

Improving Color Image Binary Segmentation Using Nonnegative Matrix Factorization

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Abstract. Image segmentation is the process of dividing a digital image into multiple segments or regions, each of which represents a different object or part of the image or shares certain visual characteristics. The goal of image segmentation is to simplify the representation of an image into something that is more meaningful and easier to analyze. Typically, segmentation creates histograms indicating edges and boundaries that use local information such as color. The color space used determines the segmentation results: while RGB is the most fundamental and widely used color space, other color spaces can also be adopted for segmentation to emphasize different aspects of an image. No single color space, however, is capable of producing satisfactory results for all types of color image segmentation tasks.

Nonnegative Matrix Factorization (NMF) is a powerful data reduction and exploration tool efficiently used to extract features that provide part-based representation for a wide range of data types. In this paper, we propose an NMF-based method for integrating different color space information from an image and then extracting from it an "optimal color space representation" which is used to improve the results of a threshold segmentation algorithm. The proposed approach uses NMF on histograms of different color spaces to generate a meta-histogram representation of the given image, which is then binary segmented. Experimental results showed that the features extracted from the proposed NMF-based approach are able to improve segmentation outcomes obtained by conventional segmentation algorithms like Otsu method.

Keywords: Image segmentation · Nonnegative Matrix Factorization · Data Integration · Color Spaces · Feature extraction

1 Introduction

In image analysis and pattern recognition, segmentation is a crucial stage. Image segmentation seeks to identify homogeneous areas, surfaces, and boundaries (such as lines or curves) in a picture that correlates to significant areas of the

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observed image. Moreover, segmentation is the process of categorizing each individual pixel in a picture, where identified common pixels share characteristics like gray level, color, texture, and gradients.

Formally, let I denote an image and $\mathcal{H}$ define a certain homogeneity property of it. The segmentation of I is a partition $\mathcal{P}$ of I into a set of N disjointed regions $\mathcal{R}_k$ for $k = 1, \ldots, N$ such that: (i) $\mathcal{P}$ covers the whole image I, i.e., $I = \cup_{k=1}^{N} \mathcal{R}_k$ with $\mathcal{R}_k \cap \mathcal{R}_j = \varnothing$ for $k \neq j$; (ii) each region is homogeneous with respect to a property $\mathcal{H}$, i.e., $\mathcal{H}(\mathcal{R}_k) = true$; (iii) two adjacent regions cannot be merged into a single region satisfying the property $\mathcal{H}$, i.e., $\mathcal{H}(\mathcal{R}_k \cup \mathcal{R}_j) \neq true$ for any adjacent $\mathcal{R}_k$ and $\mathcal{R}_j$ [3,12]. Image segmentation is performed on some features of the image I (such as color information or texture); segmentation mechanisms are thus designed to exploit only some of the image information's characteristics. There are many types of segmentation algorithms, each with its own strengths and limitations, depending on the nature of the image and the desired outcome; however, a fully efficient image segmentation algorithm is still a long way off. Color images contain more information than grayscale images. Several color image segmentation approaches are based on pixel color features; they assume that the distribution of pixel colors (homogeneous colors) corresponds to meaningful objects either in the image plane or in the color space in which the image is represented. A point in the RGB color space is determined by the color component levels of the associated pixel in the image, namely the red (R), green (G), and blue (B). RGB color space is commonly used for color image segmentation and, often, its linear or nonlinear transformations are used to define other color spaces. Different color spaces can be used to individuate other images' pixel color characteristics, however, the outcomes of image segmentation depend on the space that is used. Many studies attempted to identify the best color representation for a specific segmentation method or investigated the ability of color space to improve segmentation outcomes [3,8,10,13,15]. The performance of an image segmentation technique depends on the specific color space image representation, and it should be emphasized that no single color space can provide good results for the segmentation of all types of images.

In this work, we aim to segment color images discriminating principally from background to foreground. Information related to various color spaces is used by integrating the histograms associated to different color channels and we propose to use Nonnegative Matrix Factorization (NMF) to derive an "optimal color space" features hidden within a set of classical color spaces. NMF, in particular, represents an efficient method for extracting and processing image information represented in different 3D color spaces, which can then be used to improve the segmentation performance of a well-known thresholding region-based segmentation method, namely the Otsu algorithm.

