2022 19th International Conference on Electrical Engineering, Computing Science and Automatic Control (CCE) | 978-1-6654-5508-4/22/$31.00 ©2022 IEEE | DOI: 10.1109/CCE56709.2022.9975967

Eye Fundus Image Processing Using Fuzzy Logic

I.S. Chong-Cervantes
Electrical Engineering Department, CINVESTAV-IPN
Mexico City, Mexico
ivan.cao.c@cinvestav.mx

A. Anzueto-Ríos
Electrical Engineering Department, CINVESTAV-IPN
Mexico City, Mexico
alvaro.anzueto@cinvestav.mx

J.A. Moreno-Cadenas
Electrical Engineering Department, CINVESTAV-IPN
Mexico City, Mexico
jmoreno@cinvestav.mx

M.A. Reyes-Barranca
Electrical Engineering Department, CINVESTAV-IPN
Mexico City, Mexico
mreyes@cinvestav.mx

L.M. Flores-Nava
Electrical Engineering Department, CINVESTAV-IPN
Mexico City, Mexico
lmflores@cinvestav.mx

***Abstract*—In this work, an improvement is made to eye fundus images to highlight the characteristics associated either with diabetic retinopathy and glaucoma pathologies, considering observations collected from specialized medical personnel, which are intended to facilitate diagnosis. Migration from the RGB (Red-Green-Blue) color space to the CIE L*a*b* space, defined by the Commission International d'Eclairage (CIE), is proposed for image processing. Given this migration, the intensity levels of pixel illumination are analyzed and modified by employing two fuzzy inference systems (FIS) to improve the image's contrast and highlight the details associated with these pathologies. The results section presents the relevant data obtained in this proposal. With them, it is demonstrated that applying fuzzy logic in processing eye fundus images is a viable option to support medical personnel in elaborating a diagnosis, considering that fuzzy schemes had been scarcely used for this type of image.**

***Index Terms*—fuzzy inference system, image enhancement, eye fundus image, diabetic retinopathy, glaucoma.**

I. Introduction

One of the most relevant advances in ophthalmology is the eye fundus images capturing, called retinography. This study allows to analyze the inner tissue of the eye, which is responsible for interpreting changes in lighting and, in short, is how the process of vision occurs. Through this type of photography, it is possible to observe and analyze the characteristics of the different areas of the eyeball tissue including: macula, fovea, and optic nerve, mainly; and it is suitable to observe the distribution of the blood vessels as well. This allows the specialized physician to detect alterations in these areas and generate a diagnosis, such as diabetic retinopathy, glaucomatous papilla, age-related macular degeneration, retinal detachment or choroidal nevus.

Retinography allows to extract a lot of significative information; however, not all images tend to have the highest quality and some details are difficult to observe with the naked eye even when zoomed in. Image processing is the propper solution since its main objective is to improve picture quality. In medical images, this is translated into displaying the details of the interest areas more clearly and extracting as much information as possible, so a doctor or specialist will be able to use it, facilitating the diagnosis of any pathology or rely on them in assisted procedures by images.

Digital images are two-dimensional representations of numerical matrices, where each cell is known as a pixel which can represent information in both grayscale and color scales; in the latter, each pixel is formed by a triplet of numerical data where each one corresponds to a channel. According to the color model used, these arrays contain and organize the image information for its correct interpretation. There are several color spaces, of which one of the most used is RGB (Red-Green-Blue).

In recent years, different works have been presented [1]–[4] which main idea is to improve the sharpness and contrast of eye fundus images, seeking to emphasize features or specific regions within the images. The regions or features of interest vary according to the pathology to be analyzed, so proposals have arisen based on the morphological modification of the images [5], modifications based on the initial color space in the RGB capture [6], among other.

For this work, it has been considered, for the processing of the images, to highlight the signs associated with diabetic retinopathy and glaucoma pathologies, through contrast enhancement, considering the observations collected by the medical staff. For instance, in diabetic retinopathy the main signs that can be observed in the images are hemorrhages, aneurysms and microaneurysms, exudates, and neovascularization; on the other side, for glaucoma, being a disease that damages the optic nerve, the main signs appear on it, such as the abnormal emergence of blood vessels and the distinctive physiognomy of the optic nerve where the optic disc and the optic cup are located and, apart from an abnormal physiognomy, the non-proportional distance between them becomes relevant; but also, as with diabetic retinopathy, a sign of glaucoma is neovascularization.

