightness).

Note that, hue represents the color degree of the image, light objects in saturation is the amount of the color, and intensity is amount of light (it allows the distinction between a dark color and a light color). The relationship between HSV and RGB can be described as follows.

$$H = \begin{cases} 0. & \text{if } max = min \\ \left(60^\circ \times \frac{G-B}{max} + 360^\circ\right) mod\ 360^\circ. & \text{if } max = R \\ 60^\circ \times \frac{B-R}{min} + 120^\circ. & \text{if } max = G \\ 60^\circ \times \frac{\pi - min}{max-min} + 240^\circ. & \text{if } max = B \end{cases} \tag{1}$$

$$S = \begin{cases} 0. & \text{if } max = 0 \\ \frac{max-min}{max} = 1 - \frac{min}{max}. & \text{otherwise} \end{cases} \tag{2}$$

$$V = max \tag{3}$$

3.3 YCbCr

The YCbCr is a technique of color spaces known as transmission primaries. It is used for digital video and photography systems. It belongs to the family of television transmission color spaces. The family includes others such as YUV and YIQ [18]. The YCbCr separates RGB into Luminance (Luma Y) and (chroma [Cb and Cr]). (Luma Y) is the brightness that occurs using black and white gray shades. And Chrominance (chroma [Cb and Cr]), is the color information in a signal mainly concentrated on "YCbCr" either in a red or blue signal [19]. The following equations show to convert from RGB to YCbCr.

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 0{\cdot}2989 & 0{\cdot}5866 & 0{\cdot}1145 \\ -0{\cdot}1688 & -0{\cdot}3312 & 0{\cdot}5000 \\ 0{\cdot}5000 & -0{\cdot}4184 & -0{\cdot}0816 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{4}$$

3.4 XYZ

The XYZ is the first color space created by the international commission on illumination in 1931 so that XYZ called CIE XYZ [20]. The model can be described as the luminance component Y and the chromaticity information. The value of X, Y, Z are computed using a linear transformation from RGB color coordinates, as shown in the following equations:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0{\cdot}4125453 & 0{\cdot}357580 & 0{\cdot}180423 \\ 0{\cdot}212671 & 0{\cdot}715160 & 0{\cdot}072169 \\ 0{\cdot}019334 & 0{\cdot}119193 & 0{\cdot}950227 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{5}$$

4 Segmentation Techniques

This section reviews the K-Means, Fuzzy C-Means, Region Growing, and Graph Cut in the following subsections:

4.1 K-Means Clustering Segmentation

K-Means algorithm is the most popular partitioning-based clustering technique. K-Means algorithm is an unsupervised clustering algorithm that is used to divide an image into K clusters [21]. The aim of K-Means Clustering analysis is to group data in such a way that similar objects are in one cluster and objects of different clusters are dissimilar. Partitional clustering (K-Means) is faster than hierarchical clustering but gives different results with different initial chosen centroids. Let us consider an image with a resolution of $(x \times y)$ that has to be clustered into K number of clusters. Let $p(x, y)$ be input pixels to be clustered for the image and c_k be the cluster centers of the color image. The procedure of the K-Means algorithm is given as follows [22]:

Algorithm 1. k-means method
1. Select randomly k pixels as the initial cluster centroids.
2. For each pixel of the image, $p(x, y)$ do.
3. Calculate the Euclidean distance $d = \lVert p(x, y) - c_k \rVert$.
4. Group the pixels based on the min distance.
5. Update centroids by calculate the mean of the pixels in the same group.
6. Go to step 2, until no moving of objects between different groups.

