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Unified adaptive framework for contrast enhancement of blood vessels

Pearl Mary S., Thanikaiselvan V.
School of Electronics Engineering, Vellore Institute of Technology, India

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ABSTRACT

Information about blood vessel structures influences a lot of diseases in the medical realm. Therefore, for proper localization of blood vessels, its contrast should be enhanced properly. Since the blood vessels from all the medical angio-images have almost similar properties, a unified approach for the contrast enhancement of blood vessel structures is very useful. This paper aims to enhance the contrast of the blood vessels as well as the overall contrast of all the medical angio-images. In the proposed method, initially, the vessel probability map is extracted using hessian eigenanalysis. From the map, vessel edges and textures are derived and summed at every pixel location to frame a unique fractional differential function. The resulting fractional value from the function gives out the most optimal fractional order that can be adjusted to improve the contrast of blood vessels by convolving the image using Grunwald-Letnikov (G-L) fractional differential kernel. The vessel enhanced image is Gaussian fitted and contrast stretched to get overall contrast enhancement. This method of enhancement, when applied to medical angio-images such as the retinal fundus, Computerised Tomography (CT), Coronary Angiography (CA) and Digital Subtraction Angiography (DSA), has shown improved performance validated by the performance metrics.

Corresponding Author:

Thanikaiselvan V.,
School of Electronics Engineering,
Vellore Institute of Technology,
Vellore, India.
Email: thanikaiselvan@vit.ac.in

1. INTRODUCTION

Nowadays, a lot of diseases are closely connected with the disorders in the blood vessels such as Diabetic Retinopathy (DR) [1], hypertension, cardiovascular [2] and cerebrovascular disorders, and so on. The manual marking of blood vessels after image acquisition in the presence of low contrast is a tedious procedure that calls for training and expertise [3]. Robust segmentation of vessel structures counts on proficient image pre-processing [4] methods that enhance the contrast of blood vessels, removes noise [5], eludes non-linear illumination, highlights narrow/small vessels, retains background texture etc.

Various contrast enhancement methods are used over the years starting from histogram equalization [6]. Then, Adaptive Histogram Equalization (AHE) is introduced that uses input/output transformations to adaptively change the image contrast in accordance with the spatial attributes. Since it imposes problems such as noise amplification and over enhancement; contrast is limited by setting a clip limit within the local histogram in Contrast Limited Adaptive Histogram Equalization (CLAHE) [7]. Even though contrast is enhanced, brightness is not preserved, and the details in minor gray levels are lost. Mean brightness was preserved in Bi-Histogram Equalization (BBHE) but not the original brightness [8]. Bilateral filter [9] is rarely used to improve image contrast. But to clearly portray the small blood vessels and to achieve suppression of non-vascular structures, the bilateral filter was modified by introducing the vesselness difference obtained from frangi filter [10] in place of the intensity difference in the second Gaussian kernel. It gave improved contrast when tested on the retinal fundus image and cerebral DSA image [11]. To improve the contrast of blood vessels and to remove noise in the medical angio-images, histogram equalization was combined with filters such as Gaussian filtering techniques [12, 13].

Later, enhancement using differential functions [14] gained interest. G-L definition kernel with the fractional differential function adaptively improved the contrast of the edges in the medical image [15]. It also showed to have good contrast and higher entropy values for five different medical images. It was able to preserve the texture as well as similar regions in the image but optimal threshold selection is not robust. High boost filtering also improves the contrast and sharpness of the retinal fundus image with kernel size 21×21, but it poorly preserves the edges [16]. Top hat transform with multiple sized structuring elements [17] enhances the vessel contrast by adding the bright features from white top hat transform and neglecting the dim features from black top hat transform to the original grayscale image. Here the choice of variable sized structuring elements poses a problem in the proper enhancement of the angiogram images. A two-axis Principle Component Analysis (PCA) based coronary angiogram enhancement reduces noise as well as preserves the blood vessels. One axis is set for vessels extracted from the frangi filter and the other for the background that is separately enhanced in the PCA domain. Here, there is no clear mention of setting the threshold for both the vessels and background [18].

Generally, contrast enhancement should be simple and less complex as this is a preprocessing step [19]. Also, it should be adaptive to all images obtained from varied image sources with similar properties. All the above mentioned existing methods were capable to enhance the contrast only on specific image sources. Hence, it is tiresome and time-consuming to use varied preprocessing methods for blood vessels obtained from multiple sources such as the retinal fundus, lung, coronary and cerebrum. Therefore, designing a unified adaptive framework for contrast enhancement of blood vessels is significant. From the literature, it is found that the fractional differential based enhancement is proficient enough to enhance the contrast [20, 21] as well leave the similar pixel regions unaltered in the images obtained from multiple sources. Thus, in this paper, a novel unified adaptive fractional differential function for the contrast enhancement is framed with the aid of edge and texture smoothed information obtained from the vesselness measure. Edge and texture information associated with the vesselness measure is chosen since fractional differentials are proved to highlight the edges and preserve the textures [22]. This function when fed to the G-L kernel gives out the optimal fractional order to enhance the contrast of the blood vessels. The prominent advantage in framing the differential function is that it evades trial and error methods such as single/multilevel thresholding [23, 24] or certain area features. Further, the blood vessel contrast enhanced image is histogram stretched using Gaussian fitting to enhance the overall contrast.