Alternatively, contrast enhancement is a type of image processing where the dynamic range of the distribution of pixel values is increased [7], which improves the ability to see details in an image. It is essential to differentiate between the dynamic range of a channel and the dynamic range of the

978-1-6654-5508-4/22/$31.00 ©2022 IEEE

distribution of pixel values. The former considers all values that a pixel can take; for example, in the RGB space, this range takes values from 0 to 255 in its three channels; while in the second it is only contemplated how these values are distributed in a specific image. Due to the above, this process is carried out on a single channel; consequently, if working on the RGB color space, it is necessary to convert the image to grayscale. This is one reason why this space is not ideal for image processing, as other spaces are.

In medical images, including eye fundus images, it is essential to maintain color hue in all regions of the image, as a variation over it could result in an incorrect diagnosis. Due to this, it was chosen to work on the color space defined by the Commission International d'Eclairage (CIE) in 1976: CIE 1976 L*a*b* (CIELAB); which expresses the color with three components: "L*", that represents luminosity in range from 0 to 100; and "a*" and "b*" which represents the opposite colors red and green and yellow and blue, respectively, as a relative axis. This allows to isolate the color in two channels and work only on the lighting channel.

Several algorithms perform contrast enhancement, of which histogram equalization (HE) and its derivatives are among the most basic and widely used methods [8]. However, although they have been shown to have favorable results by increasing contrast, they are unsuitable for medical imaging because they tend to hit both the saturation and the minimum values. In the CIELAB space, the saturation values are close to 100, and the minimum values are close to 0; this means that, with these numerical values, there are very light and very dark tones. Due to this, in this work, it is proposed to use a contrast enhancement method based on fuzzy logic [9]–[11] which, when interpreting and considering the knowledge of the expert staff, avoids this problem.

Fernandes et al. [12] propose using two fuzzy inference systems (FIS) to analyze images of everyday scenes based on the RGB color space. The first FIS has as input parameter the global standard deviation of the intensity levels of the pixels in the grayscale and presents as output data the variation parameter x, which is used by the second FIS to generate the values of output sets of type singletons.

In this work a similar scheme is followed, but it is treated with eye fundus images, which presents a high value of contrast due to the dark areas outside the eyeball tissue, generated by the acquisition method itself; therefore, for the analysis of this type of images, it is proposed an expansion in the SD range. Additionally, the use of Gaussian bells is considered as input membership functions for the second FIS, which allows smoothing the abrupt tones variations in the regions of interest of the images.

II. Methodology

This work aims to support medical personnel in the diagnosing of pathologies in eye fundus images; therefore, the characteristics that the image should have so that they could interpret them were considered. These characteristics are: maintaining the color level in the blood vessels, enhancing the contrast between the different areas present in the image, and avoiding color saturation since this leads to regions of white or very dark tones.

Generally, the initial color space of the images is RGB; however, as mentioned above, this is not ideal for processing; therefore, a migration to the CIELAB space was implemented to work only on the L* channel in order to modify the dynamic range of the distribution of pixel values and to be able to preserve the colors by leaving the other two channels intact.

The method applied for contrast enhancement is based on fuzzy logic, which was chosen due its ability to adapt to the requirements in color modeling; for eye fundus image, it is required a smooth contrast improvement in order to preserve the hue of the colors and the sharpness of the regions associated with optic nerve and macula, since the former is the main area of analysis to detect alterations associated with glaucoma and in the second is where those associated with diabetic retinopathy are presented.

In this work, two zero-order Takagi-Sugeno type FIS were used; the former is in charge of adjusting two singleton output membership functions of the latter, according to the contrast level of the input image. The importance of this FIS lies in the fact that the original qualities of the images can vary a lot, therefore not all images will need the same degree of contrast enhancement, so an image with a low contrast balance will require a higher adjustment than its counterpart.

