A Comparative Study of Different Color Space Models Using FCM-Based Automatic GrabCut for Image Segmentation

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Abstract. GrabCut is one of the powerful color image segmentation techniques. One main disadvantage of GrabCut is the need for initial user interaction to initialize the segmentation process which classifies it as a semi-automatic technique. The paper presents the use of Fuzzy C-means clustering as a replacement of the user interaction for the GrabCut automation. Several researchers concluded that no single color space model can produce the best results of every image segmentation problem. This paper presents a comparative study of different color space models using automatic GrabCut for the problem of color image segmentation. The comparative study includes the test of five color space models; RGB, HSV, XYZ, YUV and CMY. A dataset of different 30 images are used for evaluation. Experimental results show that the YUV color space is the one generating the best segmentation accuracy for the used dataset of images.

Keywords: Color image segmentation · Automatic GrabCut · FCM clustering · Color space models

1 Introduction

The process of segmentation refers to partitioning a digital image into multiple segments. During this process, each pixel in the image is assigned to a label where pixels with the same visual characteristics share the same label [1]. Segmentation aims to arrange the image into regions that are simpler, meaningful and easier to analyze [2]. These regions may correspond to individual surfaces, objects or natural parts of objects [3]. Image segmentation is usually used as a pre-processing step in many applications such as; object recognition, scene analysis, automatic traffic control systems and medical imaging. Usually, the local information that is incorporated in the image, i.e. color information, edges, boundaries or texture information are used to compute the best segmentation [4].

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The image pixels' colors are considered the main feature for the problem of color image segmentation. It is usually assumed that homogeneous colors in the image correspond to separate clusters and hence meaningful objects in the image. In other words, each class of pixels sharing similar color properties can define a separate cluster. Considering that not all color spaces can provide acceptable results for all kinds of images, many trials [5] have been carried out to define which color space is most suitable for their specific color image segmentation problem.

One of the most powerful color image segmentation techniques is the GrabCut technique [6]. It extends the famous graph cut technique [7] for efficient segmentation of color images which allows it to be advantageous for several applications. One main drawback of GrabCut is being an interactive/semi-automatic technique, i.e. being more appropriate for binary-label segmentation. Binary-label segmentation (i.e. foreground segmentation) is a segmentation class where the image can be segmented into the background and foreground regions only [6]. The need to define a region of interest to be segmented out of the image requires initial user interaction. This initial user intervention is responsible for classifying GrabCut as semi-automatic technique and makes it more subject to error.

The authors in [8] presented a modification of the semi-automatic GrabCut into an automatic one using Self-Organizing Feature Map (SOFM) [9,10] as an unsupervised clustering technique. SOFM was selected as a hard clustering technique to replace the initialization phase of GrabCut and eliminate the user interaction. In this work, Fuzzy C-means (FCM) [11,12] is selected as a Soft/Fuzzy clustering for automatic GrabCut initialization. The segmentation of color images is tested using FCM for different classical color spaces; RGB, CMY, XYZ and YUV; to select the best color space for the considered kind of images. Experiments on a dataset of 30 images are carried out to test the modified automatic GrabCut for binary-label segmentation.

The paper is organized as follows; section 2 reviews the related work of image segmentation based on different color space models, in addition to the use of GrabCut and FCM clustering for image segmentation. Section 3 explains the different color space models. The proposed automatic GrabCut using FCM clustering is illustrated in Section 4. Experimental results and discussion are presented in Section 5. Finally the conclusion and future work are presented in section 6.

2 Related Work

Several segmentation problems had utilized GrabCut in different applications such as; human body segmentation [13,14,15], video segmentation [16], semantic segmentation [17] and volume segmentation [18]. Yi Hu [15] developed an iterative technique for automatic extraction of the human body from color images. In their implementation, a scanning face detector was used to initialize a tri-map that is dynamically updated using the iterated GrabCut technique. One defect was having the research constrained to human poses with frontal side faces.