4.2 Fuzzy C-Means Clustering Segmentation

The Fuzzy C-Means (FCM) is an extension of K-Means clustering which allows one pixel to belong to two or more clusters [23], unlike K-Means Clustering which each pixel is a set of membership levels are associated. This method was developed by (Dunn in 1973) and improved by (Bezdek in 1981) [24]. Fuzzy is frequently used in pattern recognition and several applications, such as medical imaging and security systems. The procedure of the FCM algorithm is given as follows [25]:

Algorithm 2. Fuzzy C-Means method
1. Receive the image in the form of data matrix X.
2. Fix the number of clusters c, $(2 \le c \le n)$ *where* n is the image length.
3. Assume the partition matrix U.
4. Calculate the cluster centers V_i, $i = 1, 2, \ldots c$ using the following equation $$V_i = \frac{\sum_{j=1}^{n} (U\,ij)^m x_j}{\sum_{j=0}^{n} (U\,ij)^m}, \qquad \text{for } i = 1,2,\ldots c \text{ and } j = 1,2,\ldots n$$
5. Calculate the Euclidean distance matrix, d, using the following equation $$d_{\,ij} = \lVert X_j - V_i \rVert.$$
6. Compute the cost or objective function. Stop if either it is below a certain tolerance value or its improvement over the previous iteration is below a certain threshold $$J\,(U, c_1, \ldots\ldots, c_c) = \sum_{i=1}^{C}\sum_{j=1}^{n} u_{ij}{}^m d_{ij}{}^2.$$
7. Compute a new U using the next equation. Go to step 2 $$U_{ij} = \sum_{k=1}^{c} \left\{ \frac{\lVert X_j - V_i \rVert}{\lVert X_j - V_k \rVert} \right\}.$$

4.3 Region Growing Segmentation

Region growing (RG) is a simple region-based image segmentation method. It is also classified as a pixel-based image segmentation method since it involves the selection of the initial seed point (pixel). It starts with a pixel and goes on adding the pixels based on similarity properties (gray level, textures, color), to the region. This is repeated until all pixels belong to some region. Connected regions have multiple criteria at the same time such as the advantages of the region growing. It gives a good result with less noise but gives inefficient segmentation when the image is noisy or has intensity variations [7, 26]. The procedure of the Region Growing algorithm is given as follows:

Algorithm 3. Region Growing method
1. Select seed point P_{seed} in the color image.
2. Check the neighbor pixels of P_{seed} and add them to the region if they are similar to the P_{seed}.
3. Repeat step 2 for each of the newly added pixels; STOP if no more pixels can be added.

4.4 Graph Cut Segmentation

The Graph Cut is used as the fundamental object/background segmentation method [27]. A graph cut is a process of partitioning a directed or undirected graph into disjoint sets. In the graph model, each pixel is considered as a node and connected to its neighbor nodes through edges. Edges between pixel nodes are called n-links (pixel similarity), additionally, there are two terminal nodes: S (source) and T (sink). These nodes represent object and background. Each pixel node has two edges connected to S and T, which are called t-links. All links between two-pixel nodes i and j are assigned to weight w_{ij}. A cut is a set of edges in the graph that completely separate the foreground this cut is calculated using Eq. (6)

$$c(A, B) = \sum\nolimits_{i \in A, j \in B} W_{ij}, \tag{6}$$

where A and B correspond to the two disjoint sets of nodes of the result of bipartitioning. This cut is determined using the min-cut/max-flow algorithm [28]. Figure 1, shows a sample example of the graph cut process for a 3 × 3 image [29].

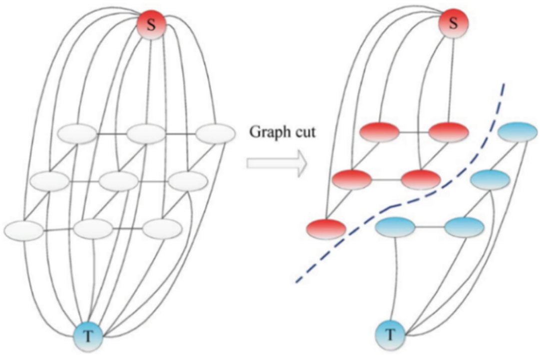


Fig. 1. An example of the graph cut process for a 3 × 3 image.