Standard deviation (SD) is a measure that provides information about the average dispersion of a variable [13]. In digital images, the SD of pixel intensities is known as root mean square contrast (RMS contrast) (1), since it indicates how dispersed pixel values are in relation to the mean [14], therefore if the SD of an image is high it means that it has both light and dark tones, otherwise the tendency will be to have very similar tones throughout the image. In other words, it is directly proportional to contrast, so if an image has a high SD, it will have a high contrast. In short, SD is an indicator of image contrast and because it was chosen as the input parameter for the first FIS, whose calculation was performed on the normalized illumination channel.

$$SD = \sqrt{\frac{1}{MN}\sum_{i=0}^{N-1}\sum_{i=0}^{M-1}(I_{i,j} - \overline{I})^2} \tag{1}$$

From (1), $I_{i,j}$ denotes the intensity of the pixel (i, j) of the matrix that represents the image of size $M \times N$ and $\overline{I}$ is the average of the intensity of all the pixels.

From the analysis of the SD or RMS contrast values calculated in eye fundus images, three types of input membership functions were used in both FIS: Z function (2), bell function (3) and S function (4).

$$Z(\sigma) = \frac{1}{1 + e^{\alpha(\sigma - \beta)}} \tag{2}$$

$$B(\sigma) = e^{-\frac{1}{2}(\frac{\sigma-\gamma}{\delta})^2} \tag{3}$$

$$S(\sigma) = \frac{1}{1 + e^{-\alpha(\sigma - \epsilon)}} \quad (4)$$

Where, adapting them to the proposed universe of discourse, σ denotes the SD, α the slope of $Z(\sigma)$ and $S(\sigma)$, β the midpoint of the slope of $Z(\sigma)$, γ the center of $B(\sigma)$, δ^2 the width of $B(\sigma)$ and ϵ the midpoint of the slope of $S(\sigma)$.

This universe of discourse represents the variations in the SD (RMS contrast) values that can exist in different eye fundus images. For its fuzzification, three linguistic labels were considered: "low", "medium" and "high", as shown in Fig. 1.

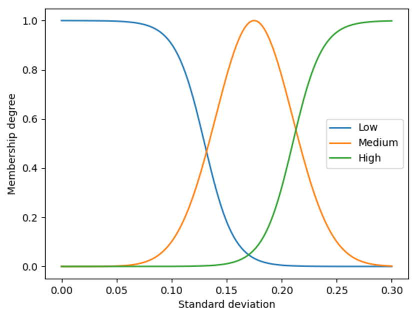


Fig. 1: First FIS input membership functions.

For the defuzzification, which will give us the crisp value x used by the second FIS, the Weighted Average Method (WAM) was used, so the output its given by (5).

$$x = \frac{(\mu_{11} \cdot f_{11}) + (\mu_{12} \cdot f_{12}) + (\mu_{13} \cdot f_{13})}{\mu_{11} + \mu_{12} + \mu_{13}} \quad (5)$$

Where μ_{11}, μ_{12} and μ_{13} are membership values obtained by evaluating (2), (3) and (4), respectively; and f_{11}, f_{12} and f_{13} are the output fuzzy singleton values. Thereby, IF-THEN rules were defined as follow:

1) IF low THEN f_{11}
2) IF medium THEN f_{12}
3) IF high THEN f_{13}

The second FIS performs image enhancement, which has the value of the normalized pixel of the L* channel as input parameter; in a nutshell, it has the original value of the illumination as input and the value resulting from the process as output, which will be assigned to that same pixel. The process is done pixel by pixel, creating a new channel (L'*) with the new values of each pixel.

In this FIS, the universe of discourse represents all the possible illumination values that each pixel can have. As mentioned before, L* channel can take values from 0 to 100, however, being normalized, it was set in the range of 0 to 1. For its fuzzification, the following linguistics labels were used: black, dark grey, medium, light grey and white; whose input membership functions, as in the previous FIS, are defined by the functions Z, bell and S. Z function was used for the linguistic variable black, the S function for white and the bell function for the rest, as shown in Fig. 2.

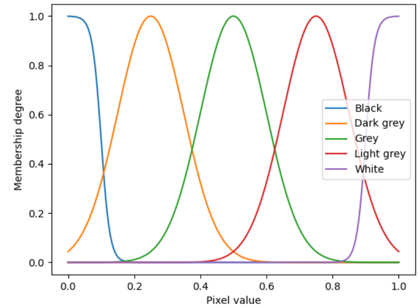


Fig. 2: Second FIS input membership functions.