The proposed method uses the medical angio-images from the retinal fundus, CA, CT of lung and DSA of the brain as its input. The resulting images after applying the proposed method are found to improve the contrast of the blood vessels as well the contrast of the entire image. This method of contrast enhancement is proved promising by analyzing the enhanced images using the perceptive and quantitative analysis in the discussion section.

2. PROPOSED METHOD

In this paper, a universal adaptive framework is designed to enhance the contrast of blood vessels, preserve background textures and similar pixel regions. It is termed universal as it can ably enhance the blood vessel structures in medical images retrieved from multiple imaging modalities. Adaptive refers to the fact that the vessel and non-vessel pixels in an image are processed separately. Here, we exploit the merits of hessian eigenanalysis, adaptive fractional differential function, G-L kernel, and histogram fitting to achieve the contrast enhancement. The proposed algorithmic workflow is depicted as a block diagram in Figure 1. This section explains the Figure 1 in detail.

From Figure 1, it is clear that the grayscale image is used as the input or just the green plane is extracted in case if the input F(x,y) is an RGB image. Blood vessel probability map is obtained using the vesselness measure framed from hessian eigenanalysis. Vesselness measure $V_\sigma(x,y)$ uses the eigenvalues λ_1 and λ_2 computed from the Hessian matrix at every pixel location. Hessian matrix is obtained by convolving every pixel in the input image with the second order derivatives of the Gaussian filter. Vessel probability map V(x,y) calculation is given in (1), (2) and (3).

$$V_\sigma(x,y)=\begin{cases}0 & ,\lambda_2<0\\ e^{\frac{-r^2}{2\beta}}(1-e^{\frac{-s^2}{2c^2}}), & otherwise\end{cases} \tag{1}$$

$$r=\frac{\lambda_1}{\lambda_2},\ s=\sqrt{\lambda_1^2+\lambda_2^2},c=\max(s)/2,\ \beta=0.5 \tag{2}$$

Where parameters β and c are the weighing factors, r denotes the deviation from a blob-like structure and s denotes the hessian norm that differentiates between vessel pixels and the background. The resulting grayscale image, V(x,y) will be in the range [0, 1]. To identify the vessel structures with varied diameters, the vesselness measure $V_\sigma(x,y)$ is computed at scales ranging from 0.5 to 2 but its maximum value is retained.

$$V(x,y)=\max_{\sigma_{\min}<\sigma<\sigma_{\max}} V_\sigma(x,y) \tag{3}$$

The resulting grayscale image consists of both the small and large vessel pixels. The major disadvantage of this approach is that it is inherently local and it never considers its neighboring vessel evidence [25]. Therefore, the neighboring pixel intensities of vessels are also considered in this paper.

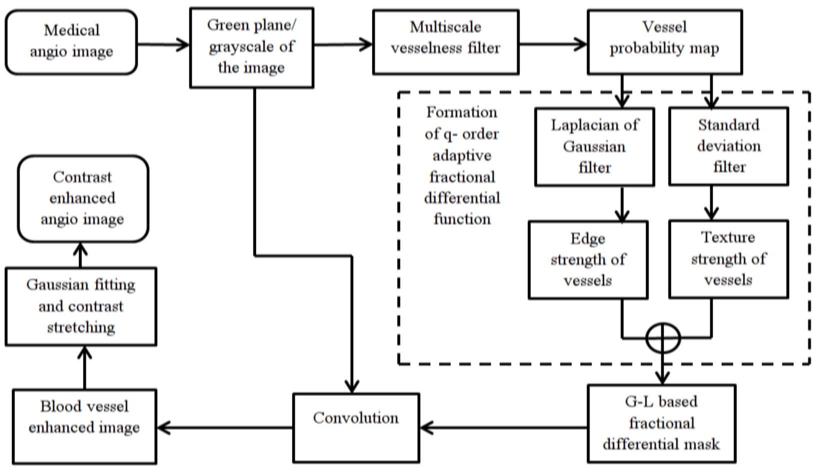

Figure 1. Block diagram of the proposed method

2.1. G-L adaptive fractional differential kernel

Fractional differentials [26] are superior to integer differentials when it comes to image enhancement as it can improve the high-frequency image contrast while preserving low-frequency information in images [27]. Grunwald–Letnikov (G-L) definition based kernel is adopted in this paper to adjust the fractional order of the medical image adaptively. According to the G-L definition, the q-order fractional differentiation of a 1D signal f(t) with equal intervals is expressed in (4)

$$\frac{d^q f(t)}{dt^q}\approx f(t)+(-q)f(t-1)+\frac{(-q)(-q+1)}{2}f(t-2)+.....+\frac{\Gamma(-q+1)}{n!\Gamma(-q-n+1)}f(t-n) \tag{4}$$

Similarly, for the vesselness image V(x,y) with equal neighboring distance, the backward difference of q-order fractional differential on the negative x and y-axes is given as follows:

$$\frac{d^q V(x,y)}{dx}\approx V(x,y)+(-q)V(x-1,y)+\frac{(-q)(-q+1)}{2}V(x-2,y)+...+\frac{\Gamma(-q+1)}{n!\Gamma(-q-n+1)}V(x-n,y) \tag{5}$$

$$\frac{d^q V(x,y)}{dy} \approx V(x,y)+(-q)V(x,y-1)+\frac{(-q)(-q+1)}{2}V(x,y-2)+...+\frac{\Gamma(-q+1)}{n!\Gamma(-q-n+1)}V(x,y-n) \tag{6}$$