5 Experimental Results

5.1 Dataset

In this paper, we have applied the four algorithms described above on 150 images from Berkeley Segmentation Database (BSD300) [30]. The images are 481 × 321 pixels. For each color image, a set of benchmark segmentation results (called ground truth) is available.

5.2 Accuracy Criteria

The accuracy is measured by the following equation [31]:

$$Accuracy(\%) = \frac{TP + TN}{TP + TN + FP + FN} * 100. \tag{7}$$

This method computes the accuracy depending on the use of a confusion matrix. True Positive (TP) is the number of object pixels correctly identified as an object, True

Negative (TN) is the number of background pixels correctly identified as background, False Positive (FP) is background pixels incorrectly identified as an object, False Negative (FN) is object pixels incorrectly identified as back ground. To objectively evaluate the segmentation results we used two different measures which are MSE (Mean Square Error) [32] and PSNR (Peak to Signal Noise Ratio) [33].

5.3 Results

In this study, we evaluated four different segmentation methods, namely K-Means, FCM, Region Growing, and Graph Cut. We used these segmentation methods with different color space models, including RGB, HSV, YCbCr, and XYZ. Each color space model was applied on a single color component. In addition, we vote between the segmented three components for every color space in one vector. The final segmentation results are obtained for all 150 images from Berkley Segmentation Database. Figure 2 shows some examples of images that were used to perform the experiments presented in this study.

Fig. 2. Some samples of images of Berkely database.

For a quantitative comparison, the first experiment was carried out to measure the accuracy of the four segmentation methods (K-Means, FCM, Region Growing, and Graph Cut) with the $R.G.$ and B components individually besides the vote between three segmented components in one vector. Table 1 presented PSNR, MSE, and segmentation accuracy for four algorithms using the $R.G.$ *and* B components and voting between the three components. In this experiment, the B component achieved better performance than the G and R components. Voting RGB also provided good results compared to the G and R components. The PSNR has the highest value with the Graph Cut and FCM algorithms. MSE has the lowest value with the the Graph Cut and FCM algorithm. Also, they have the best segmentation accuracy (see Fig. 4).

Figure 3 shows a sample example of the original image of the three components ($R.G.$ and B) and ground-truth and Fig. 4 presents results of the k-means segmentation, FCM segmentation, Region Growing segmentation, and Graph Cut segmentation.

The second experiment was performed using the HSV color space. The results are shown in Table 2 where PSNR, MSE, and segmentation accuracy for the four algorithms using the H, S, and V components and vote between the three segmented components (voting HSV).

Table 1. Average of PSNR, MSE, and accuracy of k-means, FCM, Region Growing, and Graph Cut.

Color component		R	G	B	voting RGB
K-Means	PSNR	0.3609	0.3704	0.3765	0.3805
	MSE	0.1375	0.1321	0.1127	0.1112
	Accuracy	84.026	83.385	84.650	85.370
FCM	PSNR	0.3703	0.3753	0.3801	0.3858
	MSE	0.1423	0.1220	0.1077	0.1040
	Accuracy	83.884	84.178	86.847	85.130
Region Growing	PSNR	0.3680	0.3730	0.3736	0.3731
	MSE	0.1524	0.1331	0.1177	0.1191
	Accuracy	82.766	83.969	84.205	84.075
Graph Cut	PSNR	0.3714	0.3853	0.3917	0.3939
	MSE	0.1217	0.1120	0.1066	0.1120
	Accuracy	84.249	85.390	86.028	86.077

Fig. 3. (a) Original image, (b) Ground truth, (c) Red component, (d) Green component, and (e) Blue component.