To achieve suitable contrast enhancement for these images, both the boundary values and hues close to the mean were kept, and the other values, which represent medium-light and medium-dark tones, were adjusted towards their closest boundaries. Namely, values below the medium will represent darker tones and the values above it will represent lighter tones, avoiding reaching the saturation values. Therefore, seven IF-THEN rules were defined as follows:

1) IF black THEN black.
2) IF dark grey THEN darker grey.
3) IF grey THEN grey.
4) IF light grey THEN lighter grey.
5) IF white THEN white.
6) IF dark grey THEN black.
7) IF light grey THEN white.

As seen in rules above, five output sets with their singleton values were defined as shown below:

1) Black = f_{21}
2) Darker grey = $f_{22} = x$
3) Grey = f_{23}
4) Lighter grey = $f_{24} = 1 - x$
5) White = f_{25}

Where x is the adjustment parameter obtained from the output of the first FIS (5).

For defuzzification, the WAM method was used again, which allows, with rules 6 and 7, to have a sizeable increase in contrast fulfilling the aforementioned conditions. So, the output is given as follows:

$$output = \frac{\sum_{i=1}^{n} \mu(I)_{2i} \cdot f_2}{\sum_{i=1}^{n} \mu(I)_{2i}} \quad (6)$$

Where $\sum$ indicates the algebraic sum, n the number of rules, $\mu(I)_{2i}$ the membership value of the rule i and f_2 its output singleton value.

The process described in this section was developed using python programming language, specifically Python 3.9.7; and its flow diagram is shown in Fig. 3.

III. Results

Images used in this work were taken from FAU database [15], which contains 15 healthy images, 15 with diabetic retinopathy and 15 with glaucoma. As mentioned in previous

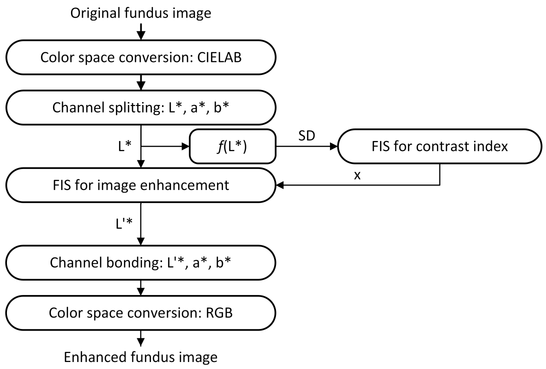


Fig. 3: Flow diagram for the proposed eye fundus image enhancement.

section, image processing was performed on the normalized L* channel of CIELAB color space. The calculation of the RMS contrast was conducted by (1) and, from the analysis of the results in all images, the universe of discourse of the first FIS was established in the range from 0 to 0.3.

Table I shows the parameters of the input membership functions used in both FIS and table II the output singleton values.

TABLE I: Membership functions parameters

Membership Function	Parameters	Value
Z_{11}	α	0.75
	β	0.130
B_{12}	γ	0.175
	δ	0.035
S_{13}	α	0.75
	ϵ	0.210
Z_{21}	α	0.75
	β	0.10
B_{22}	γ	0.25
	δ	0.10
B_{23}	γ	0.50
	δ	0.10
B_{24}	γ	0.75
	δ	0.10
S_{25}	α	0.75
	ϵ	0.90

With the values shown in table II, the defuzzification described by (5) results in the transfer curve in Fig. 4.

And for the second FIS, the defuzzification described by

TABLE II: Fuzzy singleton values.

Fuzzy singleton	Numeric value
f_{11}	0.10
f_{12}	0.25
f_{13}	0.35
f_{21}	0.0
f_{22}	x
f_{23}	0.5
f_{24}	$1-x$
f_{25}	1.0

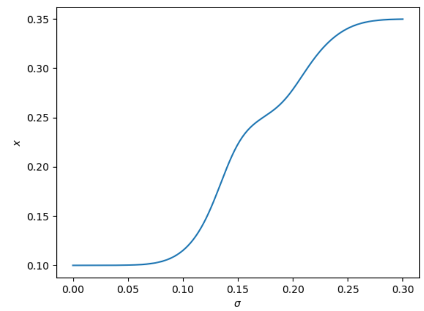


Fig. 4: First FIS transfer curve.

(6) will result in a different transfer curve for each image, depending on the parameter x obtained by the first FIS. Fig. 5 shows the resulting transfer curves with three values of x: 0.1, 0.25 and 0.35.