It is obvious in (5) and (6) that the first coefficient of the image V(x,y) is 1 and it is a constant whereas the remaining coefficients depend on the fractional order q. Hence, the total sum of all the coefficients in (5) and (6) is nonzero as is opposed to integer differentials. Also in areas of gradual changes in the slope, fractional differentials have a specific value that is neither zero nor a constant whereas in integer differentials it is a constant. In similar pixel regions, fractional differentials gradually vary from a specific value to zero whereas in integer differential it is zero. Therefore, it is proven that fractional differentials enhance the edge related information, preserves the texture related information while leaving the smooth regions undisturbed. By leaving the smooth regions unaltered, the background non-vessel structures remain the same which is an advantage over classical enhancement approaches. Basic kernels x and y obtained from (5) and (6) are given in (7). G-L fractional differential kernel K of window size 5×5 is obtained by rotating the basic kernels x and y at each 45° orientation. Kernel K is given in (8).

$$x=\begin{bmatrix} 0 & 0 & 0 \\ \frac{(-q)(-q+1)}{2} & -q & 1 \\ 0 & 0 & 0 \end{bmatrix};\ y=\begin{bmatrix} 0 & \frac{(-q)(-q+1)}{2} & 0 \\ 0 & -q & 0 \\ 0 & 1 & 0 \end{bmatrix}; \tag{7}$$

$$K=\frac{1}{8-12q+4q^2}\begin{bmatrix} \frac{(-q)(-q+1)}{2} & 0 & \frac{(-q)(-q+1)}{2} & 0 & \frac{(-q)(-q+1)}{2} \\ 0 & -q & -q & -q & 0 \\ \frac{(-q)(-q+1)}{2} & -q & 1\times 8 & -q & \frac{(-q)(-q+1)}{2} \\ 0 & -q & -q & -q & 0 \\ \frac{(-q)(-q+1)}{2} & 0 & \frac{(-q)(-q+1)}{2} & 0 & \frac{(-q)(-q+1)}{2} \end{bmatrix} \tag{8}$$

2.2. Design of the adaptive fractional differential function

Classical fractional differentials use a single fractional order such as higher or lower fractional order to process certain regions of interest in the image. In such a case, higher frequencies will be preserved when the higher fractional order is selected and lower frequencies are preserved when the fractional order is low. In this paper, a unique adaptive fractional differential function is designed to provide the most optimal fractional order for contrast improvement. Each pixel in the image is approximated with a fractional order obtained using the adaptive fractional differential function. This fractional order when substituted in K helps in adjusting the contrast of the blood vessels.

Information about the edge [28] and texture [29] plays an important role in improving the contrast. Also, it is well proven that G-L kernel is capable to enhance the edges and preserve the textures. Hence, from the local vessel probability map, we extract the edge and texture maps to highlight its edge and preserve its texture related information. Laplacian of Gaussian (LOG) operator gives the edge points whereas the computation of standard deviation paints a picture of texture patterns inscribed in the image. Since the edge and texture patterns obtained from the vesselness map is inherently local, its neighborhood dependency is considered. Here, the 8 neighborhood dependency of the edge and texture map is obtained by a simple 3×3 averaging filter operation. The advantage of averaging is that it smoothens the edge and texture information of blood vessels and removes noise. It also takes the neighboring pixel intensity into consideration which makes it less locally inherent. The adaptive fractional differential function is framed by combining the edge and texture smoothed information at every pixel location. The computation of the proposed q-order adaptive fractional differential function is given in (9).

$$q=\frac{1}{255}\left(\sum_{s=-1}^{1}\sum_{t=-1}^{1}a(s,t)*E_{LOG}(x+s,y+t)+\sum_{s=-1}^{1}\sum_{t=-1}^{1}a(s,t)*T_{SD}(x+s,y+t)\right) \tag{9}$$

Where, a(s, t) is the averaging filter kernel and $E_{LOG}(x, y)$ is obtained by convolving the 5×5 LOG operator on the vessel probability map. $T_{SD}(x, y)$ is obtained by replacing every pixel in the vessel probability map with the standard deviation of its 8 neighborhood pixels. This q-order is the optimal adaptive fractional order that can be adjusted by substituting in K and convolving with the input image. Convolution operation of input F(x,y) with the kernel K to get the blood vessel contrast-enhanced image $F_{ce}(x,y)$ is given in (10).

$$F_{ce}(x,y) = \sum_{s=-2}^{2}\sum_{t=-2}^{2} K(s,t) * F(x+s, y+t) \tag{10}$$

The fractional order is adjusted adaptively for both blood vessel and non-vessel structures at every pixel location in the image. The contrast is improved as it enhances the edges and preserves the texture information of blood vessels. Also, it preserves the background and leaves the smooth regions unaltered. It is simple, less complex and adaptive to each and every pixel in the image.

It is found that the histogram of the blood vessel enhanced image follows a Gaussian distribution. Therefore, Gaussian fitting is used to find the lower and upper limits for contrast stretching. The Gaussian function u(x) is used to fit the histogram of $F_{ce}(x,y)$ using least squares algorithm and is expressed in (10).

$$u(x) = p \times e^{\frac{(x-a)^2}{b^2}} \tag{11}$$

Where, the parameters p, a, b represents the peak, mean and width of the Gaussian distribution. Hence, the lower and upper limits $[u_{max}, u_{min}]$ are found as [a-2b, a+2b] so as to cover 95% of pixels in the blood vessel enhanced image. The entire image is contrast-enhanced after contrast stretching.

