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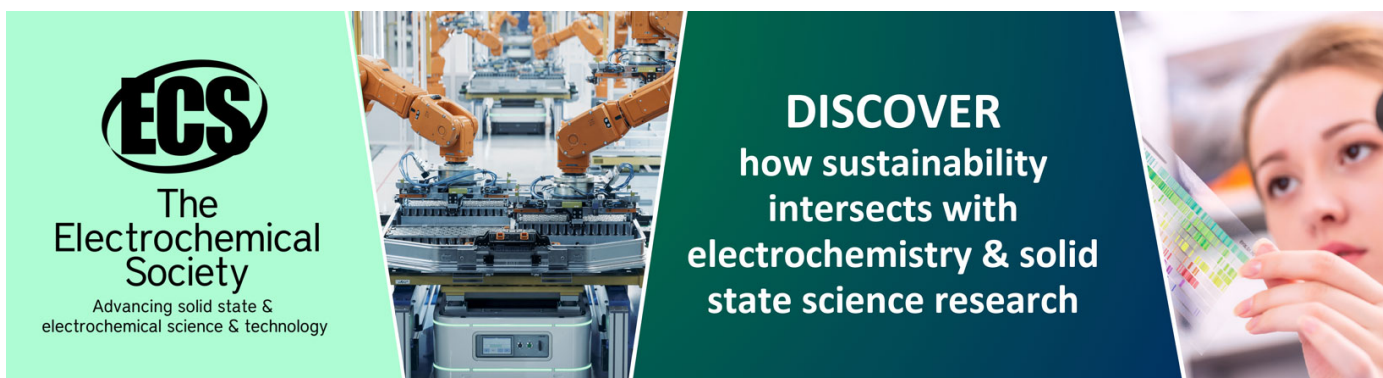
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Medical Image Segmentation using the HSI color space and Fuzzy Mathematical Morphology

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Abstract. Diabetic retinopathy is the most common cause of blindness among the active population in developed countries. An early ophthalmologic examination followed by proper treatment can prevent blindness. The purpose of this work is develop an automated method for segmentation the vasculature in retinal images in order to assist the expert in the evolution of a specific treatment or in the diagnosis of a potential pathology. Since the HSI space has the ability to separate the intensity of the intrinsic color information, its use is recommended for the digital processing images when they are affected by lighting changes, characteristic of the images under study. By the application of color filters, is achieved artificially change the tone of blood vessels, to better distinguish them from the bottom. This technique, combined with the application of fuzzy mathematical morphology tools as the Top-Hat transformation, creates images of the retina, where vascular branches are markedly enhanced over the original. These images provide the visualization of blood vessels by the specialist.

1. Introduction

Diabetic retinopathy is the most common cause of blindness among the active population in developed countries. An early ophthalmologic examination followed by proper treatment can prevent up to 95% of blindness [1-3]. The study of the characteristics of retinal blood vessels, such as width and branching pattern, provides crucial information to the ophthalmologist.

The retinal angiography is a diagnostic test that uses special cameras to evaluate the structure of the ocular background. For this test eye drops are given to dilate the pupil and then pictures are taken of the inside of the eye. After taking the first set of images, a special dye, called fluorescein, is injects into a vein. A special camera takes pictures of the eye as the dye passes through blood vessels in the back of the eye. This test is used to detect leaks or damage in the blood vessels in the retina. It can also be used to diagnose eye problems or to evaluate the success of a treatment.

The images obtained after this test are color images. The use of color images for processing and analysis is increasing relative to gray-level images, because of the additional information that they can provide. Traditionally, color images were not widely used because the capacity of the acquisition and processing equipment were limited and the cost and time of processing were prohibitive. For that reason, very few subjects took into account the potential that they offer. The growth in computing power, storage capacity and the upgrading of low-cost systems for capturing and printing images have prompted a growing interest in the use of color images in the development of many applications.