In the following section, we review some basic concepts needed to introduce the proposal. In particular, we revise color spaces commonly used to describe a color image and generate useful image histograms, as well as some fundamental concepts of thresholding image segmentation techniques (such as the Otsu algorithm). Then the NMF learning method is introduced and applied to integrate different color space representations of a given image I. NMF is able to

extract features (also known as factors) able to integrate and describe the optimal color space information hidden in a given image. These new features will provide a meta-histogram representation of I that can be then used to segment the image. In Sect. 4, the proposed NMF-based approach demonstrated its ability to improve segmentation outcomes when compared to the conventional Otsu segmentation algorithm on different types of color images. We conclude the paper by outlining some observations and potential future research.

2 Color Spaces and Thresholding Segmentation

A color space is a three-dimensional geometric representation of colors that uses three numerical values to characterize each specific color. There are a variety of color spaces that enable the special definition of certain attributes of color image pixels. The RGB color space is the most widely utilized, since it captures color as it is seen by humans -a combination of the tristimuli R (red), G (green), and B (blue), often known as primary colors. The RGB space can be transformed linearly or nonlinearly to create other color spaces. According to a rough classification [3,14], the four most common color spaces are: (i) the primary spaces (based on the trichromatic theory and representing any color by combining the right amounts of the three primary colors), (ii) the luminance–chrominance spaces (in which one component represents the luminance and the two others the chrominance), (iii) the perceptual spaces (that quantify the color perception using the intensity, the hue, and the saturation), and (iv) the independent axis spaces (which provide as less correlated components as possible in some statistical sense).

Some of these color spaces are adopted in this paper to represent the color image I to segment. Each color channel in the different color image representations will then integrate into a new structured data matrix. This enlarged representation of the image I allows extracting from it the hidden properties of the image I which can be used as basis information for a threshold-based segmentation algorithm.

Primary spaces. The primary spaces are based on trichromatic theory and can be used to match any color by combining appropriate amounts of three primary colors. They are divided into two types: real primary spaces, in which the primary colors are physically realizable (as in RGB), and imaginary primary spaces, in which the primaries do not exist physically (in the sense that they cannot be generated with any light spectrum).

Any primary space can be converted into RGB space using matrix linear transformations on color space components (particularly, additive or subtractive color models are used). In terms of the imaginary primary space XYZ, it defines the coordinate Y as luminance, while the coordinates X and Z carry information about all possible chromaticities at that luminance (that is how the cones in the human eye respond to light waves of varying frequencies). As previously stated, not every set of XYZ tristimulus values corresponds to a color visible to human eyes.

Luminance-Crominance spaces. Other characteristics of color include luminance and chrominance information, which are used to define the luminance-chrominance spaces $LChr_1Chr_2$. The luminance component L, in particular, can represent the lightness, brightness, luminous intensity, or luma of a color image pixel, whereas the two components Chr_1, Chr_2 represent color chrominance, typically represented as two color-difference components. Luminance-chrominance space can be created using either linear or nonlinear transformations from RGB color space. An example is the YC_bC_r luminance-chrominance space, in which one dimension (the Y color component) is the luminance (specifying the perceived brightness) and the chrominance components C_b and C_r represent the difference between the blue (B) and red (R) channels and a reference value, respectively [3]. The $L^*a^*b^*$ space, instead is derived from a nonlinear transformation of the RGB space. Its first coordinate L^* represents the color lightness of the image from black to white on a scale of zero to 100, while the a^* and the b^* components represent chromaticity with no specific numeric limits (i.e., the position of the color between magenta and green and the position of the color between yellow and blue, respectively). This color space describes all colors visible to the human eye and serves as a device-independent reference model.

Perceptual spaces. Perceptual spaces attempt to quantify subjective human color perception using: (i) brightness/intensity which characterizes the luminous level of a color stimulus (how dark or luminous an area appears), (ii) hue which measures how an area appears to be similar to one of the main primary colors (red, green, blue, and yellow), (iii) saturation which allows one to estimate an area's colorfulness in relation to its brightness (it represents the purity of a perceived color). Complex transformation functions from and to RGB space can be used to obtain perceptual spaces. The HSV is a perceptual color space that can be obtained by cylindrical-coordinate transformation of RGB; it represents a color pixel by a given hue (the chromatic content), saturation (the ratio of chromatic and achromatic contents), and brightness.