In the vessel enhanced image from Figure 2, the blood vessels are clearly enhanced, the background preserved and the smooth regions left unaltered. This shows the effectiveness of adaptive fractional differentials over integer differentials. The edge strength is highly enhanced whereas the texture strength is preserved. Also, it doesn't weaken the non-vessel regions like other classical vessel enhancement algorithms. Overall image contrast is improved using Gaussian fitting and contrast stretching.

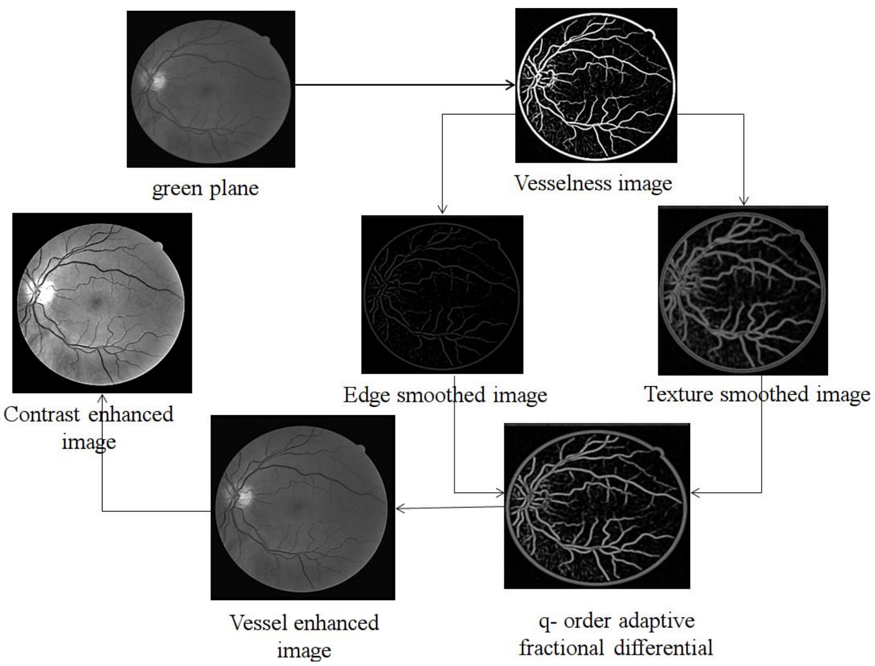

Figure 2. Pictorial representation of the proposed approach

3. EXPERIMENTAL RESULTS AND DISCUSSIONS

3.1. Dataset

The datasets used for validating the results of the proposed algorithm are taken from four different medical image sources. They include the 2D retinal image, DSA of the brain and Coronary Angiogram of the heart and CT of the lung. Retinal fundus images are taken from three popular databases namely Digital Retinal Images for Vessel Extraction (DRIVE) [30], STructured Analysis of the Retina (STARE) [31] and High Resolution Fundus (HRF) [32]. Twenty test images from DRIVE and STARE (set for vessel segmentation) and 15 images from HRF (DR patients) are clubbed together as the retinal dataset in this paper. CT, CA and DSA images are obtained from freely available web sources. CT of lung image dataset consists of 13 images with and without pathological conditions. Coronary Angiogram (CA) data comprises of 16 images taken from arbitrary patients depicting both the right and left artery of heart with normal and various cardiovascular ailments. DSA of brain dataset comprises of 16 images taken from patients with normal and abnormal brain symptoms.

3.2. Analysis

The implementation of the proposed algorithm is done in MATLAB academic version 2016. The angio-images obtained from the datasets follow the steps given in section 2. The resulting contrast enhancement is discussed both perspectively and quantitatively.

3.2.1. Perspective analysis

The contrast-enhanced images obtained from the proposed enhancement are compared against various existing methods for the four datasets. It is depicted in Figures 3-6. Modified bilateral filter, which is used to enhance the retinal fundus image as seen in Figures 3(b) and 6(d) gives a moderate overall contrast-enhanced image. It also well delineates small vessel structures. Combination of HE and Gaussian method blurs the image greatly as seen in Figure 3(c). High boost filtering technique in Figure 3(d) is unable to preserve the edges.

Constant q-orders are obtained by substituting constant values to the kernel K and convolving with the input image. For reference, three q-orders namely 0.5, 0.7 and 0.9 are considered in this paper for comparison. Constant q-order of 0.5 shown in Figures 3(e), 4(e), 5(e) and 6(e) improves the low-frequency components in the image leaving any higher intensity in the image. Also, q-order of 0.7 intensifies higher intensity edge components in the image. It slightly includes noise and blurring as shown in Figure 3(f), 4(f), 5(f) and 6(f). Higher q-order of 0.9 completely increases the edge information and other noise in the image. It is shown in Figure 3(g), 4(g), 5(g) and 6(g). It makes the image unuseful. On the other hand, adaptive q-order framed using the proposed method improves the contrast of edges and preserves the texture, leaving similar pixel regions unchanged. Also, contrast enhancement using Gaussian fitting well enhances the overall contrast of the image as shown in Figure 3(h), 4(h), 5(h) and 6(h).

From the Figures 4(b), 5(b) and 6(b), it is evident from the perspective analysis [33] that CLAHE locally enhances the contrast of the image unlike HE, but still its contrast is poor and has ring artifacts in regions of strong edges. From Figure 4(c), the multi-scale top hat filtering technique tends to achieve better contrast but it is indiscriminate to noise and interference. 2-axis PCA method effectively enhances the image as seen in Figure 4(d) but principal component and threshold selection for the vessel and non-vessel regions is not clear.