Image segmentation is a fundamental step for a correct diagnosis. Segmenting an image is a process of decomposing an image into regions of interest, to partition them based on its major structural components according to some criterion. This criterion depends on the outcome expected for the image [4]. The methods for

carrying out the segmentation task vary widely depending on the specific application, image type and other factors. Actually there is no a segmentation method to reach acceptable results for all types of medical images and there are no methods that are general and can be applied to any variety of data.

Due to the low contrast, in the images under study, between the background and blood vessels, the segmentation of these vessels is not an easy task. This paper proposes to combine Fuzzy Mathematical Morphology and process of the HSI (Hue, Saturation, Intensity) color space in order to enhance them for better viewing, and thus assist the experts in their diagnosis. The processing is based on changing only the tone, in the hue matrix, without modifying the saturation and intensity matrices, in order to maintain the appearance and effects of shading of the objects in the image.

2. Theoretical Concepts

2.1. HSI color space

Color spaces provide a way to specify order and manipulate colors. While there are several color spaces, the choice of a suitable space for color representation remains a challenge for scientists researching processing and analysis of color images [5, 6]. The most of the color spaces have been developed for specific applications, but all come from the same concept: the trichromatic theory of primary colors red, green and blue.

The HSI color space (Hue, Saturation and Intensity) define a model in terms of its components. This space has the ability to separate the intensity of the intrinsic color information, which would refer to the hue and saturation. For this reason its use is recommended for processing images when they are affected by lighting changes, characteristic of the images under study in this paper [7].

HSI space representation is through a double cone, as shown in figure 1. The center of this double cone is a circumference divided into angles of equal magnitude. For this reason the value of H, which describes the color by its wavelength, covering angles whose amplitude varies between 0° and 360° . The letters R, Y, G, C, B and M refer to Red (0°), Yellow (60°), Green (120°), Cyan (180°), Blue (240°) and Magenta (300°) respectively. The distance from the center of the exterior circumference represents the saturation found in every color and takes values from 0 to 1, indicating how the color is diluted with white light. Finally, the axis through the two cones corresponds to the intensity component. This has a normalized value from 0 (black) to 1 (white) and indicates the amount of light in a color. Removing a small circumference of the figure formed by two cones, colors close to an intensity of 1 are lighter than those close to zero. When the saturation component is close to 0, colors only reflect a change between black and white. When this component is close to 1, the color will reflect the true value represented by the hue [8, 9].

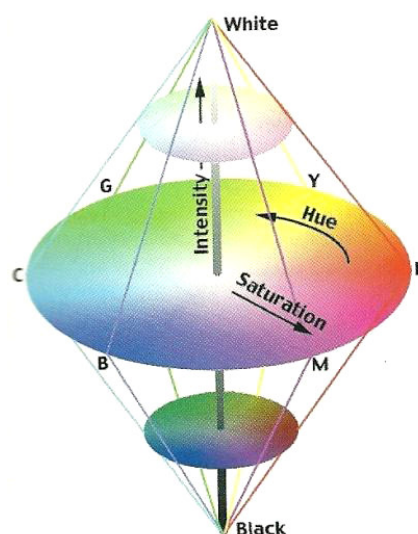


Figure 1: HSI space representation.

2.2. Fuzzy Mathematical Morphology

The Mathematical Morphology (MM) is a theory for image processing based on concepts of geometry, algebra, topology and set theory, created originally with the goal to characterize physical and structural properties of different materials [10, 11]. Currently the MM has become a solid mathematical theory based on the powerful tools for Digital Image Processing. The central idea of this theory is to analyze the geometric structures in an image to overlap with small patterns located in different parts of it, called structuring elements (SE). The MM allows enhancing areas, edge detection, analyzing structure and segment regions, among others. Based on solid theoretical foundations, the MM has achieved excellent results in the segmentation of structures and deployment fast and simple algorithms. Anyhow, in images of high texture and vague edges, a new approach is indispensable.