Independent spaces. Using methods such as Principal Component or Independent Component analysis, the classical space RGB can be transformed into a new color space. The color space $I_1I_2I_3$ can be obtained using principal components, where the first and most discriminant coordinate represents a luminance component, and the other two color components represent the blue-red and magenta-green color oppositions, respectively.

2.1 Segmentation by Histograms

The methods based on pixel property analysis in a color space make use of the characterization of each pixel by its color representation. The basic assumption is that homogeneous image plane regions correspond to a class of pixels with similar color properties. Color histograms can be used to identify these classes and segment the original image. The majority of gray-level image segmentation

techniques are applicable to color images: they can be applied to each component of a color space and the results can then be combined to obtain a final segmentation of a color image. Histogram thresholding is a popular technique for gray-level image segmentation. The histogram of a single component color image can be divided into a number of peaks, each corresponding to a region of pixels with similar properties. A histogram method assumes that there is a threshold value corresponding to the valley between two adjacent peaks that can distinguish two different adjacent regions. However, because color information is represented by a three-dimensional color space, representing a color image's histogram and then selecting a proper threshold in this histogram reveals to be a difficult task [4].

Otsu Algorithm. The simplest type of segmentation is thresholding, in which each image pixel is divided into foreground and background points using a preset intensity value k (threshold), separating the picture objects and backdrop into distinct sets. Otsu method is a thresholding technique that works by finding an optimal threshold value that maximizes the separation between the two regions. The basic idea behind this method is to minimize the intra-class variance defined as the weighted sum of the variances of the foreground and background regions. It is computed as

$$\sigma(k) = \frac{(m_G P_1 - m(k))^2}{P_1(1 - P_1)},$$

where m_G is the mean of the image intensity, $m(k)$ is the cumulative mean at a level k, and P_1 is the probability that a pixel is assigned to one class. The optimal threshold value is the one minimizing this intra-class variance and can be computed as $\tilde{k} = \text{argmax}_{k=0,\ldots,L-1}\, \sigma(k)$, being L the number of the distinct intensity level of the image. The main steps performed by Otsu algorithm are described in Algorithm 1.

Algorithm 1. Otsu algorithm

1: Calculate the pixel frequency distribution histogram of I;
2: Normalize the histogram so that it sums to one, and calculate the cumulative sum;
3: Calculate the cumulative mean and cumulative variance of pixel values;
4: For each threshold value t calculate the intra-class variance;
5: Find $\tilde{k}$ that maximizes the intra-class variance;
6: Use $\tilde{k}$ to binarize I.

3 Integrating Image Color Features via Low-Rank Factorization

As previously discussed, the color image I can be represented using different color spaces, each of them highlighting some embedded image property. However, none of these representations have proven to outperform the others in terms

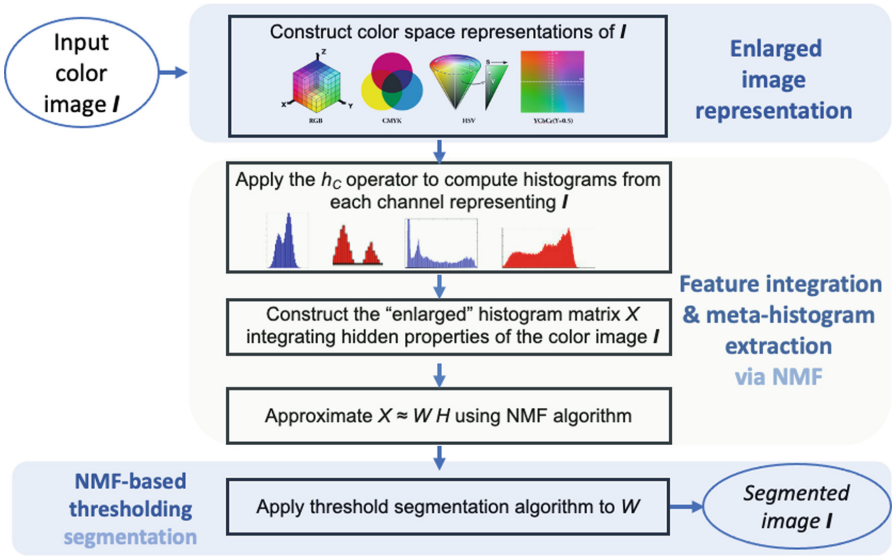


Fig. 1. Flow-chart of NMF-based segmentation algorithm. The sequential phases of the proposed approach are: creation of an enlarged representation of the input color image, feature integration, and meta-histograms extraction, and a final threshold segmentation step. (Color figure online)

