Electronic Letters on Computer Vision and Image Analysis 21(2):62-76, 2022

AN EFFICIENT HYBRID APPROACH FOR MEDICAL IMAGE ENHANCEMENT

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Received 7th of July, 2022; accepted 22th of September, 2022

Abstract

Medical images have various critical usages in the field of medical science and healthcare engineering. These images contain information about many severe diseases. Health professionals identify various diseases by observing the medical images. Quality of medical images directly affects the accuracy of detection and diagnosis of various diseases. Therefore, quality of images must be as good as possible. Different approaches are existing today for enhancement of medical images, but quality of images is not good. In this paper, we have proposed a new hybrid approach that uses principal component analysis (PCA), multi-scale switching morphological operator (MSMO) and contrast limited adaptive histogram equalization (CLAHE) methods in a unique sequence for this purpose. We have conducted exhaustive experiments on large number of images of various modalities such as MRI, ultrasound, and retina. Obtained results demonstrate that quality of medical images processed by proposed approach has significantly improved and better than other existing methods of this field.

Key Words: Medical image, image enhancement, MSMO, SNR, CNR.

1 Introduction

Medical images usage and their applications are increasing rapidly today. These images mainly have been used in the field of medical science, forensic science, healthcare engineering, industries, study and research. There are various types of medical images such as retinal image, MRI, ultrasound, X-ray, CT scan, etc. During the process of capturing and transmitting of medical images, several factors affect the quality of these images. Generally, medical images are too dark, bright, unclear and have poor contrast. Due to these, quality of medical images is generally poor. In modern medical science, diseases are detected and diagnosed by observing the medical images. Quality of a medical image directly affects accuracy of identification and diagnosis of various diseases. Poor quality of medical images sometimes leads to false identification of diseases. This leaves patients in more panic and critical situations. Therefore, there is need to enhance the quality of medical images as good as possible[19] [20].

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Recommended for acceptance by Angel D. Sappa
https://doi.org/10.5565/rev/elcvia.1574
ELCVIA ISSN: 1577-5097
Published by Computer Vision Center / Universitat Autonoma de Barcelona, Barcelona, Spain

Medical image enhancement has always been challenging and main task of image processing. Characteristics of medical images make it more tedious. Different types of medical images have different characteristics. In that scenario, a method suits all types of medical images is little difficult. There are existing various methods for medical image enhancement. These are classified in the Fig. 1.1. Various approaches are given by many researchers for medical image enhancement, but they have some limitations and have scope of improvement.

In the paper, a new hybrid approach based on PCA, MSMO and CLAHE methods has been proposed. It is efficient and works on different modalities. PCA is used to mitigate the noise and minimize the dimensions of data. MSMO is used to smooth the images. CLAHE is applied to enhance the contrast and remove the noise of images [9]. The performance of the proposed approach is good [4][6][38]. The major contributions of the paper are as follows:

1. Detailed study of various medical image enhancement techniques.
2. Designed an appropriate methodology for medical image enhancement.
3. Conducted exhaustive experiments on various types of medical image datasets to test and validate the proposed approach.

Remaining portions of the paper are organized as: In Section 2, various related findings are investigated for better enhancement of medical images. Background study is described in Section 3. In Section 4, a new hybrid approach for medical image enhancement is presented. In Section 5, performance of the proposed method is evaluated. At last, conclusion and future research directions are discussed in Section 6.