In video sequences, a fully automatic Spatio-Temporal GrabCut human segmentation methodology was developed by Hernández et al. [14]. In their work, face detection and a skin color models were assigned to generate a set of seeds that were used to initialize the GrabCut algorithm. Another application to human segmentation developed by Gulshan et al. [13] utilized the local color model based GrabCut to automatically segment humans from cluttered images. According to them, segmentation masks were learned from sparsely coded local HOG descriptors using trained linear classifiers. Afterward, the GrabCut local color model was used to refine a crude segmentation of the human figure.

Corrigan et al. [16] had applied a more robust segmentation technique in the field of video segmentation. In order to include temporal information in the segmentation optimization process, they extended the Gaussian Mixture Model (GMM) of the GrabCut algorithm so that the color space was complemented with the derivative in time of pixel intensities. GrabCut was integrated into a semantic segmentation framework by Göring et al. [17] by labeling objects in a given image. In the field of 3D segmentation, a fully parallelized scheme using GrabCut had been adapted to run on GPU by Ramírez et al. [18]. Advantages of the scheme for the case of volume meshes included producing efficient segmentation results, in addition to reducing the computational time.

Fuzzy clustering is a natural type of clustering since no exact division is possible in real life due to the presence of noise. It is the process of assigning membership levels and then using these levels to assign data elements to one or more clusters or classes in the image/data set. In Soft/Fuzzy clustering, data elements can belong to more than one cluster with a degree of some membership value [19]. The Fuzzy C-means (FCM) algorithm [11,12] is one of the most popular fuzzy clustering methods widely used in various tasks of pattern recognition, data mining, image processing and gene expression data recognition, etc.. Various authors [20, 21, 22, 23] have used FCM clustering in recently proposed image segmentation techniques in the literature. Beevi and Sathik [23] had developed a robust segmentation technique that exploited a histogram based FCM algorithm for the segmentation of medical images. Their approach converged more quickly than the conventional FCM and attained reliable segmentation accuracy apart from noise levels [19].

Krinidis and Chatzis [20] had developed a Fuzzy Logic Information C-Means Clustering (FLICM) algorithm with a new factor in the objective function of FCM. The algorithm proved to be more robust because of the new factor incorporated in the objective function which was noise insensitive and preserved image details. Kannan et al. [22] proposed a Novel Fuzzy Clustering C-Means Algorithm (NFCM) where a center knowledge method was presented to reduce the running time of the algorithm. The advantage of NFCM was that it can be applied at an early phase of automated data analysis and was found to deal effectively with image intensity inhomogeneities and noise present in the image [19]. Beevi et al. [21] proposed an improved Spatial Fuzzy C-Means algorithm (ISFCM), where spatial neighborhood information was incorporated into the standard FCM by a priori probability. The advantage of ISFCM was that it can overcome the noise sensitiveness of the standard

FCM. The incorporation of spatial information in the clustering process made the algorithm robust to noise and blurred edges.

Because no specific color space can be best for every image segmentation problem, several researchers [24,25] worked out on different color spaces to show which is useful for their works. A comparative study of different color spaces has been carried out by Jurio et al. [26] using two similar clustering algorithms in cluster based image segmentation. In order to identify the best color representation, they tested four color spaces; RGB, HSV, CMY and YUV. The best results were obtained using the CMY color space for most cases.

An automatic method to select a specific color space between classical color spaces was proposed by Busin et al. [5]. An evaluation criterion was used for the selection that was based on a spectral color analysis. The best color space was selected based on the quality of its segmentation, i.e. the one that preserved its own specific properties. Chaves-González et al. [27] presented a study of the ten most common color spaces for skin color detection. Based on their study, HSV was the best color space to detect skin in an image. Du and Sun [28] applied another study for the classification of pizza topping. Again among five different color spaces, they proved that the polynomial SVM classifier combined with HSV color space is the best approach. Another best accuracy was achieved using HSV representation by Ruiz-Ruiz et al. [29] in order to achieve real time processing in real farm fields for crop segmentation. They compared between the RGB and HSV models.