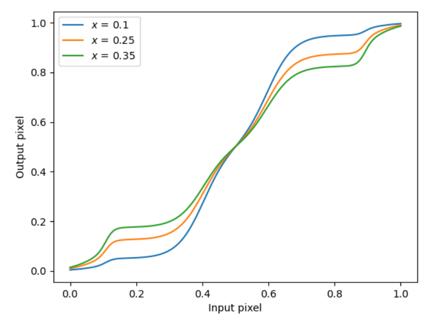


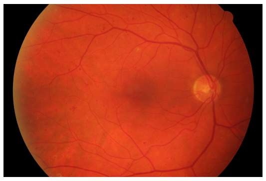
Fig. 5: Second FIS transfer curves with three different values of x.

In Fig. 4, it can be seen that input covers the entire range of the universe of discourse and the output x has a range from 0.1 to 0.35. This means that for images with high contrast the output of the first FIS will be close to 0.35 and 0.1 for the opposite case. Hence, for images with low contrast, the adjustment of midtones made by second FIS will be higher because those tones below average should be adjusted to values closer to 0 and those above average to values closer to 1. This is confirmed by Fig. 5, since it can be seen that the smaller the value of x, the steeper the slope; so, the pixel adjustment will be greater and, consequently, there will be a greater increase in contrast.

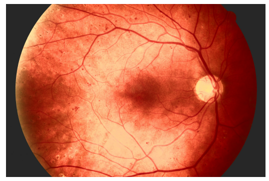
In order to evaluate the effectiveness of the proposed method, it was applied to the 45 images in the database and results were compared against two other image enhancement methods: HE and mean preserving bi-histogram equalization (BBHE) [16].

This comparison can be seen in Fig. 6, where 6a shows the original image with diabetic retinopathy, 6b the resulting image when applying HE, 6c BBHE and 6d the resulting image when applying the proposed method. Additionally, Fig. 7 shows the histograms of the L*-channel of these four images.

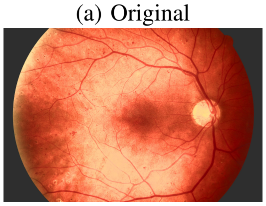
The histogram of a digital image is a graphical representation of the tones distribution in that image, thus it is possible to observe its dynamic range in it, therefore, from its analysis it is possible to obtain information on the contrast of the image.



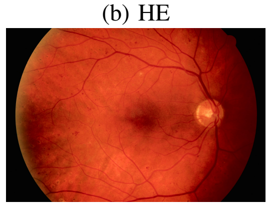
(a) Original



(b) HE



(c) BBHE



(d) Fuzzy method

Fig. 6: Process comparison

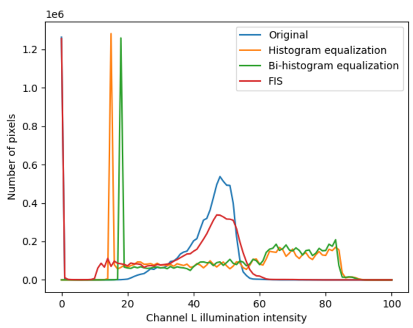


Fig. 7: Histograms.

Visually in Fig. 6 and with the histograms in Fig. 7, it is possible to notice that the processed images have a higher contrast than the original; however, three metrics were calculated on L* channel of each image in order to make a numerical comparison: the SD or RMS contrast, the Peak Signal-to-Noise Ratio (PSNR) and the Measurement of Contrast Index (MCI).

As its name says, PSNR is the ratio between the maximum possible power of a signal and the power of noise. In processed images, PSNR is calculated considering the original image as signal and the processed image as noise (7) and it indicates the quality of the process [17], so a high PSNR value means a good image enhancement quality, but to high values are not desirable since it means that a lot of noise was added to original image, and this may represent loss of information.

$$PSNR = 10\log(\frac{MAX_I^2}{MSE}) \qquad (7)$$

In (7), MAX_I is the maximum value a pixel can have and MSE is the mean square error between original image and the processed image, which is calculated as follows:

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[I_{i,j} - J_{i,j}]^2$$

Where M and N represents the image matrix size and $I_{i,j}$ and $J_{i,j}$ the value of the i, j pixel of the original and the processed image, respectively.