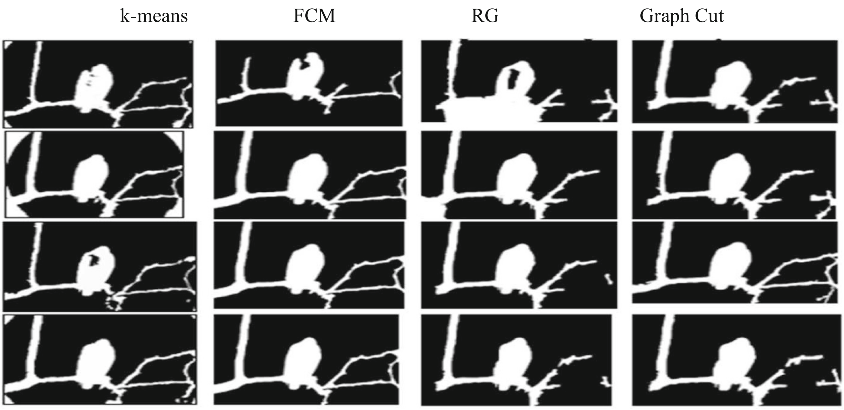


Fig. 4. First row for red (*R*) component segmentation, second row for green (*G*) component segmentation, third row for blue (*B*) component segmentation, and fourth row for voting RGB.

Table 2. Average of PSNR, MSE, and accuracy of k-means, FCM, Region Growing, and Graph Cut for the component $H.S.V.$ and voting HSV.

Color component		H	S	V	voting HSV
K-Means	PSNR	0.3574	0.3670	0.3961	0.3865
	MSE	0.2622	0.1764	0.1193	0.1214
	Accuracy	79.054	84.569	87.538	87.338
FCM	PSNR	0.3505	0.3565	0.3842	0.3625
	MSE	0.1918	0.1514	0.1400	0.1504
	Accuracy	79.060	82.054	85.361	85.776
Region Growing	PSNR	0.3190	0.3562	0.3809	0.3780
	MSE	0.2139	0.1596	0.1164	0.1368
	Accuracy	77.456	82.532	86.541	85.081
Graph Cut	PSNR	0.3669	0.3799	0.3752	0.3613
	MSE	0.1758	0.1491	0.1276	0.1355
	Accuracy	80.567	81.355	85.396	84.783

It is clear that voting HSV is not the best as V component is giving good results in some cases, while the H component is the worest in the most cases. The PSNR has the highest value with the Graph Cut algorithm. MSE has the lowest value with the the Graph Cut algorithm. Also, has the color space that was converted from the RGB color space model. It shows the ground truth of the image.

Figure 6 shows the results of the k-means segmentation, FCM segmentation, Region Growing segmentation, and Graph Cut segmentation using HSV color space.

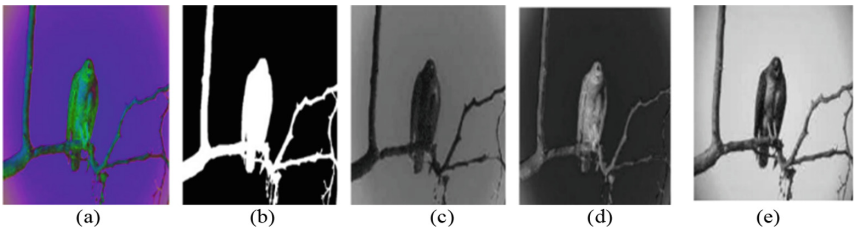


Fig. 5. (a) HSV image, (b) Ground truth, (c) H component, (d) S component, and (e) V component.

The third set of experiments was performed using the YCbCr color space with the segmentation methods presented in this study. Table 3 shows the PSNR, MSE, and segmentation accuracy for the four algorithms using the Y. Cb. and Cr components and vote between the three segmented components (voting YCbCr).