of segmentation results for all types of images. As a result, choosing the best color space remains one of the most difficult aspects of color image segmentation. In this paper, rather than looking for the best color space representation, we propose to integrate different color space image properties and derive from them new global features which describe I. Particularly, we propose to integrate histograms derived by different color space representations of I via a low-rank matrix factorization to automatically extract an "integrated representation". The new characterization will allow sharing hidden properties in each single color image histogram representation. This extracted knowledge can then be used as input features of any segmentation method, such as the thresholding Otsu approach described in Algorithm 1. In the following, we formalize the main steps this integration approach is based on, while Fig. 1 sketches its main phases.

3.1 Enlarged Histogram Matrix Representation of Color Images

Images can be represented as three-dimensional nonnegative data, with two of the dimensions (rows and columns) describing the position of each pixel in the image and the third being the pixel intensity value of the gray/color channel used to represent the image. The histogram of a gray-scale image shows the number of image pixels found at each different intensity. Because there are 256 different intensities in an 8-bit gray-scale image, the histogram can be formalized as a vector of 256 numbers displaying the distribution of pixels among those gray-

scale values. In a color image I, histograms can be computed for each individual channel of the color space used to represent I. For example, if the RGB color space is used, histograms of the red, green, and blue channels can be generated.

Let $I \in \mathbb{R}^{p\times q}$ be a color image with pq pixels and let RGB, YC_bC_r, $L^*a^*b^*$ and HSV be the color spaces chosen to describe I. Formally, let h_C indicate the n-bin histogram operator which computes the distribution of image pixel intensities in the color channel C:

$$h_C : \mathbb{R}^{p\times q} \to \mathbb{R}^n_+. \tag{1}$$

From each of the previously considered color channels, we apply the operator h_C to the given image I to obtain the "enlarged" histogram matrix representation of I, that is

$$X = [h_R, h_G, h_B, h_Y, h_{C_b}, h_{C_r}, h_{L^*}, h_{a^*}, h_{b^*}, h_H, h_S, h_V]. \tag{2}$$

The matrix $X \in \mathbb{R}^{n\times 12}_+$ is a nonnegative matrix whose columns are histograms of the color channel in the chosen color image representation of I. It represents all the underlying color distributions in I measured in the chosen color components and provides an integrated representation of the hidden properties of the color image I. It represents –in a single structured matrix– different characteristics of the image I. In fact, the HSV color space codifies intensity, hue, and luminosity, which are not covered by the RGB color space. The YCbCr space allows for the comparison of color luminance, as well as blue and red chromaticity, whereas the L*a*b* space extracts luminance, hue, and saturation while separating luminance from chromaticity.

3.2 Feature Integration and Meta-Histograms Extraction

Since the enlarged histogram matrix X is nonnegative and incorporates different color representations of the picture I, we may decompose it using NMF[6,9,11]. This is a low-rank dimensionality reduction technique for feature extraction, data analysis, and signal processing that has found wide use in image processing too. NMF decomposes a nonnegative data matrix $X \in \mathbb{R}^{n\times m}_+$ into a basis matrix $W \in \mathbb{R}^{n\times r}_+$ and an encoding factor $H \in \mathbb{R}^{r\times m}_+$, both having non-negative elements, such that $X \approx WH$; with the rank value r usually chosen so that $(n+m)r < nm$. NMF provides an additive combination of non-negative matrix factors representing realistic building blocks for the original data. When factorizing the enlarged histogram matrix $X \in \mathbb{R}^{n\times 12}_+$, that integrates histograms of some fundamental color channel of the image I, the factor W can be interpreted as the meta-histogram factor since it represents an additive combination of color histograms. The columns of W extract hidden information from the different representations of the picture I and can be considered as an "ideal" color representation of image pixels. The matrix factor W stores the information of the image in the selected 3-D color spaces and can be adopted to segment I.