The MM has been applied successfully to a large number of image processing problems. However, MM does not allow a complete representation of the uncertainties in images with high texture or a high degree of uncertainty in structural components. From the binary MM different extensions have been made for grayscale images. One of these extensions is the Fuzzy Mathematical Morphology (FMM). The fuzzy sets have several advantages to represent the uncertainties in the images and turn out to be a useful tool for their segmentation. The FMM has been applied successfully in medical image segmentation [12, 13]. The following operators are defined to be used in this work.

In what follows μ and ν denote two fuzzy sets, where the first corresponds to a grayscale image and the second is the structuring element. Importantly, for most cases the images in gray levels are defined so that the gray level intensity at each pixel is an integer value belonging to the natural range $\llbracket 0, 255 \rrbracket$. Therefore, to be able to apply the FMM operators need to generate a function that changes the scale of these images, leading them to the range $[0, 1]$. This process of scaling it is called "fuzzification", while the reverse process is called "defuzzification".

For the development of this work fuzzification function $g: \{0, 1, 2, \dots, 255\} \rightarrow [0, 1]$ used is:

$$g(x) = \frac{x}{255} \quad (1)$$

The reverse process by which the intensities of the gray levels of an image, belonging to the interval $[0, 1]$, are brought to the set $\{0, 1, 2, \dots, 255\}$ is defined from the function $h: [0, 1] \rightarrow \{0, 1, 2, \dots, 255\}$ given by:

$$h(x) = \lfloor 255 \cdot x \rfloor \quad (2)$$

where $\lfloor \cdot \rfloor: \mathbb{R} \rightarrow \mathbb{Z}$ represents the integer part function, ie, $\lfloor a \rfloor$ is the nearest integer to a with $a \in \mathbb{R}$.

Importantly, this process not converts the image into a fuzzy representation of an object, but that models a grayscale image as a fuzzy set in order to apply the theory of fuzzy sets.

The definition of the basic operations of the FMM is shown below [16, 17].

Fuzzy dilation of the image μ by the SE ν [10]:

$$\mu \oplus \nu = \sup_{y \in U} \left[t(\mu(y), \nu(y-x)) \right] \quad (3)$$

where $t[a, b]$ is a t-norm [16].

Fuzzy erosion of the image μ by the SE ν [15]:

$$\mu \ominus \nu = \inf_{y \in U} \left[s(\mu(y), c(\nu(y-x))) \right] \quad (4)$$

where $s[a, b]$ is a s-norm and $c(a)$ is the fuzzy complement [17].

Fuzzy morphological closing of the image μ by the SE ν is given by:

$$\mu \bullet \nu = (\mu \oplus \nu) \ominus \nu \quad (5)$$

Within the FMM an image segmentation technique very useful is the Fuzzy Top-Hat transform by closing, which highlights locally dark objects that have been deleted in a grayscale image by the closing filtering. For this use a structuring element larger than the structures to detect. The choice of form, size and orientation of this element

makes it possible to filter the image greatly increasing the contrast of the areas eliminated, ignoring the regions which are not relevant in the analysis to be performed. This operator is defined, then, as the residue between the fuzzy morphological closing and the image:

$$\rho(\mu, \nu) = (\mu \bullet \nu) - \mu \quad (6)$$

3. Materials and methods

Were used 40 digital retinal images belonging to the public database DRIVE (Digital Retinal Images for Vessel Extraction) [18]. The images were acquired using a Canon CR5 non-mydratic 3CCD camera with a 45 degree field of view (FOV). Each image was captured using 8 bits per color plane at 768 by 584 pixels.

The purpose of this work is to develop a processing on HSI color space in order to enhance the blood vessels in these images. Color space is divided into subspaces, each of which characterizes an object in the image. A false color in the hue component is assigned to the subspace that characterizes the blood vessels, while saturation and intensity components are not modified so that the resulting image has the same shading effects.