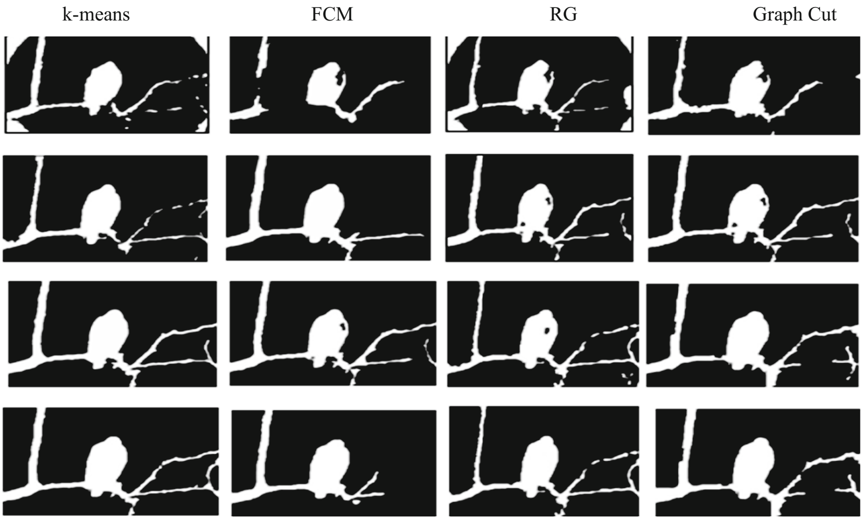


Fig. 6. First row for H component segmentation, second row for S component segmentation, third row for V component segmentation, and fourth row for voting (HSV).

Table 3. Average of PSNR, MSE and accuracy of k-means, FCM, Region Growing, and Graph Cut for the component $Y.Cb.Cr$ and voting YCbCr.

Color component		Y	Cb	Cr	voting YCbCr
K-Means	PSNR	0.4168	0.3540	0.3734	0.3686
	MSE	0.0629	0.1368	0.1129	0.1089
	Accuracy	87.091	84.703	84.518	85.441
FCM	PSNR	0.4094	0.3396	0.3434	0.3677
	MSE	0.0779	0.1566	0.1671	0.1001
	Accuracy	86.103	80.476	80.890	85.273
Region Growing	PSNR	0.3742	0.3054	0.3398	0.3489
	MSE	0.1184	0.2540	0.1829	0.1547
	Accuracy	85.815	75.055	80.072	82.027
Graph Cut	PSNR	0.3982	0.3414	0.3438	0.3811
	MSE	0.0990	0.1452	0.1530	0.1078
	Accuracy	87.821	82.830	80.750	84.104

Fig. 7. (a) YCbCr image, (b) Ground truth, (c) Y component, (d) Cb component, and (e) Cr component.

We observed that the Y component has good results in most cases. In addition, the voting YCbCr had good results. The Graph Cut and the K-Means have the best performance accuracy Fig. 7 shows a sample example of the Y, Cb, and Cr components of YCbCr color space that was converted from the RGB color space model. It also shows ground truth of the image. Figure 8 shows the results of the segmentation.