3 Color Space Models

The most widely used color space is the RGB color space, where a color point in the space is characterized by three color components of the corresponding pixel which are Red (R), Green (G) and Blue (B). However, since there exists a lot of color spaces, it is useful to classify them into fewer categories with respect to their definitions and properties. Vandenbroucke [30] proposed the classification of the color spaces into the following categories:

1. The primary spaces

Which are based on the theory that assumes it is possible to match any color by mixing an appropriate amount of the three primary colors. The primary spaces are the real RGB, the subtractive CMY and the imaginary XYZ primary spaces. The conversion from RGB to CMY is:

$$
\begin{aligned}
&C' = 1 - R && C = \min(1, \max(0, C' - K'))\\
&M' = 1 - G && M = \min(1, \max(0, M' - K'))\\
&Y' = 1 - B && Y = \min(1, \max(0, Y' - K'))\\
&K' = \min(C', M', Y')
\end{aligned}
\tag{1}
$$

And the conversion from RGB to XYZ is:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.412453 & 0.357580 & 0.180423 \\ 0.212671 & 0.715160 & 0.072169 \\ 0.019334 & 0.119193 & 0.950227 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{2}$$

2. The luminance-chrominance spaces

Which are composed of one color component that represents the luminance and two color components that represent the chrominance. The YUV color space is an example of the luminance-chrominance spaces. The conversion from RGB to YUV is:

$$\begin{bmatrix} Y \\ U \\ V \end{bmatrix} = \begin{bmatrix} 0.2989 & 0.5866 & 0.1145 \\ -0.147 & -0.289 & 0.436 \\ 0.615 & -0.515 & -0.100 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{3}$$

3. The perceptual spaces

That try to quantify the subjective human color perception by means of three measures; intensity, hue and saturation. The HSV is an example of the perceptual color space. The conversion from RGB to HSV is:

$$\mathbf{H} = \begin{cases} \mathbf{0}, & \textbf{if Max = Min} \\ \left(\mathbf{60^o} \times \dfrac{\mathbf{G-B}}{\mathbf{Max-Min}} + \mathbf{360^0}\right) \textbf{ mod } \mathbf{360^o}, & \textbf{if Max = R} \\ \mathbf{60^o} \times \dfrac{\mathbf{B-R}}{\mathbf{Max-Min}} + \mathbf{120^0}, & \textbf{if Max = G} \\ \mathbf{60^o} \times \dfrac{\mathbf{R-G}}{\mathbf{Max-Min}} + \mathbf{240^o}, & \textbf{if Max = B} \end{cases} \tag{4}$$

$$S = \begin{cases} 0, & \text{if max} = 0 \\ \dfrac{\text{Max}-\text{Min}}{\text{Max}} & \text{otherwise} \end{cases} \tag{5}$$

$$V = \text{Max} \tag{6}$$

4 Automatic GrabCut Using FCM

The original GrabCut technique developed by Rother et al. [6] is considered as one of the state-of-the-art semi-automatic techniques for image segmentation. It is a powerful extension of the graph cut algorithm [7] to segment color images iteratively. The first main step to initialize the segmentation process of the GrabCut algorithm requires a degree of user interaction. This user interaction is implemented by simply dragging a rectangle around the desired object to be segmented as shown in Fig. 1. Accordingly, the image is separated into initial foreground and background regions. Both the foreground and background regions are modeled as Gaussian Mixture Models (GMMs). The GrabCut algorithm learns the color distributions by giving each pixel a probability to belong to the most feasible Gaussian component in one of the foreground or background GMMs. A graph is built from the image, and the final segmentation is performed using the iterative minimization algorithm of the graph cut to get a new classification of foreground and background pixels. This process is repeated until classification converges.