The subspace representing the blood vessels is obtained from the fuzzy segmentation of grayscale image that emerges from the combination of RGB components of the original image. The steps to obtain this subspace are the following:

Step 1: Chromatic Filter: A color image consists of three components: Red, Green and Blue. Each of these components is stored in a matrix of $M \times N$ and takes values between 0 and 255. By combining them a RGB color image is generated [19]. The chromatic filter allows modifying the intensity of each color, i.e., it modifies the values in each of the matrices according to a criterion. This criterion depends on the objects available on the image. That allowed enhancing the areas of interest. For this purpose we attenuated the red component, since this component is homogeneous present in the ocular background and in the blood vessels. The green and blue components were set at a level slightly higher than it was originally to be those that contain high frequency information corresponding to the vessels under study. Therefore, the red component is multiplied by the scalar 0.4, while the green component is multiplied by 1.8 and the blue by 2.

Step 2: Fuzzy Top-Hat transform by closing: From the image obtained in the previous step, a grayscale image was obtained doing a weighted average of the three components that define it. The way to do it is apply the following formula to the value of each pixel:

$$I_{Gray} = 0.2989 \times R + 0.5870 \times G + 0.1140 \times B \quad (7)$$

where R, G and B are the value of the pixel in the red, green and blue components, respectively. Then it applies a fuzzy Top-Hat transform to the grayscale image, since this transform enhancing dark objects against from a not uniform background.

Step 3: Binarization: The result of applying the fuzzy Top-Hat transform is also a grayscale image where enhanced regions represent the blood vessels in the image. To remove noise in the filtered image, binarization is applied, where 0 represents the background of the image and 1 represents the objects of interest.

Step 4: Enhancement and visualization: The image obtained in the previous step is the subspace that characterizes the blood vessels. Assigning tonality 0° in the hue component, an enhancement of objects characterized by this subspace is obtained, maintaining the original value of tonality in the rest of the image.

The results obtained from the proposed method are compared in the next section with the gold standard, which is provided by the database.

The algorithm was developed in Matlab. Standard functions of this language and a specific library with functions of Fuzzy Mathematical Morphology [20] were employed.

4. Results

This section presents the results obtained with the proposed method. In figures 1 to 3 show some resulting images. In each case, first the original image is shown, then the segmented image using the operators of the FMM and finally the original image enhanced. To validate the obtained enhanced image, we used the gold standard image obtained from manual blood vessels segmentation by an expert. The computational cost of execution the algorithm is negligible given the low computational cost of the morphological operators used.

Tables 1 to 3 show the classification error as an error matrix or confusion matrix [21]. The boxes on the main diagonal of each matrix show the percentage of pixels correctly classified. The values for the blood vessels and the ocular background are very high. It also follows from the results that the greatest degree of confusion arises in the corresponding pixels in the ocular background that are classified as ocular vasculature. Table 4 shows the average percentages of correct classification the 40 images processed. The percentages of correct classification for blood vessels and ocular background are 98.4737% and 91.7861%, respectively.