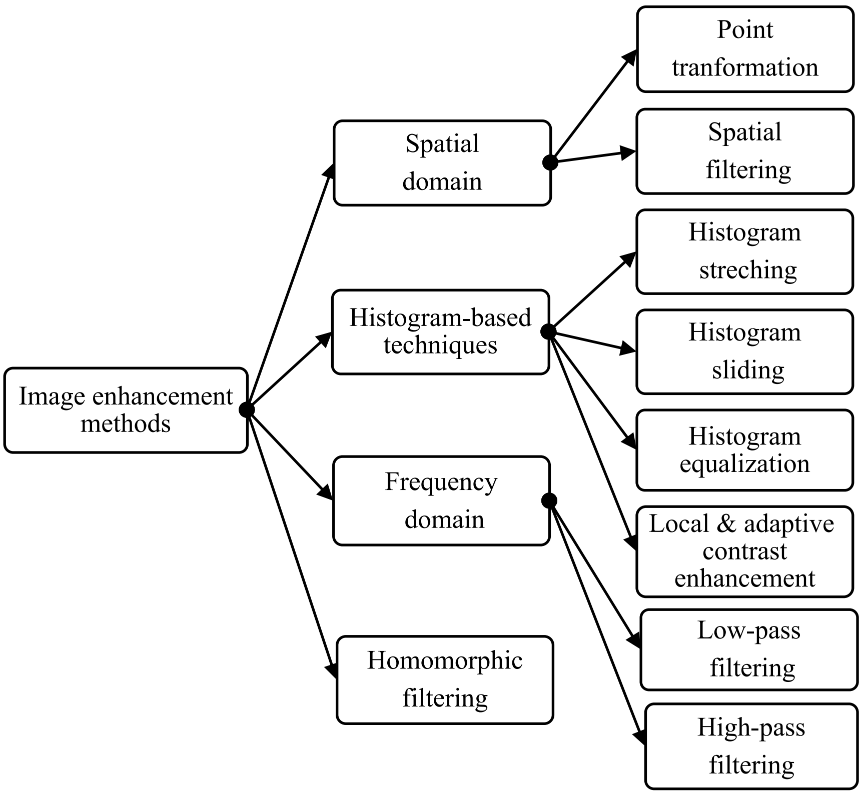


Figure 1: Taxonomy of image enhancement techniques

2 Related Work

Medical image enhancement has emerged as one of the important problems in the field of image processing due to its critical use in diseases detection and diagnosis. Therefore, many researchers have explored this area and proposed several approaches to enhance the quality of medical images [10] [13] [14]. Some prominent approaches proposed by many authors for medical image enhancement are analyzed as follows:

Salem et al. [2] have proposed an approach for medical image enhancement based on histogram algorithms. Authors have analyzed various histogram algorithms on various types of medical images in their approach. They have tested and validated the histogram equalization (HE), cumulative histogram equalization (CHE), CLAHE and quadrant dynamic histogram equalization (QDHE) on breast, retina, endometrium,knees and brain images. The approach presented in their literature is not novel. They have just analyzed these algorithms on various medical images. Vidyasaraswathi et al.[12] have presented an approach in which they have used mean intensity replacement based on Grey Wolf Optimization Histogram Equalization (GWOHE) algorithm for enhancement of brain MR images. The approach has been implemented on single image data set that is FLAIR image data set. The approach is computationally heavy. Also, it is needed to test and compare more with such other algorithms.

Hossain et al. [17] have proposed an approach based non-linear technique and logarithmic transform coefficient histogram matching for medical image enhancement. The approach is computationally and experimentally complex. Also, it is tested and validated on single image of one type by single parameter. The approach needs to be tested and validated on many medical images of various modality. Li et al. [1] have proposed an approach for medical CT image enhancement that combines the wavelet and spatial domains. The approach is based on histogram equalization and passive migration. Histogram equalization is used to pre-process an image. 2-D wavelet transform is applied to divide an image into sub-images. Median filtering is applied to de-noised image here. Various and too many operations have been performed to get enhanced image. The approach has been tested on only one type of medical images.