As mentioned before, SD in images provides information about its contrast and is known as the RMS contrast. This parameter is used to obtain the MCI, which is the ratio between the SD of the processed image and the original, so values greater than 1 indicates that the processed image has a higher contrast than original. Therefore, the higher the MCI value, the better contrast will be; however, very high values indicates there is an over-improvement.

These three metrics were calculated on the four images shown in Fig. 6 and results are presented in table III.

TABLE III: Comparison parameters.

Image	SD	MCI	PSNR	Medical opinion
Original	0.174	1.0	-	Good
HE	0.237	1.360	15.270	Not suitable
BBHE	0.222	1.273	14.774	Not suitable
FIS	0.185	1.060	23.509	Very good

In order to have a more complete criteria of the proposed method performance, the three methods: HE, BBHE and fuzzy; were applied to each of the 45 images in the database and the MCI and PSNR were calculated in all of them, the results are shown in the graphs of Fig. 8 and Fig. 9, respectively.

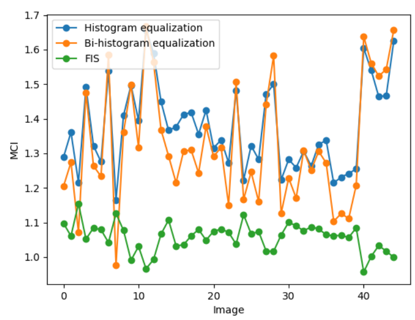


Fig. 8: MCI of processed images.

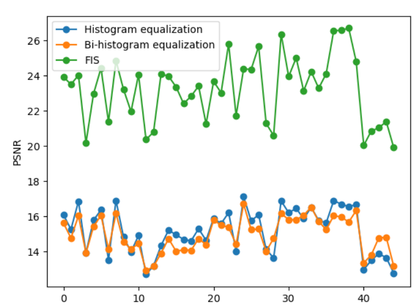


Fig. 9: PSNR of processed images.

In Fig. 8 it is observed that HE and BBHE generate images with a similar level of contrast and, in general, both are higher than the fuzzy method; however, regarding the quality of the process, Fig. 9 shows that both are widely surpassed by the proposed method, presenting a considerably higher PSNR in all images.

Based on medical staff´s recommendations, three aspects have been considered to determinate if the image enhancement is appropriate for this type of photographs. The former is the intensity of light colors, that refers to when a saturated zone in the image is represented by a white color, can falsely indicate the presence of a zone with possible retinal detachment; that is why, care must be taken that the image processing method keeps a balance regarding the original image. This undesired case is presented in the HE and BBHE, where is clearly seen, both in Fig. 6 as in its histogram of Fig. 7, an excessive saturation due to the math of the method.

The second aspect refers to the detail showed in the optic nerve. For the glaucoma diagnosis the optic nerve physiognomy is analyzed: the emergency of blood vessels, the optical disc appearance and the distance between it and the optical cup. These details are kept by the fuzzy method, while in the others two methods there is a saturation in this zone that impede an adequate diagnosis.

The last aspect implies not to lose detail in macula zone. In the methods based on modification of histogram this is not achieved since its contrast causes loss of information in the area and when applying the fuzzy method the interest zone is conserved with no alteration.

The three image enhancement methods have been presented to medical specialists; from the collected observations, the verdicts presented in the last row of table III are the trend in terms of their comments and this prove that the fuzzy logic-based method has a superior performance than other two, and even turns out to be better than the original one. These comments support the PSNR higher value in all images processed with this method. This medical verdict is fundamental since the work presented have the interest of applying image enhancement in the medical field to facilitate the elaboration of diagnostics in the evaluation of clinical cases.

IV. Conclusions

In this work, a fuzzy logic-based method for contrast enhancement on digital eye fundus images has been presented and its superiority in this task has been demonstrated against traditional methods based on histogram modification, mainly with two criteriums: the comments by the medical staff, which suggest that fuzzy method improves the original image; and with the PSNR results, which indicates that the proposed method presents a higher quality than the others.

The results obtained of the RMS contrast and MCI have to be carefully analyzed since, although these present high values and indicate a higher contrast, in medical images it can lead to the loss of information in areas of interest and, specifically in eye fundus images, if there are saturated areas it could indicate a non-existent pathology.