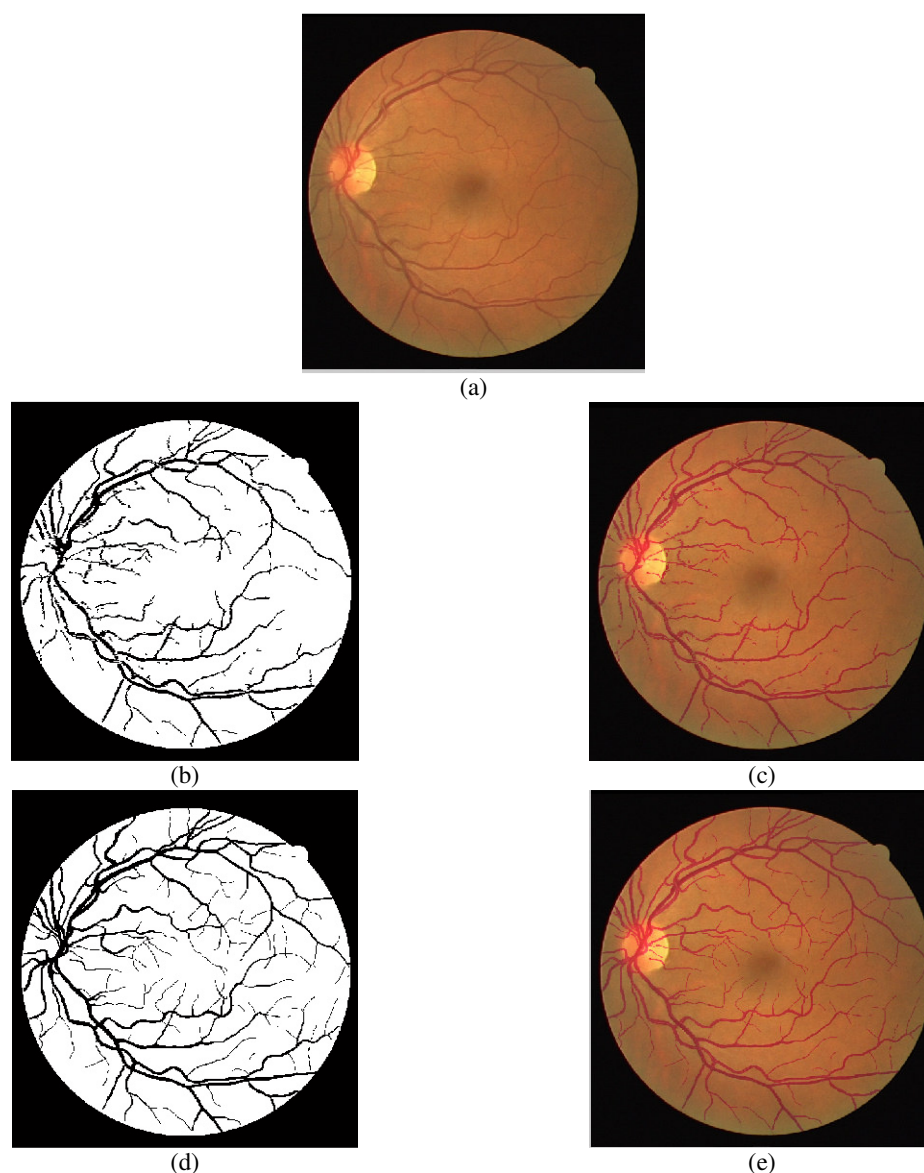


Figure 2: (a) Original image. (b) Segmented image. (c) Original image enhancement using the segmented image. (d) Gold standard image. (e) Original image enhancement using the gold standard image.

Table 1: Average percentage of pixels by subspace for image of figure 2.

	% of pixels to be classified as blood vessels...	% of pixels to be classified as ocular background...
... that would have been classified as blood vessels	97.9955	6.4165
...that would have been classified as ocular background	2.0045	93.5835