Maddan et al. [30] have given an approach for medical image enhancement. In this approach, low pass and high pass filters have used for normalization. Various filters have used here for removal of noise. Contourlet transformation has applied for medical image enhancement. PSO method has used to optimize contourlet transformation. The approach has been tested on very few images of one type. Also, performance of the approach is low. Priyanka et al. [7] have proposed an approach for low light image enhancement. they have applied PCA method to decompose an image into chrominance-luminance components. They have used local and global mapping techniques to eliminate ghosting and halo artifacts. They have used multi-scale retinex based adaptive filter for image enhancement and collaborative filters to remove the Poisson noise. Real night and implemented images look similar. Quantitative values of performance metrics of the approach hints that the method can be improved further.

Singh et al. [15] have presented an approach for medical image enhancement. They have used wiener filter to remove noise in the pre-processing stage. They have applied local transform histogram (LTH) to enhance the contrast. Finally, they have applied Neural based Fuzzy Technique (NFT) for image enhancement. NFT is a hybrid of Fuzzy system and Artificial Neural Network (ANN). Here, fuzzy system is used to identify the uncertainty in input image whereas ANN is used to identify the typical features of sample data. The approach is tested and validated on very few images and image is enhanced slightly. Guan et al. [8] have proposed a method for medical image enhancement. In this method, authors have applied the fractional differential and direction derivative methods. In this article, gradients of an image are computed in eight directions with difference of 45 degree thereafter masks of the image for each direction are constructed. Finally, an energy gradient clarity function applied to measure the enhancement of image. The method needs to test and validate on more images. Also, performance of the approach is low.

Chouhan et al. [3] have proposed an approach for enhancement of dark and low contrast images. In this article, internal noise of image is used to generate noise induced transition of dark image from low contrast state to high contrast state. To obtain this, dynamic stochastic resonance (DSR) is used here in repeated fashion by correlating bi-stable system variables of a double well potential with intensity values of low contrast image [31]. The approach is not suitable for enhancement of bright images because it may lead to loss of information. Also, the approach is tested and validated on very few images.

Based on study of above works and their limitations, it is found that there is still required an efficient and appropriate method for enhancement of medical images [21] [23]. Therefore, we propose a new hybrid approach based on unique combinations of PCA, MSMO and CLAHE methods for this purpose [29].

3 Background

In the paper, we have applied PCA, MSMO and CLAHE methods for enhancement of medical images. These methods are described in detail as follows:

3.1 PCA Method

PCA is a standard linear method which discovers dependent variables in the data or images. It maps many dependent variables into a smaller number of new independent variables known as principal components. It is used for dimensionality reduction, image enhancement, compression and correlation. It is also used to convert color image into gray-scale image. It preserves both color and texture features discriminability effectively [22][33]. Also, image quality and conversion speed are very good. It does not require any user specific parameter for conversion. Gray-scale image generated by this method has better contrast. It takes mean of all pixels due to which noise is very less. Also, complexity of computation is very low which can be used in real-time applications. These break throughs are achieved using Eigen value weighted Linear Sum of Subspace Projections (ELSSP) algorithm [11] [18].

`Algorithm:`

1. Input original color image.
2. Vectorize color image with the help of three-color channels.
3. Compute zero mean YCbCr image to split chrominance and luminance channels.
4. Compute eigen values of three channels and related normalized eigen vectors.
5. Generate gray-scale image using ELSSP.
6. Get gray-scale image.

3.2 MSMO Method

We know that morphological operations such as dilation and erosion work with two sets: gray-scale image and structuring-element. The dilation ($\oplus$) and erosion ($\ominus$) operations on gray-scale image 'A' using structuring-element 'B' are described as follows:

$$D = A \oplus B = \{(x, y) + (u, v) : x, y \in A; u, v \in B\} \tag{1}$$

$$E = A \ominus B = \{(x, y) - (u, v) : x, y \in A; u, v \in B\} \tag{2}$$

SMO is a morphological operator that uses the dilation and erosion operations as its sub functions. The operation dilation or erosion increases or decreases the tiny regions of an image according to size of structuring-element. Then matching with actual image, outcome of erosion or dilation operation primarily modifies tiny regions of the image. Due to this, SMO smooths regions of the image and replaces grey values of tiny regions with grey values of dilation or erosion operation. SMO is defined as follows:

if ((D – A)<(A – E)) **then**
  SMO = D;
else if ((D – A)>(A – E)) **then**
  SMO = E;
else
  SMO = A;
end if