The segmentation of color images usually presents different issues. Firstly, the choice of the color space: color information is represented by tristimulus R,G, and

B or by their linear/nonlinear transformations. Secondly, when dealing with a thresholding algorithm: selecting the cutoff value in the histogram is not a trivial job, and detecting the clusters of points within this space will be computationally expensive. Using the information embedded in different color spaces, the meta-histogram factor W computed by NMF could produce some improvement in the segmentation process.

3.3 The NMF-Based Segmentation Approach

The approach proposed in this paper is based on the idea of using NMF to integrate different features extracted from a given color image using a histogram of image pixel intensities in the selected color channel. The generated data matrix X, which incorporates several picture features, is then factorized into W and H, where each column of the basis matrix W serves as a meta-histogram for any segmentation technique based on thresholding. Particularly, we apply Otsu method described in Algorithm 1. We refer to this method as NMF+Otsu. As regarding the computation of the NMF of the enlarged matrix X, to obtain $W \in \mathbb{R}^{n \times r}$ and $H \in \mathbb{R}^{r \times 12}$ we used the 2-block coordinate descent method Alternating Nonnegative Least Square (ANLS), based on the alternating solution two convex sub-problems related to the NMF factorization of X, that is:

$$\min_{H \geq 0} \|X - WH\|_F^2, \quad \text{with } W \text{ fixed}$$

and

$$\min_{W \geq 0} ||X^\top - H^\top W^\top \|_F^2, \quad \text{with } H \text{ fixed.}$$

The algorithm adopted to solve the ANLS is based on the following update rules [1]:

$$W_{ia}^{k+1} = W_{ia}^{k} \frac{(X(H^k)^\top)_{ia}}{(W^k H^k (H^k)^\top)_{ia}}, \quad \forall i, a \tag{3}$$

$$H_{bj}^{k+1} = H_{bj}^{k} \frac{((W^{k+1})^\top X)_{bj}}{((W^{k+1})^\top W^{k+1} H^k)_{bj}}, \quad \forall b, j \tag{4}$$

being k the iteration step and the final value of k represents the total number of iterations performed by the algorithm before reaching its stopping criterium. The ANLS algorithm has been initialized using random nonnegative factors W_0 [5].

The rank value has been selected as $r = 3$, coherently with the dimension of the color spaces used to describe the meta-histogram information extracted from I. The Otsu algorithm then uses the columns of the factor W as input meta-histograms to adaptively detect r thresholds. A probability mask can be finally produced by averaging the segmentation outcomes for each meta-histogram.

4 Numerical Experiments

To demonstrate the effectiveness of the proposed NMF-based segmentation strategy, namely NMF+Otsu, we reported here some experimental results on some well-known color images. Lacking commonly used metrics, to evaluate the image segmentation results, we selected empirical goodness and discrepancy which simply qualitatively evaluate segmentation results with respect to the original image according to human intuition (as described in [16]).

Moreover, the NMF+Otsu approach has been compared with the standard Otsu segmentation method (namely, Otsu). Accuracy and Precision measures have been used as additional quantitative metrics for images having foreground truth image segmentation results. Particularly, $Precision = \frac{TP}{TP+FP}$ is the proportion of pixels in the segmentation that correspond to boundary pixels in the ground truth; while pixel accuracy is computed as $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$ where TP indicates the number of pixels classified correctly for a given class c, FP the number of pixels classified incorrectly as class c, TN the number of pixels classified correctly as not c, and FN the number of pixels classified incorrectly as not c.

4.1 Experimental Results

To assess the qualitative validity of the proposed NMF-based methodology, the segmentation results on different color images are presented. Firstly, Fig. 2 illustrates the original color images used as benchmarks: (a) Palm tree on the seafront with a shadowed sky as background; (b) two flower vases with clear background and flower stems inside; (c) some Martini glasses with a gray background and back lighting. Figure 3 illustrates the color channels used to represent the two flower vases image in the selected color spaces. It should be observed that twelve initial feature histograms can be extracted using four color spaces.