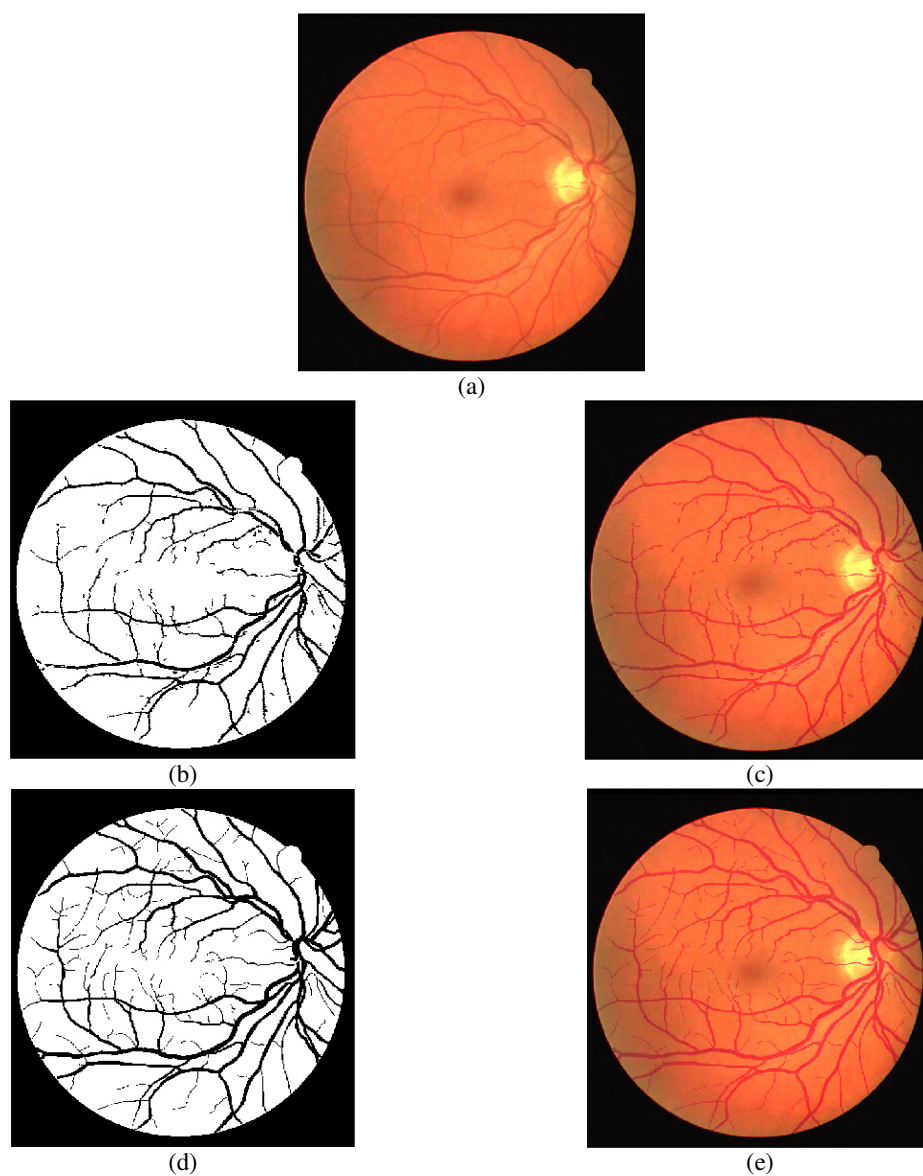


Figure 3: (a) Original image. (b) Segmented image. (c) Original image enhancement using the segmented image. (d) Gold standard image. (e) Original image enhancement using the gold standard image.

Table 2: Average percentage of pixels by subspace for image of figure 3.

	% of pixels to be classified as blood vessels...	% of pixels to be classified as ocular background...
...that would have been classified as blood vessels	98.6596	7.8025
...that would have been classified as ocular background	1.3404	92.1975