Above definition of SMO implies that every pixel of enhanced image by SMO is particularly substituted by same pixel in the dilation or erosion result with a grey value which is closed to grey value of same pixel in the actual image. However, SMO with small size structuring-element is less efficient whereas SMO with large size structuring-element yields more noise. To reduce noise and make SMO more efficient, it is applied at multiple stages with structuring-elements having different sizes. Since SMO is applied as multi-scale with varying size of structure elements, it is called multi-scale SMO (MSMO). Some most frequently applied shapes into the structuring-element are circle, square, hexagon and rectangle. Hexagon, rectangle and square shapes of structuring-elements generally have rough edges and yield block-effect which crash image region shape, particularly when structuring-element size is large. Circle shape of structuring-element has smooth edge due to which block-effect is very low. Hence, we opt circle as a shape of structuring-element in our literature. Scale number (n) is essential factor in MSMO. Large n generally leads to heavy noise whereas small n is inefficient for medical image enhancement.

`Algorithm:`

1. Input gray-scale image ‘A’ and structuring-element ‘B’.
2. Perform dilation and erosion operations on ‘A’ using ‘B’ with size s for every scale s $(1 \leq s \leq n)$.
3. Outcome of SMO is computed for every scale s $(1 \leq s \leq n)$.
4. End result is formed along pixel wise taking mean of all multi-scale outputs generated by SMO.
5. Get enhanced gray-scale image.

3.3 CLAHE Method

CLAHE method restricts contrast amplification by cropping the histogram at a pre-defined stage before calculating a cumulative distribution function (CDF). The value at which a histogram is cropped, called clip-limit, depends on histogram normalization and the size of neighborhood region. It is beneficial not to discard the portion of histogram that exceeds the clip limit but to re-distribute it evenly among all the histogram bins. The re-distribution will push some bins over the clip limit again resulting an effective clip limit that is larger than the prescribed limit. If this is undesirable, the re-distribution process can be repeated recursively until the excess is negligible [16][32].

CLAHE method works on small regions called tiles in the image rather than on whole image. The adjacent tiles are then grouped using bi-linear interpolation to remove unnatural boundaries. The algorithm can be used to enhance the contrast of images. CLAHE works on both homogeneous as well as heterogeneous images. It also works on color as well as gray-scale images. CLAHE can also work with images having non uniform intensity distribution. Gray-scale image generated by CLAHE method has less noise as compare to its ancestors [5][24][25].

`Algorithm:`

1. Image is acquired.
2. Image is segmented in almost equal size and non overlapping contextual-regions.

3. Histogram is computed for every contextual-region.
4. Contrast limited histogram of each contextual-region is computed by clip limit (CL) value as follows:

$$N_{avg} = \frac{N_x * N_y}{N_{gray}} \tag{3}$$

where,

$N_{avg} \rightarrow average\ number\ of\ pixels$

$N_{gray} \rightarrow\ number\ of\ gray\ levels\ incontextual\ region$

$N_x \rightarrow number\ of\ pixels\ in\ x - direction\ of contextual\ region$

$N_y \rightarrow number\ of\ pixels\ in\ y - direction\ of contextual\ region$

4.1. Thereafter, actual clip limit is computed by following equation:

$$N_{CL} = N_{CLIP}\ *\ N_{avg} \tag{4}$$

where,

$N_{CL} \rightarrow actual\ clip\ limit$

$N_{CLIP} \rightarrow normalized\ clip\ limit$

4.2. Pixels exceed actual clip limit are cropped.

4.3. Average of remaining pixels is distributed to every gray-level.

5. Remaining pixels are re distributed until all exhaust.
6. Intensity values are enhanced in every region by the Rayleigh transform.
7. Sudden change effect is reduced and re-scaled by linear contrast stretching.
8. New gray-level assignment of pixels is computed within a sub-matrix contextual region using bi-linear interpolation among four distinct mappings to reduce the artifacts.
9. Finally, input image is enhanced.