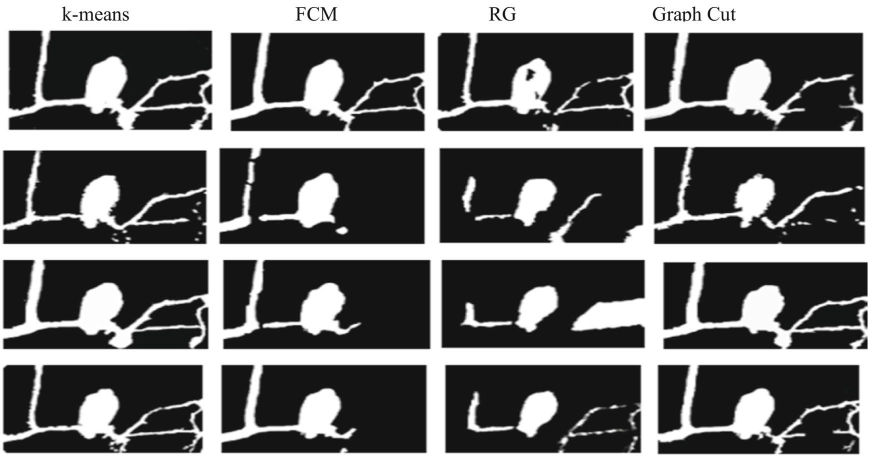


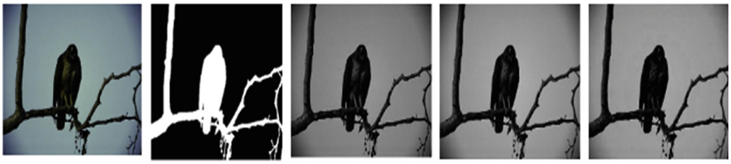
Fig. 8. First row for Y component segmentation, second row for Cb component segmentation, third row for Cr component segmentation, and fourth row for voting YCbCr.

The last experiment was carried out to measure the accuracy of segmentation using the XYZ color space with the four segmentation methods used in this paper. Table 4 shows PSNR, MSE, and segmentation accuracy for four algorithms using single individual components of color space XYZ and voting XYZ. The results show the X and Y component gives better results in most experiments. the votingXYZ between the three segmented components achieved good results. Graph Cut achived the highest PSNR and highest performance accuracy in addition to the lowest MSE.

Table 4. Average of PSNR, MSE and accuracy of k-means, FCM, Region Growing, and Graph Cut based for Segmentation for the X. Y. Z and voting XYZ.

Color component		X	Y	Z	voting XYZ
K-Means	PSNR	0.3678	0.3890	0.3646	0.3730
	MSE	0.1184	0.1009	0.1329	0.1042
	Accuracy	84.236	85.899	81.731	84.813
FCM	PSNR	0.3742	0.3760	0.3781	0.3720
	MSE	0.1151	0.1066	0.0910	0.1091
	Accuracy	84.313	84.312	84.033	85.996
Region Growing	PSNR	0.3625	0.3760	0.3521	0.3720
	MSE	0.1223	0.0928	0.1162	0.1140
	Accuracy	83.959	84.164	81.802	83.084
Graph Cut	PSNR	0.3727	0.3752	0.3766	0.3849
	MSE	0.1107	0.1426	0.1177	0.1122
	Accuracy	85.033	84.821	83.538	86.007

Figure 9 shows three component $X.Y.\,and\,Z$ of the three components and ground truth of original image. Figure 10 shows the results of the segmentation algorithms.



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

Fig. 9. (a) XYZ image, (b) Ground truth, (c) X component, (d) Y component, and (e) Z component

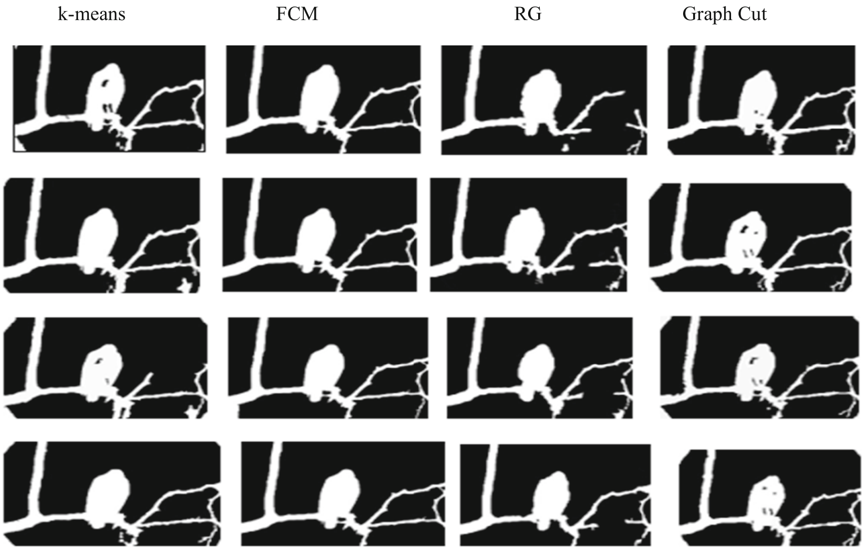


Fig. 10. First row for X component segmentation, second row for Y component segmentation, third row for Z component segmentation, and fourth row for voting XYZ.