Fig. 1. Example of original GrabCut segmentation. (left) GrabCut allows the user to drag a rectangle around the object of interest to be segmented. (right) The segmented object.

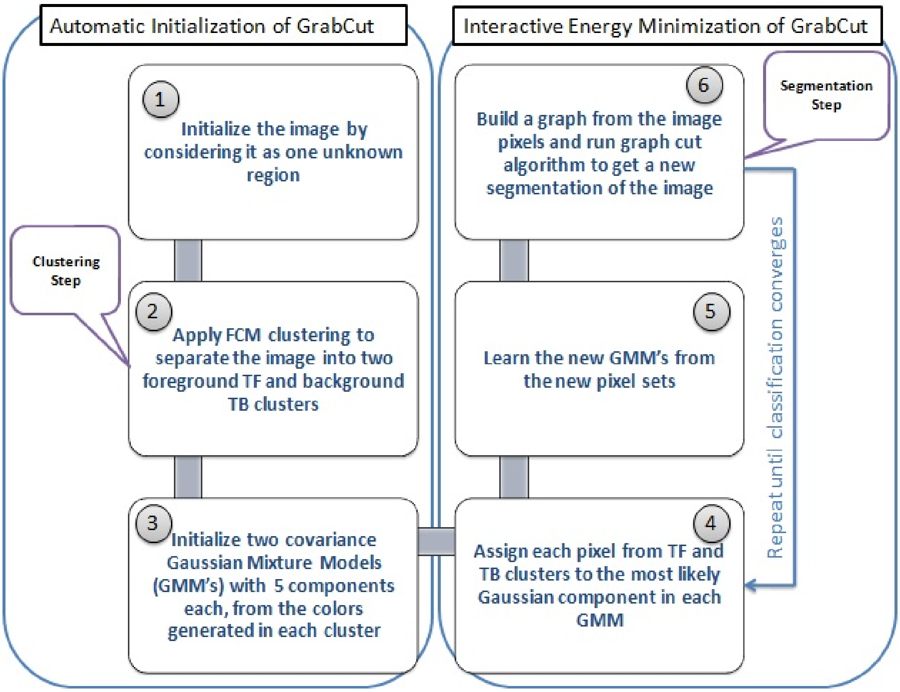

Fig. 2. Flowchart of the automatic GrabCut using FCM clustering for initialization

The initial user interaction is one main disadvantage of GrabCut. It allows GrabCut to be most appropriate for binary-label segmentation and classifies it as a semi-automatic segmentation technique. The modified technique developed by Khattab et al. [8] tried to avoid the previous limitation by modifying GrabCut into an automatic version, where the image can be segmented into proper segments without any user guidance. The novel contribution consists of replacing the semi-automatic/supervised step of GrabCut initialization with a completely automatic/unsupervised one. The modification included the use of the unsupervised image clustering technique of SOFM [9-10] for the GrabCut initialization. Fig. 2 illustrates the flowchart of the automatic GrabCut algorithm as proposed in [8] with the use of FCM as replacement of SOFM clustering technique. The main difference between the automatic and semi-automatic GrabCut occurs mainly in the initialization phase. In this phase, the user selection to create initial foreground and background regions is replaced with the clustering step (Fig. 2, steps 1 – 3). The interactive energy minimization phase of the automatic GrabCut runs exactly as the original semi-automatic GrabCut (Fig. 2, steps 4-6).