Figure 4 illustrates the qualitative comparisons between NMF+Otsu and Otsu algorithm on the three used color images (palm tree on the seafront, flower vase, six Martini glasses) to discriminate principally from background to foreground. As it can be observed, for all three images, Otsu algorithm (applied on the histogram obtained from a single space image representation) is able to identify and extract the main objects in the image with respect to the background on which they are located (palm three, sea and wall in Fig. 4a; the two vases and parts of the flowers in Fig. 4b; the six glasses in Fig. 4c). However, the final segmentation also includes parts of clouds in the sky for the Palm image or parts of the shadows generated by the light on the background on which the vases and the glasses are located in. Instead, the NMF+Otsu proposed approach produced a better segmentation of all the images. For instance, a clear simplification of the numerous segments within the image can be seen for the flower vases image where the shadow areas formed by the vessels are not treated as segments pertaining to the vessels themselves. Moreover, in the Martini glasses image, it can be appreciated a distinct distinction between the glasses and their



(a) (b) (c)

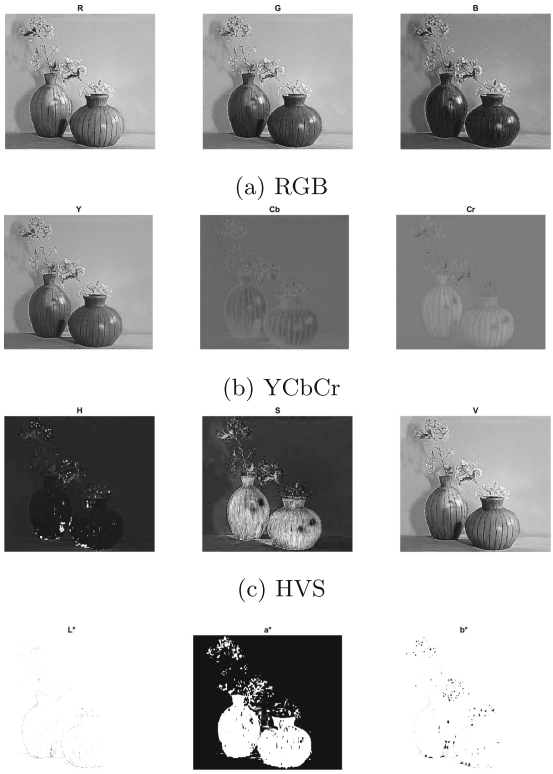
Fig. 2. Original color images used to test the empirical goodness of the proposed approach: (a) Palm tree on the seafront with a shadowed sky as background; (b) Flower vases with clear background and some flower stem inside; (c) Six Martini glasses in the gray background and with back lighting.

shadows, and also it exhibits a well-defined separation between the glasses and the background.

To better evaluate the efficiency of our proposed method we also test it on some pictures with ground truth, selected from a dataset adopted for a Kaggle challenge [7]. The three images considered are depicted in Fig. 5 with their corresponding ground truth.

We compare three different approaches to produce a segmented image for each picture by applying: (i) Otsu method on the gray image (used as its standard description, i.e., a thresholding algorithm acting on a single histogram), (ii) Otsu method on each band of the color image (i.e., Otsu on each of the color 12 bands before the application of NMF reduction), and (iii) the proposed NMF+Otsu approach. Results for each selected image can be observed in panel (a) of Figs. 6, 7, and 8, respectively. It is important to note that the NMF+Otsu approach in this paper has also the advantage of supplying a probability mask. This mask will display a probability grayscale that the user or the expert of domain, may interpret and utilize to independently segment the image under consideration. The probabilities mask for each selected images are shown in Figs. 6a, 7b, and 8b, respectively; whereas results for panels (a) are associated with a binarization of the mask values equal to 0.5.

Beside the advantage of the probability mask, the use of this particular dataset, which provides the ground truth as well, gives us the possibility to make also a quantitative comparison between the methods under analysis. Table 1 reports the values of the quantitative metrics for images in Fig. 5. The last column of Table 1 reports the accuracy and precision values for NMF+Otsu, which works on the extracted meta-histogram features. Evaluation has been performed using a binarization threshold. As can be observed, for the more complex pictures (Vessel and running dog) the NMF-based approach overcomes the basic threshold algorithm, providing highly accurate results.