Considering the specialized medical staff's observations, it can be concluded that fuzzy logic-based method highlights areas of interest without saturating the image, which is consistent with PSNR values. Therefore, the objective of improving the image to make it easier for the medical specialist to generate a diagnosis has been fulfilled.

The working group is currently testing a method that measures the quality of luminosity of the image, considering that for dark images it will be necessary, as a previous step, to improve the luminosity, and then apply the contrast enhancement, in order to reduce the degradation of the edges.

Acknowledgments

The principal author appreciate the support received from CONACYT and special thanks to the optometrists Cristina Rodríguez López and Sergio Arturo Basave Garnica for their corrections made for this work.

References

[1] A. W. Setiawan, T. R. Mengko, O. S. Santoso, and A. B. Suksmono, "Color retinal image enhancement using clahe," in *International Conference on ICT for Smart Society*. IEEE, 2013, pp. 1–3.

[2] P. Dai, H. Sheng, J. Zhang, L. Li, J. Wu, and M. Fan, "Retinal fundus image enhancement using the normalized convolution and noise removing," *International journal of biomedical imaging*, vol. 2016, 2016.

[3] M. Zhou, K. Jin, S. Wang, J. Ye, and D. Qian, "Color retinal image enhancement based on luminosity and contrast adjustment," *IEEE Transactions on Biomedical engineering*, vol. 65, no. 3, pp. 521–527, 2017.

[4] L. Cao, H. Li, and Y. Zhang, "Retinal image enhancement using low-pass filtering and α-rooting," *Signal Processing*, vol. 170, p. 107445, 2020.

[5] D. Li, L. Zhang, C. Sun, T. Yin, C. Liu, and J. Yang, "Robust retinal image enhancement via dual-tree complex wavelet transform and morphology-based method," *IEEE Access*, vol. 7, pp. 47 303–47 316, 2019.

[6] G. S. Nugraha, B. A. Riyandari, and E. Sutoyo, "Rgb channel analysis for glaucoma detection in retinal fundus image," in *2020 International Conference on Advancement in Data Science, E-learning and Information Systems (ICADEIS)*. IEEE, 2020, pp. 1–5.

[7] B. R. Lim, R.-H. Park, and S. Kim, "High dynamic range for contrast enhancement," *IEEE Transactions on Consumer Electronics*, vol. 52, no. 4, pp. 1454–1462, 2006.

[8] K. G. Dhal, A. Das, S. Ray, J. Gálvez, and S. Das, "Histogram equalization variants as optimization problems: a review," *Archives of Computational Methods in Engineering*, vol. 28, no. 3, pp. 1471–1496, 2021.

[9] L. A. Zadeh, "Fuzzy logic," *Computer*, vol. 21, no. 4, pp. 83–93, 1988.

[10] N. Sabri, S. Aljunid, M. Salim, R. Badlishah, R. Kamaruddin, and M. Malek, "Fuzzy inference system: Short review and design," *Int. Rev. Autom. Control*, vol. 6, no. 4, pp. 441–449, 2013.

[11] T. J. Ross, *Fuzzy logic with engineering applications*. John Wiley & Sons, 2005.

[12] S. Fernandes, H. Vashi, A. Shetty, and V. Kelkar, "Adaptive contrast enhancement using fuzzy logic," in *2019 International Conference on Advances in Computing, Communication and Control (ICAC3)*. IEEE, 2019, pp. 1–6.

[13] B. Moulden, F. Kingdom, and L. F. Gatley, "The standard deviation of luminance as a metric for contrast in random-dot images," *Perception*, vol. 19, no. 1, pp. 79–101, 1990.

[14] E. Peli, "Contrast in complex images," *JOSA A*, vol. 7, no. 10, pp. 2032–2040, 1990.

[15] A. Budai, "High-resolution fundus (hrf) image database," available online: https://www5.cs.fau.de/research/data/fundus-images/ (accessed on 29 March 2022).

[16] Y.-T. Kim, "Contrast enhancement using brightness preserving bi-histogram equalization," *IEEE transactions on Consumer Electronics*, vol. 43, no. 1, pp. 1–8, 1997.

[17] S. Yao, W. Lin, E. Ong, and Z. Lu, "Contrast signal-to-noise ratio for image quality assessment," in *IEEE International Conference on Image Processing 2005*, vol. 1. IEEE, 2005, pp. I–397.