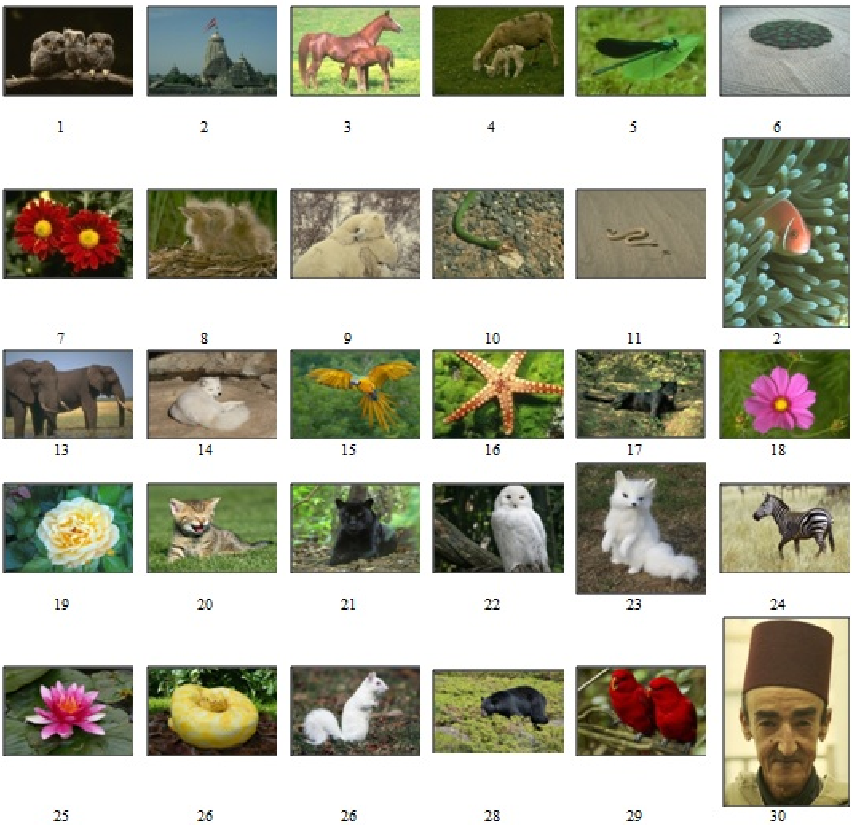

Fig. 3. The dataset of images

5 Results and Discussions

A dataset of 30 images, shown in Fig. 3, is used for the evaluation of the proposed automatic GrabCut. The images of the dataset include examples from the benchmark of the Berkeley's database [31] and others from the free images on the internet. These images are selected by certain criteria that include their fitting to the class of binary-label segmentation i.e. to include one object as foreground. Other criteria include having good visual separation in the color regions between the foreground and background.

Two measures; the error rate and the overlap score rate are used for calculating the segmentation accuracy. The error rate is calculated as the fraction of pixels with wrong segmentations (compared to ground truth) divided by the total number of pixels in the image. The overlap score rate is given by $y_1 \cap y_2 / y_1 \cup y_2$, where y_1 and y_2 are any two binary segmentations representing the ground truth and the generated segmentation result respectively.

The automatic GrabCut, which is initialized using FCM, is applied to the dataset images in different color space models, including RGB, XYZ, CMY, YUV and HSV. The features that identify each image pixel are only the values of its three components in the selected color space. The final segmentation results are obtained for all used images. For a quantitative comparison, Table 1 shows the accuracy rates generated for the whole dataset, while Fig. 4 summarizes the average accuracy rates in graph plots for all different color spaces. The results in Table 1 are presented in ascending order from left to right in terms of the total number of good image segmentation results and the average error rates. We can observe from Table 1 that the YUV representation generates better results for most of the images and outperforms the other color space models in terms of the average error rate of 6.2%. The overlap score rates of YUV and RGB are almost identical with 82.27% and 82.79% respectively.