6 Conclusion

In this study, we have focused on different color spaces for color image segmentation. Different color spaces carry out a different amount of information. Four different color spaces were examined. The results were obtained using the single components of RGB, HSV, YCbCr, and XYZ color spaces. We also voted between the segmented single components based on the K-Means, Fuzzy C-Means, Region Growing, and Graph Cut segmentation techniques. A comparative study of color spaces based on segmentation methods shows that the results of all color spaces are close to each other and the V and Y components have the high performance compared to the other signal components. Also, we found that the voting of the segmented color components of all color spaces has the best performance.

References

1. Jeevitha, K., Iyswariya, A., RamKumar, V., Basha, S.M., Kumar, V.P.: A review on various segmentation techniques in image processing. Eur. J. Mol. Clin. Med. **7**(4), 1342–1348 (2020)
2. Manoharan, S.: Performance analysis of clustering based image segmentation techniques. J. Innov. Image Process. (JIIP) **2**(01), 14–24 (2020)
3. Zheng, X., Lei, Q., Yao, R., Gong, Y., Yin, Q.: Image segmentation based on adaptive K-means algorithm. EURASIP J. Image Video Process. **1**, 1–10 (2018)
4. Bora, D.J., Gupta, A., Khan, F.A.: Comparing the performance of L*A*B* and HSV color spaces with respect to color image segmentation. Int. J. Emerg. Technol. Adv. Eng. **5**(2) (2015)
5. Agrawal, S., Xaxa, D.K.: Survey on image segmentation techniques and color models. Int. J. Comput. Sci. Inf. Technol. **5**(3), 3025–3030 (2014)