Histogram Equalization combined with Gaussian filtering method tends to smooth the image and enhance the unwanted information as seen in Figure 5(c). G-L based adaptive contrast enhancement which takes the area features to frame the q-order is shown in Figure 5(d). But threshold setting is not optimal for all CT images and contrast enhancement is still moderate. From Figure 6(c), it is clear that though BBHE improves the contrast and brightness, it does not preserve the original brightness of the angio-image.

Perceptional analysis vividly proves that the proposed contrast enhancement method has given favorable results by improving both the contrast of the blood vessels and the contrast of the entire image. In the enhanced image, it is noted that compared to the existing methods, the fractional differential function is adaptive to each and every pixel in the image. The convolution of the designed G-L fractional function with the input image adaptively enhances the contrast by not disturbing the similar pixel properties. It is seen that this single method is capable to improve the contrast of the blood vessels in the medical angio-images obtained from four different imaging sources namely the retinal fundus, coronary angiogram, CT of the lung, and DSA of the brain.

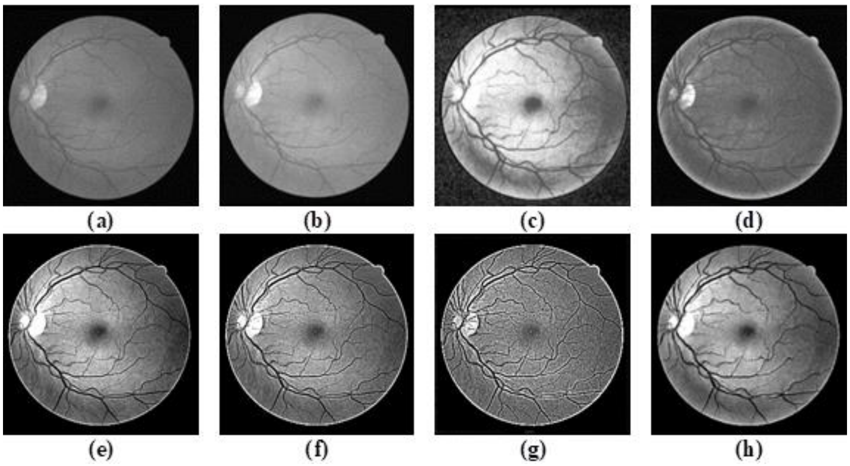

Figure 3. (a) Original retinal image from DRIVE, (b-d) resulting image from methods in [11, 13, 16], (e-g) resulting image for q orders 0.5, 0.7, 0.9, (h) enhanced image after applying the proposed method

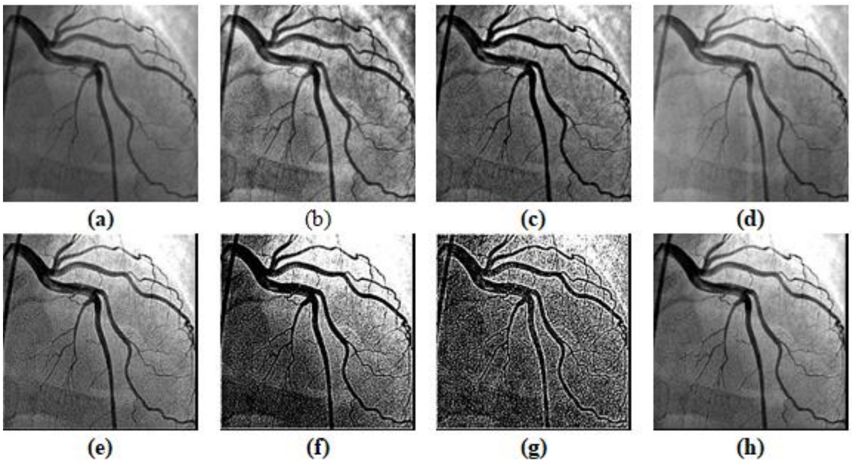

Figure 4. (a) Original CA image, (b-d) resulting image after applying CLAHE, methods in [17, 18], (e-g) resulting image for q orders 0.5, 0.7, 0.9, (h) enhanced image after applying the proposed method

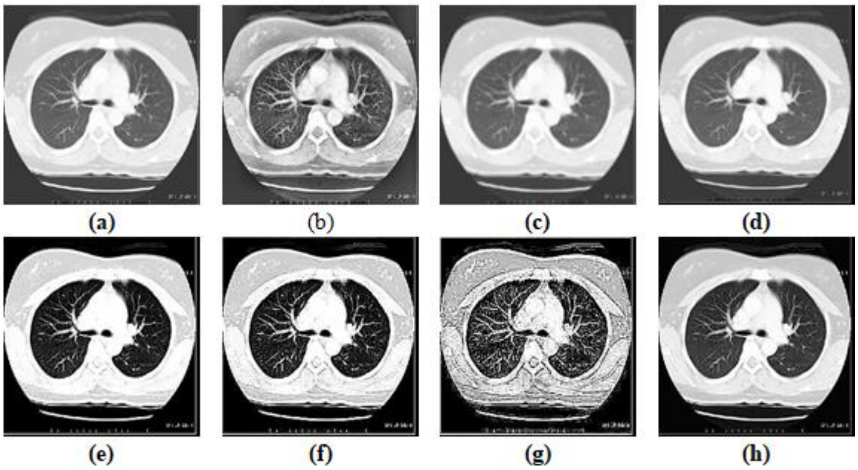

Figure 5. (a) Original CT image, (b-d) resulting image after applying CLAHE, methods in [12, 15], (e-g) resulting image for q orders 0.5, 0.7, 0.9, (h) enhanced image after applying the proposed method