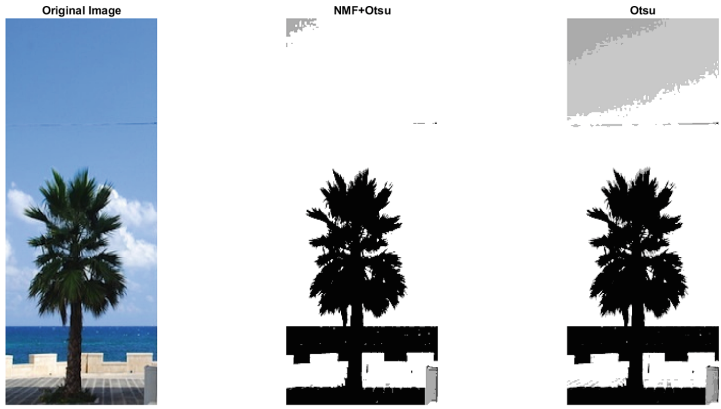
(a) RGB

(b) YCbCr

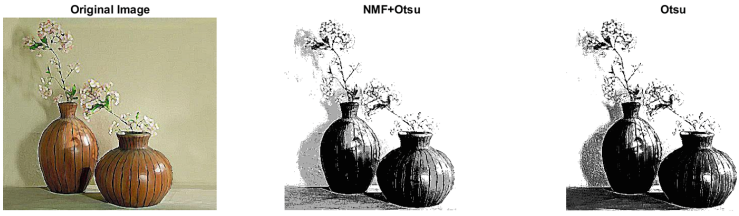
(c) HVS

(d) L*a*b*

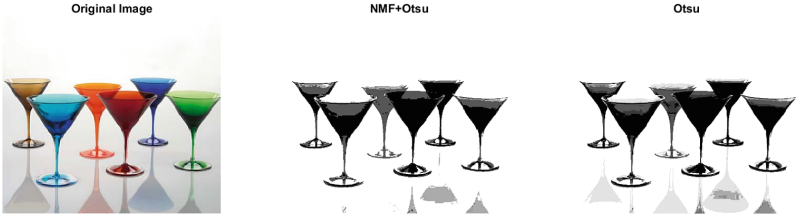
Fig. 3. Color spaces used to describe the flower vase image (nine and twelve initial feature histograms can be extracted using three or four color spaces, respectively).



(a) Palm tree on the seafront



(b) Flower vases



(c) Martini glasses

Fig. 4. Qualitative results obtained using Otsu and NMF+Otsu segmentation process with different color image inputs.



(a) Table

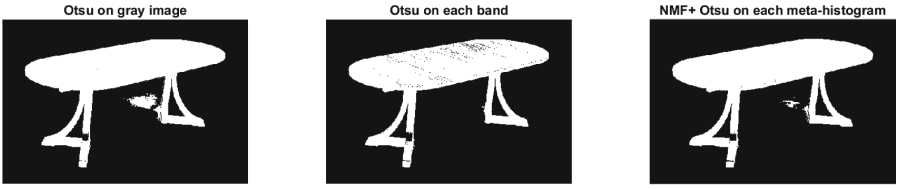


(b) Vessel into the sea

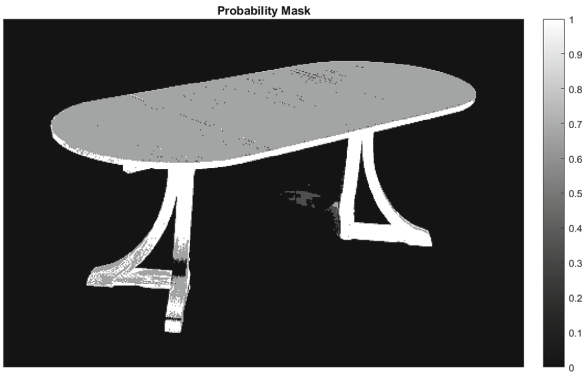


(c) A running dog

Fig. 5. Test color images used with corresponding ground truth. These images are from the image database in [7].