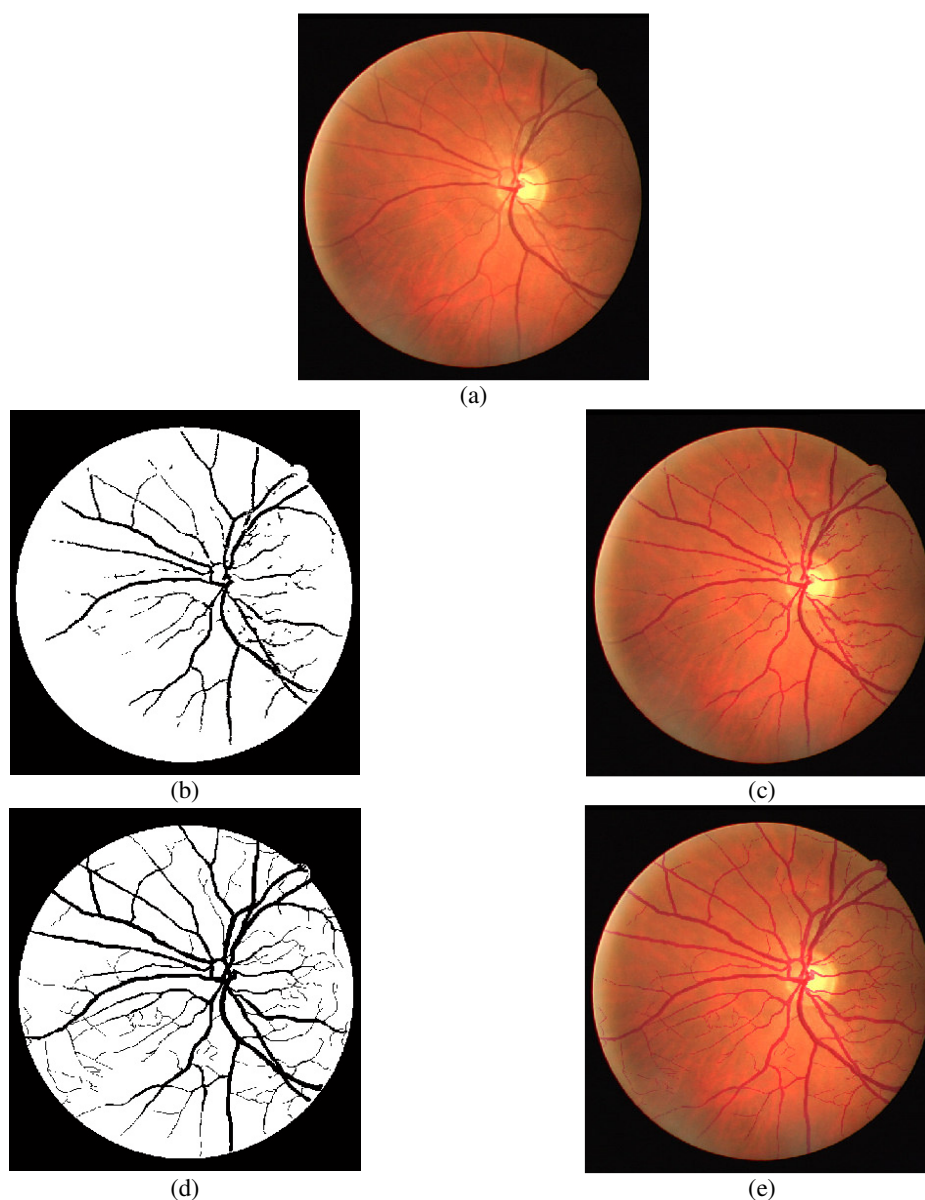


Figure 4: (a) Original image. (b) Segmented image. (c) Original image enhancement using the segmented image. (d) Gold standard image. (e) Original image enhancement using the gold standard image.

Table 3: Average percentage of pixels by subspace for image of figure 4.

	% of pixels to be classified as blood vessels...	% of pixels to be classified as ocular background...
...that would have been classified as blood vessels	99.1898	9.7479
...that would have been classified as ocular background	0.8102	90.2521

Table 4: Average percentage of pixels by subspace for the 40 images analyzed.

	% of pixels to be classified as blood vessels...	% of pixels to be classified as ocular background...
...that would have been classified as blood vessels	98.4737	8.2139
...that would have been classified as ocular background	1.5263	91.7861

5. Conclusions

This paper proposed a method for enhancement of blood vessels in retinal angiography in the HSI color space in order to assist experts in the formulation of diagnoses. The color space was segmented into subspaces using Fuzzy Mathematical Morphology, allowing assign a false color on the hue component of the subspace that representing blood vessels and thereby improve visualization of these ramifications.

To validate the proposed method we used images provided from the public database DRIVE, which includes the ideal segmentation, a tool necessary to carry out the validation of any method of segmentation. As a result of the processing of the 40 images, were obtained that on average 98.4737% of the pixels corresponding to blood vessels have been correctly segmented.

After doing the necessary tests and receiving the views of specialists, as future work, a graphical user interface will be proposed to facilitate the task of the experts.

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