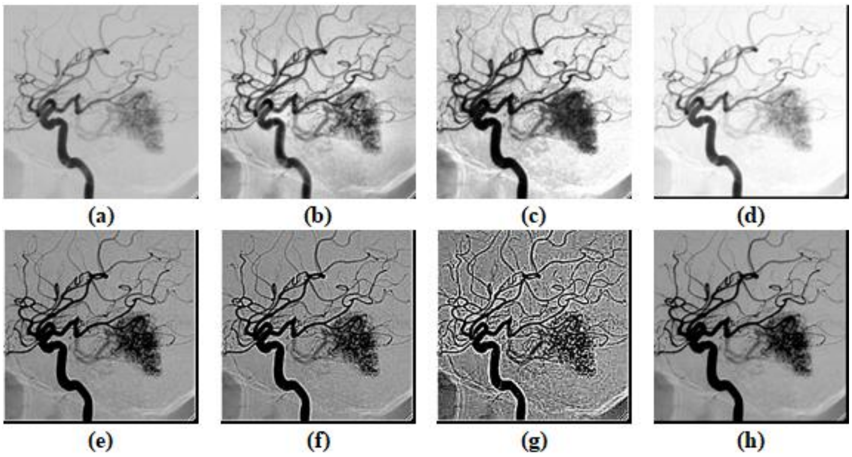

Figure 6. (a) Original DSA image, (b-d) resulting image after applying CLAHE, BBHE and method in [11], (e-g) resulting image for q orders 0.5, 0.7, 0.9, (h) enhanced image after applying the proposed method

3.2.2. Quantitative analysis

The quantitative evaluation measures that are used to validate the contrast of the proposed method includes the Contrast (C), Contrast Improvement Index (CII), Absolute Mean Brightness Error (AMBE), Entropy (E) and Enhancement Measure by Entropy (EME). The evaluation measures with the formula and parameters are tabulated in Table 1. Local contrast C is obtained by sliding the 3×3 window over the entire image and at each window, the newly computed A_{max} and A_{min} are summed up to the previous A_{max} and A_{min} values. Then these values are substituted in the calculation of C. Higher values for both the C and CII measure shows improvement in the contrast of the image. Lower values of AMBE confirm that the original brightness is preserved. Both E and EME values should be reasonably high for the image to have better contrast. Extreme high and low values of E, EME, C, and CII make the image look unnatural, hence it is not acceptable. Using the quantitative performance metrics, the input images from all the four datasets are compared against various contrast enhancement methods. They are listed in Tables 2-5.

Table 1. List of contrast enhancement evaluation measures

Measure	Formula	Parameters
Contrast (C)	$C = \frac{1}{mn} \times \frac{\sum \hat{A}_{\max} - \hat{A}_{\min}}{\sum \hat{A}_{\max} + \hat{A}_{\min}}$	m,n: total no. of. rows and columns in the enhanced angio-image Â A_{max}: maximum intensity of Â A_{min}: minimum intensity of Â
Contrast Improvement Index (CII)	$CII = \frac{C_{en}}{C_o}$	C_o: Contrast of the input angio-image C_{en}: Contrast of the enhanced image
Absolute Mean Brightness Error (AMBE)	$AMBE = \lvert A - \hat{A} \rvert$	A: mean value of input angio-image Â: mean value of enhanced angio- image
Entropy (E)	$E = -\sum_a P_a \times log_2 P_a$	P_a: Normalized histogram count of the input a: no. of. gray levels in the histogram
Enhancement Measure by Entropy (EME)	$EME = \frac{1}{L}\sum_{i=1}^{L} 20 \times log(\frac{A_{max}(i)}{A_{min}(i)})$	L: no. of. blocks (L=16)

Table 2. Evaluation of performance measures for images in the retinal fundus dataset

Measure Method	AMBE	E	C	CII	EME
Input image	-	6.12307	0.026723	-	13.42804
CLAHE	5.261177	6.98194	0.03414	1.308413	25.77123
Method in [11]	24.94107	6.4676	0.036083	1.383317	10.66022
Method in [13]	39.55723	7.28862	0.044903	1.72065	14.3942
Method in [16]	12.88636	6.453943	0.048497	1.88547	12.42763
0.5 order	14.07818	6.113863	0.133397	5.130157	12.9962
0.7 order	13.63913	6.17138	0.184377	7.107467	13.6395
0.9 order	12.00983	6.157237	0.410507	15.79373	9.557937
Proposed method	13.589	7.347707	0.128413	4.907567	15.1836

Table 3. Evaluation of performance measures for images in CA dataset

Measure Method	AMBE	E	C	CII	EME
Input image	-	6.96719	0.02824	-	12.1439
CLAHE	27.4926	7.50488	0.04716	1.6352	28.0978
Method in [17]	32.1932	7.34596	0.09229	3.5901	17.7819
Method in [18]	32.3372	6.62472	0.0758	2.98916	11.1121
0.5 order	20.8321	7.33102	0.16567	6.97502	15.8301
0.7 order	18.3378	7.09987	0.60335	28.1236	6.46145
0.9 order	18.5237	6.89321	0.86644	40.8345	1.12696
Proposed method	24.4346	7.59999	0.1181	4.87974	17.4148