6. Zaldivar, D., Cuevas, E., Perez, M.A.: Color spaces advantages and disadvantages in image color clustering segmentation. In: Hassanien, A., Oliva, D. (eds.) Advances in Soft Computing and Machine Learning in Image Processing. SCI, vol. 730, pp. 3–22. Springer, Cham (2018). https://doi.org/10.1007/978-3-319-63754-9_1
7. Zaitoun, N.M., Aqel, M.J.: Survey on image segmentation. Techniques **65**, 797–806 (2015)
8. Singh, K.K.: A study of image segmentation algorithms for different types of images. Int. J. Comput. Sci. Issues (IJCSI) **7**(5), 414 (2010)
9. Garcia-Lamont, F., Cervantes, J., López, A., Rodriguez, L.: Segmentation of images by color features a survey. Neurocomputing **292**, 1–27 (2018)
10. Jurio, A., Pagola, M., Galar, M., Lopez-Molina, C., Paternain, D.: A comparison study of different color spaces in clustering based image segmentation. In: Hüllermeier, E., Kruse, R., Hoffmann, F. (eds.) Information Processing and Management of Uncertainty in Knowledge-Based Systems. Applications. IPMU 2010. CCIS, vol. 81, pp. 532–541. Springer, Berlin, Heidelberg (2010). https://doi.org/10.1007/978-3-642-14058-7_55
11. Burney, S.A., Tariq, H.: K-means cluster analysis for image segmentation. Int. J. Comput. Appl. **96**(4), 1–8 (2014)
12. Khattab, D., Ebied, H.M., Hussein, A.S., Tolba, M.F.: Color image segmentation based on different color space models using automatic grab cut. Sci. World J. (2014)
13. Mythili, C., Kavitha, V.: Color image segmentation using ERKFCM. Int. J. Comput. Appl. **41**, 21–28 (2012)
14. Shih, F.Y., Cheng, S.: Automatic seeded region growing for color image segmentation. Image Vis. Comput. **23**(10), 877–886 (2005)
15. Wang, X., Hänsch, R., Ma, L., Hellwich, O.: Comparison of different color spaces for image segmentation using graph-cut. In: International Conference on Computer Vision Theory and Applications (VISAPP), pp. 301–308. IEEE (2014)
16. Busin, L., Vandenbroucke, N., Macaire, L.: Advances in imaging and electron physics. **151**, 65–168 (2008)
17. Pm, N., Chezian, R.: Various colour spaces and colour space conversion algorithms. J. Glob. Res. Comput. Sci. **4**, 44–48 (2013)
18. Gopinathan, S., Gayathri, M.S.: A study on image enhancement techniques using YCbCr color space methods. Int. J. Adv. Eng. Res. Sci. **3**(8), 236818 (2016)
19. Ibraheem, N.A., Hasan, M.M., Khan, R.Z., Mishra, P.K.: Understanding color models: a review. ARPN J. Sci. Technol. **2**(3), 265–275 (2012)
20. Plataniotis, K., Anastasios, N.: Venetsanopoulos, Color image Processing and Applications. Springer Science & Business Media, Heidelberg (2013)
21. Jipkate, B.R., Gohokar, V.V.: A comparative analysis of fuzzy c-means clustering and k means clustering algorithms. Int. J. Comput. Eng. Res. **2**(3), 737–739 (2012)
22. Dhanachandra, N., Chanu, Y.J.: Image segmentation method using k-means clustering algorithm for color image. Adv. Res. Electr. Electron. Eng. **2**(11), 68–72 (2015)
23. Li, X., Lu, X., Tian, J., Gao, P., Kong, H., Xu, G.: Application of fuzzy c-means clustering in data analysis of metabolomics. Anal. Chem. **81**(11), 4468–4475 (2009)
24. Bezdek, J.C., Ehrlich, R., Full, W.: FCM: the fuzzy c-means clustering algorithm. Comput. Geosci. **10**(2–3), 191–203 (1984)
25. Ganesan, P., Rajini, V., Sathish, B.S., Kalist, V., Basha, S.K.: Satellite image segmentation based on YCbCr color space. Indian J. Sci. Technol. **8**(1), 35 (2015)
26. Hore, S., et al.: An integrated interactive technique for image segmentation using stack based seeded region growing and thresholdin. Int. J. Electr. Comput. Eng. **6**(6), 2088–8708 (2016)
27. Boykov, Y., Veksler, O.: Graph cuts in vision and graphics: theories and applications. In: Paragios, N., Chen, Y., Faugeras, O. (eds.) Handbook of Mathematical Models in Computer Vision, pp. 79–96. Springer, Boston, MA (2006). https://doi.org/10.1007/0-387-28831-7_5

28. Boykov, Y., Kolmogorov, V.: An experimental comparison of min-cut/max-flow algorithms for energy minimization in vision. IEEE Trans. Pattern Anal. Mach. Intell. **26**(9), 1124–1137 (2004)
29. Zheng, Q., Li, W., Hu, W., Wu, G.: An interactive image segmentation algorithm based on graph cut. Procedia Eng. **29**, 1420–1424 (2012)
30. Martin, D.R., Fowlkes, C.C., Tal, D., Malik, J.: A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics. In: Proceedings Eighth IEEE International Conference on Computer Vision. ICCV 2001, vol. 2, no. 2, pp. 416–423 (2001)
31. Prabha, D.S., Kumar, J.S.: Performance evaluation of image segmentation using objective methods. Indian J. Sci. Technol. **9**(8), 1–8 (2016)
32. Wang, Z., Bovik, A.C.: Mean squared error: love it or leave it? A new look at signal fidelity measures. IEEE Signal Process. Mag. **26**(1), 98–117 (2009)
33. Moreno, J., Jaime, B., Saucedo, S.: Towards no-reference of peak signal to noise ratio. Int. J. Adv. Comput. Sci. Appl. (IJACSA) **4**(1) (2013)