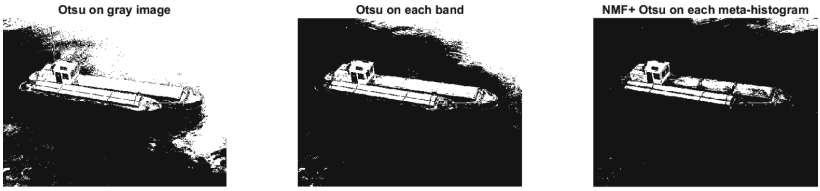


(a)

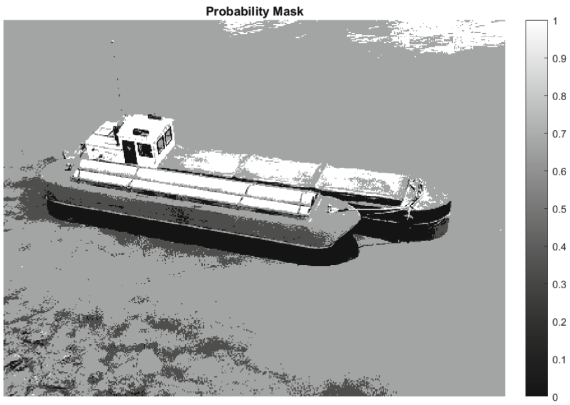


(b)

Fig. 6. The three panels (a) report (from left to right) the segmentation results obtained from Otsu algorithm applied to the grayscale image, on each color channel, and of NMF+Otsu framework. The panel (b) reports the probability mask which is additionally provided by the NMF+Otsu framework. (Color figure online)



(a)

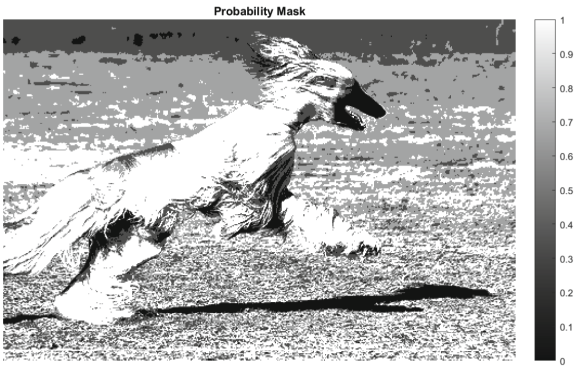


(b)

Fig. 7. The three panels (a) report (from left to right) the segmentation results obtained from Otsu algorithm applied to the grayscale image, on each color channel, and the segmentation provided by NMF+Otsu framework. The panel (b) reports the probability mask which is additionally provided by the NMF+Otsu framework on the vessel pictured. (Color figure online)



(a)



(b)

Fig. 8. The three panels (a) report (from left to right) the segmentation results obtained from Otsu algorithm applied to the grayscale image, on each color channel, and the segmentation provided by NMF+Otsu. The panel (b) reports the probability mask of the dog picture additionally obtained with the NMF+Otsu approach. (Color figure online)

Table 1. Accuracy and precision of the segmentation results for the test color images with ground truth. Highest values are marked in bold.

	Otsu on gray image	Otsu on each color histogram	NMF+Otsu on meta-histograms
Table image			
Accuracy	98.24	98.78	**98.83**
Precision	93.28	**96.99**	95.88
Vessel image			
Accuracy	56.48	76.47	**85.79**
Precision	20.99	37.07	**76.75**
Dog image			
Accuracy	34.42	34.42	**71.77**
Precision	21.28	21.28	**39.75**

5 Summary and Discussion

In this paper, we addressed the problem of segmenting color images discriminating principally from background to foreground. Information related to various color channels, represented by color spaces, is used by integrating the different associated histograms and extracting hidden knowledge that can be used to improve the segmentation process. Particularly, given a color image I to segment, it is firstly represented using different color channels (four color spaces are used each of them having three color features). This information is then integrated into a new data matrix X embedding features extracted by the histogram operator on each original color feature. This is the enlarged histogram matrix representation of the image I. Hence, the new data matrix X is mined using Nonnegative Matrix Factorization algorithm to extract meta-histograms on which a thresholding algorithm is applied to segment the original image providing a probability mask.

The proposed NMF-based approach is demonstrated to provide better binary segmentation results compared with Otsu algorithm on single color space or on gray image representation. It has the advantage of creating a probability mask that indicates, for each pixel of the color image, an associated probability that pixel is or is not a feature pixel. It can also synthesize the image information expressed through the histogram operator on various color channels. Future developments will include the detection of various objects in color image, rather than just concentrating on the foreground and background.

This probability mask could be also used to feed a supervised learning algorithm for image classification tasks. Future works would concentrate to define different models based on constrained NMF that can improve the extraction of latent properties of the meta-histograms such as sparsity and soft-orthogonality [2].

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