Table 4. Evaluation of performance measures for images in CT dataset

Measure Method	AMBE	E	C	CII	EME
Input image	-	6.67682	0.09607	-	19.6567
CLAHE	23.3205	7.49591	0.08446	0.92943	19.6955
Method in [12]	24.1028	6.76261	0.15762	1.67279	23.0912
Method in [15]	24.7175	6.68556	0.13621	1.79379	16.6225
0.5 order	18.8462	5.37821	0.45434	5.81231	5.08266
0.7 order	21.2028	5.49864	0.51387	6.471	2.68639
0.9 order	23.6942	5.6649	0.65372	8.47113	4.48314
Proposed method	27.2101	7.50798	0.25467	3.15121	19.6642

Table 5. Evaluation of performance measures for images in DSA dataset

Measure Method	AMBE	E	C	CII	EME
Input image		5.51423	0.04033	-	9.38165
CLAHE	5.4081	6.84235	0.05466	1.45951	19.2205
BBHE	19.1256	5.37615	0.07252	1.93997	25.369
Method in [11]	42.243	5.72747	0.07738	1.98427	8.24737
0.5 order	41.6645	6.70563	0.2569	8.01018	9.98095
0.7 order	39.7104	6.85663	0.31831	9.66469	10.2542
0.9 order	45.4487	6.8566	0.78939	24.357	2.88069
Proposed method	35.8682	6.87196	0.19748	5.69191	10.41405

After careful analysis of the results in Tables 2, 3 4 and 5, the following conclusions are drawn. AMBE values for the proposed enhancement are not much improved when compared to CLAHE and some other methods. But highest entropy E shows that the contrast is well preserved by the proposed method. C and CII values for the proposed method are higher, significant and acceptable whereas, for the 0.5, 0.7 and 0.9 q-orders, the values show a very sharp increase which is unacceptable. EME is an important measure that well denotes the contrast enhancement. Very low values for EME affect the contrast, as well as very high values for CLAHE, leads to excessive contrast enhancement making the image look unnatural. EME for the proposed enhancement is well balanced as given in Tables 2, 3, 4 and 5 which clearly justifies the improved contrast of the blood vessel structures.

Analysis of the contrast enhancement of the proposed approach both perspectively and quantitatively proves that the contrast is well enhanced on all the four medical angio-images. Moreover, it preserves the texture details, enhances the contrast of the blood vessels and also it does not change the similar pixel regions in the images. Unchanged similar pixel region is an added advantage when compared to other enhancement approaches. This method is universal, novel, less complex and superior to other existing contrast enhancement methods for blood vessels.

4. CONCLUSION

Contrast enhancement of the medical angio-images is a prerequisite which has an edge over other methods for effective screening and diagnosing of blood vessel related disorders. In this paper, a unified adaptive contrast enhancement framework is proposed. Here, the design of adaptive optimal q-order for the G-L kernel includes both the edge and texture smoothed information taken from the vessel probability map. Clearly, the proposed method enhances the contrast of the blood vessels, preserves textures and leaves the smooth information unaltered. Therefore, the blood vessels are enhanced in the image. This vessel enhanced image is then contrast stretched using a Gaussian curve fitting to enhance the overall contrast of the image. The proposed contrast enhancement is tested on the retinal fundus image, CA of the heart, CT of the lung and DSA of the brain. All the evaluation measures for contrast improvement are tabulated and analyzed in comparison to other existing approaches to show that this method can be effectively used for universal medical angio-image enhancement. The proposed method is simple, adaptive, universal, contains minimal complexity, and far more effective in enhancing the contrast of blood vessels as well as the image contrast as an overall feature.

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REFERENCES

[1] Nugroho H. A., "Towards development of a computerised system for screening and monitoring of diabetic retinopathy," *4th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI), Yogyakarta, Indonesia*, pp. 1-1, 2017.

[2] Nasr E. E., *et al*., "Segmentation of vessels in angiograms using convolutional neural networks," *Biomedical Signal Processing and Control*, vol. 40, pp. 240-51, 2018.

[3] Aziah A., *et al*., "Retinal blood vessel segmentation from retinal image using B-COSFIRE and adaptive thresholding," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 13, pp. 1199-1207, 2019.

[4] Akram U., "Retinal image preprocessing: background and noise segmentation," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 10, pp. 537-44, 2012.

[5] Bhargava S. and Somkuwar A., "Evaluation of Noise Exclusion of Medical Images Using Hybridization of Particle Swarm Optimization and Bivariate Shrinkage Methods," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 5, pp. 421-8, 2015.

[6] Gonzalez R. C. and Woods R. E., "Image processing," *Digital image processing*, pp. 2, 2007.

[7] Pizer S. M., *et al*., "Contrast-limited adaptive histogram equalization: speed and effectiveness," *Proceedings of the First Conference on Visualization in Biomedical Computing. Atlanta, GA*., pp. 337-345, 1990.

[8] Kim Y. T., "Contrast enhancement using brightness preserving bi-histogram equalization," *IEEE transactions on Consumer Electronics*, vol. 43, pp. 1-8, 1997.

[9] Tomasi C. and Manduchi R., "Bilateral filtering for gray and color images," *IEEE International Conference on Computer Vision*, vol. 1, pp. 839-846, 1998.

[10] Frangi A. F., *et al*., "Multiscale vessel enhancement filtering," *International Conference on Medical Image Computing and Computer-Assisted Intervention. Berlin, Heidelberg*, pp. 130-137, 1998.