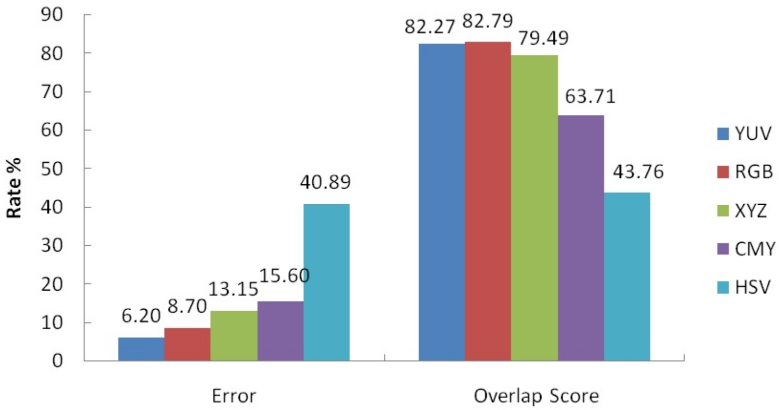

Fig. 4. Average accuracy measures for applying automatic GrabCut using FCM on different color space models

Table 1. Error and overlap score rates for different color space models

Image	Error rate %					Overlap Score rate %				
	YUV	RGB	XYZ	CMY	HSV	YUV	RGB	XYZ	CMY	HSV
1	17.46	17.53	18.76	10.23	52.10	62.22	62.04	59.15	79.22	43.36
2	4.25	4.22	4.23	3.67	66.35	94.05	94.15	94.12	95.13	33.65
3	4.91	4.95	3.90	3.76	40.89	91.48	91.21	94.73	95.09	45.39
4	6.13	5.05	7.41	49.58	11.48	86.51	90.00	82.01	26.72	72.30
5	3.51	2.80	2.84	24.47	43.11	89.31	93.70	93.69	11.94	21.13
6	0.97	0.86	0.88	9.69	70.07	96.41	97.16	97.07	44.37	17.49
7	3.14	61.00	61.07	3.07	19.53	96.88	38.40	38.38	96.36	68.83
8	6.47	6.27	24.97	6.86	17.42	94.81	95.00	67.15	94.19	81.07
9	4.25	3.13	3.21	4.26	4.19	91.62	94.53	94.34	93.15	91.83
10	9.45	2.40	2.32	1.21	71.36	0.01	69.00	69.86	84.30	6.20
11	2.96	2.99	97.04	2.98	2.73	55.70	55.30	2.96	54.94	58.56
12	0.72	1.92	1.08	2.43	69.12	94.62	82.98	90.75	75.40	10.01
13	14.29	2.15	7.78	36.14	46.31	79.41	97.35	88.17	52.77	52.51
14	23.96	2.16	2.17	15.21	20.87	45.45	94.75	94.77	60.61	52.57
15	2.57	2.56	5.12	2.76	76.94	93.95	93.78	83.78	93.15	21.97
16	3.08	24.92	38.96	4.01	53.59	95.89	43.97	38.94	91.67	31.80
17	26.69	36.54	36.94	28.44	56.77	0.27	29.13	28.84	0.33	16.70
18	4.18	4.15	4.15	4.22	22.36	94.56	94.26	94.31	94.19	55.62
19	2.05	2.17	2.16	40.82	2.60	97.03	96.71	96.76	8.23	95.81
20	6.97	4.92	5.08	38.74	70.67	82.31	89.35	88.54	18.02	25.83
21	3.61	2.33	2.38	42.92	68.24	90.95	95.53	95.47	38.01	17.75
22	3.10	2.89	2.86	5.28	38.51	93.41	94.05	94.09	87.19	18.40
23	3.00	2.98	2.93	8.78	38.09	94.58	94.26	94.55	79.26	21.27
24	3.86	3.88	3.87	36.48	73.61	91.05	90.98	90.91	34.25	19.81
25	2.88	37.10	37.14	5.51	59.28	93.48	38.35	38.31	83.63	27.65
26	4.06	2.49	3.11	4.18	8.44	93.05	96.59	95.20	93.03	83.70
27	1.81	1.47	1.46	26.19	65.69	95.11	96.33	96.32	0.21	21.33
28	1.28	1.28	1.31	1.57	38.17	94.58	94.61	94.47	93.01	27.96
29	3.47	3.17	3.29	5.34	4.80	93.01	93.71	93.46	88.51	89.78
30	10.83	10.70	6.03	39.25	13.48	86.48	86.67	93.55	44.51	82.54
Avg.	6.20	8.70	13.15	15.60	40.89	82.27	82.79	79.49	63.71	43.76

Fig. 5 displays visual comparisons of the generated segmentation results for some images having high variance of error rate among the different color models. It can be noticed that the automatic GrabCut using FCM almost failed to get accurate segmentations with the HSV model. One of the interesting results is the segmentation achieved for image no. 11 in the XYZ color space. In this image the GrabCut failed completely to segment the image considering the whole image as one segment. This explains the large error rate of 97.04% and poor overlap score rate of 2.96%. Fig. 6 shows the XYZ conversion of image no. 11 (left) and the initial clustering generated using the FCM (right) before running the segmentation part.

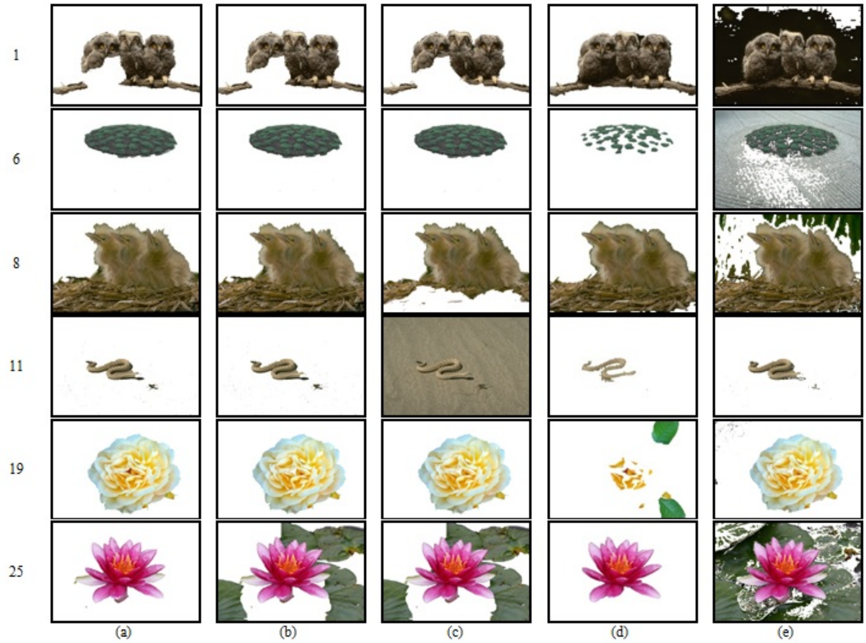

Fig. 5. Samples of image segmentations applied to different color space models, (a) YUV, (b) RGB, (c) XYZ, (d) CMY and (e) HSV

Fig. 6. Image no. 11 in the XYZ color space representation. (left) Original image and (right) initial clustering using FCM.

6 Conclusions and Future Work

User interaction is considered a disadvantage of the GrabCut technique for image segmentation. It allows the segmentation to be more susceptible to errors and the technique to be more appropriate for binary-label segmentation. Automatic GrabCut is used to eliminate the need for initial user interaction. In this paper, the unsupervised clustering of Fuzzy-C means (FCM) is used for GrabCut automation as a replacement of the initial user interaction. As no specific color space is recommended for every segmentation problem, the performance of the FCM-based automatic GrabCut was evaluated on different color space models including RGB, CMY, XYZ, YUV and HSV. Based on a dataset of different 30 images, the YUV representation generated the best segmentation accuracy and outperformed other color spaces. It provided an average error rate of 6.2% and overlap score rate of 82.27%. The future work aims to evaluate the automatic GrabCut on different color spaces for the problem of multi-label image segmentation, where the image can be segmented into more than two segments.

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