[11] Shi F. and Yang J., "Multiscale vesselness based bilateral filter for blood vessel enhancement," *Electronics letters*, vol. 45, pp. 1152-4, 2009.

[12] Jagatheeswari P., *et al*., "Quadrant dynamic with automatic plateau limit histogram equalization for image enhancement," *Mathematical Problems in Engineering*, vol. 2014, pp. 1-8, 2014.

[13] Wang S., *et al*., "Hierarchical retinal blood vessel segmentation based on feature and ensemble learning," *Neurocomputing*, vol. 149, pp. 708-17, 2015.

[14] Zhao D., "Total variation differential equation with wavelet transform for image restoration," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 12, pp. 4747-55, 2014.

[15] Li B. and Xie W., "Adaptive fractional differential approach and its application to medical image enhancement," *Computers & Electrical Engineering*, vol. 45, pp. 324-35, 2015.

[16] Panda R., *et al*., "New binary Hausdorff symmetry measure based seeded region growing for retinal vessel segmentation," *Biocybernetics and Biomedical Engineering*, vol. 36, pp. 119-29, 2016.

[17] Nasr E. E., *et al*., "Vessel extraction in X-ray angiograms using deep learning," *38th Annual international conference of the IEEE engineering in medicine and biology society. Orlando, FL*, pp. 643-646, 2016.

[18] Lee Y. G., *et al*., "Low-dose 2D X-ray angiography enhancement using 2-axis PCA for the preservation of blood-vessel region and noise minimization," *Computer methods and programs in biomedicine*, vol. 123, pp. 15-26, 2016.

[19] Tang J. R. and Isa N. A., "An Adaptive Contrast Enhancement Algorithm with Details Preserving," *Proceeding of the Electrical Engineering Computer Science and Informatics*, vol. 1, pp. 391-5, 2014.

[20] Zhuzhong Y., "Image enhancement based on fractional differentials," *Journal of Computer Aided Design and Computer Graphics*, vol. 20, pp. 343-348, 2008.

[21] Chen S. and Zhao F., "The Adaptive Fractional Order Differential Model for Image Enhancement Based on Segmentation," *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 32, no. 03, 2018.

[22] Chen Q., *et al*., "Fractional differential algorithm for texture and contrast enhancement," *Eighth International Conference on Digital Image Processing. Chengu, China*, vol. 10033, pp. 1003323, 2016.

[23] Salamah U., *et al*., "Incorporating Index of Fuzziness and Adaptive Thresholding for Image Segmentation," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 8, pp. 2406-2418, 2018.

[24] Erwin S. and Saputri W., "Hybrid Multilevel Thresholding and Improved Harmony Search Algorithm for Segmentation," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 8, pp. 4593-602, 2018.

[25] Mukherjee S. and Acton S. T., "Oriented filters for vessel contrast enhancement with local directional evidence," *12th International Symposium on Biomedical Imaging. New York, USA*, pp. 503-506, 2015.

[26] Yong Z. H., *et al*., "Basic theory of fractional differential equations," *World Scientific*, vol. 2, 2016.

[27] Pearl M. S. and Thanikaiselvan V., "Medical Angio-Image Enhancement Using Adaptive Fractional Differential Filter," *Far East Journal of Electronics and Communications*, vol. 17, pp. 399-408, 2017.
[28] Na'am J., "Edge detection on objects of medical image with enhancement multiple morphological gradient method," *4th International Conference on Electrical Engineering, Computer Science and Informatics. Yogyakarta, Indonesia*, pp. 1-7, 2017.
[29] Senapati R. K., "Bright Lesion Detection in Color Fundus Images Based on Texture Features," *Bulletin of Electrical Engineering and Informatics (BEEI)*, vol. 5, pp. 92-100, 2016.
[30] Staal J., *et al*., "Ridge-based vessel segmentation in color images of the retina," *IEEE Transactions on Medical Imaging*, vol. 23, pp. 501-9, 2004.
[31] Hoover A. D., *et al*., "Locating blood vessels in retinal images by piecewise threshold probing of a matched filter response," *IEEE Transactions on Medical imaging*, vol. 19, pp. 203-10, 2000.
[32] Odstrcilik J., *et al*., "Retinal vessel segmentation by improved matched filtering: evaluation on a new high-resolution fundus image database," *IET Image Processing*, vol. 7, pp. 373-83, 2013.
[33] Subrahmanyam C. H., *et al*., "Performance Analysis of No Reference Image quality based on Human Perception," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 4, pp. 939-43, 2014.

BIOGRAPHIES OF AUTHORS

Pearl Mary S received her B.E. degree from Anna University, India in 2013 in Electronics and Communication Engineering and her M.Tech. Degree from Karunya University, India, in 2015 in Embedded Systems. She is currently a Senior Research Fellow in the School of Electronics Engineering at Vellore Institute of Technology, Vellore, India. Her research interests include medical image processing, pattern recognition, artificial intelligence, machine vision, and Deep learning concepts.

Dr. Thanikaiselvan V received his Ph.D. degree in the field of Information security in Images from VIT University, Vellore, Tamil Nadu, India in the year 2014. Currently, he is working as an Associate Professor in the School of Electronics Engineering, VIT University. His teaching and research interest include Digital communication, Digital signal and Image Processing. So far he has published 32 research articles in peer-reviewed Scopus indexed journals and conferences. Currently, he is guiding five Ph.D. candidates in the areas of Information Security and Digital Image Processing.