4 Proposed Approach

We have seen that PCA, MSMO and CLAHE methods have several advantages. Also, they work good for image enhancement individually but they perform better when we apply them in certain combination and sequence. In the paper, we have proposed a new hybrid approach that uses PCA, MSMO and CLAHE methods. We have applied PCA method for conversion of color image into gray-scale image. We may also use rgb2gray in place of PCA method for this purpose which is a built-in command of MATLAB. But we choose PCA method over rgb2gray because gray-scale image generated by PCA has quality better. Also, PCA method preserves both texture and color features discriminability effectively. MSMO and CLAHE have been used for contrast and image enhancement.

In this approach, first PCA is applied to transform RGB image into gray-scale image. Thereafter, MSMO method is applied on obtained gray-scale image. In the last, CLAHE method is applied on the output generated by MSMO method for image enhancement. In this unique combination and specific sequence, proposed approach has produced better quality of medical images. The proposed approach is one that has applied hybrid of these methods first time for medical image enhancement. The block diagram of the proposed approach for medical image enhancement is shown in the Figure 2.

5 Performance Evaluation

In this section, we have presented the Experimental Setup, Performance Metrics, and Result Analysis subsections.

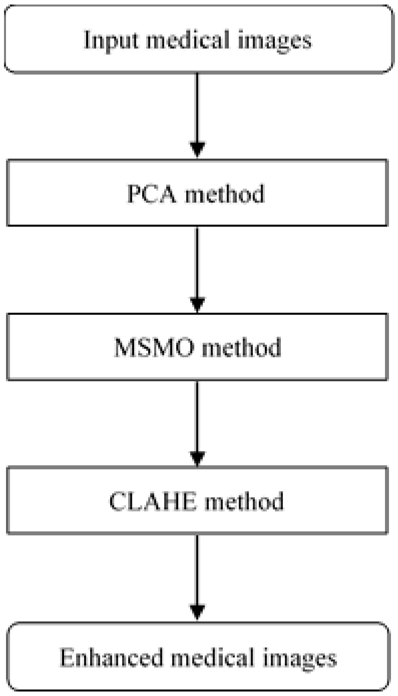


Figure 2: Block diagram of the proposed approach

5.1 Experimental Setup

The proposed method has been implemented and validated on retinal image datasets: HRF, DRIVE and STARE which are freely available online. The method has also been implemented and validated on other medical image datasets such as MRI and Ultrasound. These datasets are briefly described as follows:

DRIVE dataset consists 40 images. These images are classified into test and training sets. Both sets contain 20 images each. The test set contains two sets of manual segmented images while training contains single set of manually segmented images. Mask images for all 40 images are also available showing region of interest. Each image is captured using Canon CR-5 non-mydriatic 3 CCD camera at 45°field of view (FOV). These captured images contain 8-bits/plane. These images are cropped around FOV. Each image has 565 x 584 dimensions [40]. STARE dataset has 400 raw images in which 20 images are selected at random. Out of 20, 10 images are healthy and rest images are unhealthy. All the images are acquired using TOPCON TRV 50 camera with 35°FOV. These images contain 8 bits/plane. Each image has 700 x 605 dimension. Ground truth images are provided by A. Hoover and V. Kouznetsova [37]. HRF dataset has 45 original color images out of which 15 images are healthy, 15 images have glaucoma and 15 images have diabetic. HRF data-set has high resolution images. Images are captured with Canon CR-1 fundus camera at 45° FOV. Every image of this dataset has dimension 3504 x 2336 [35].

The proposed method is implemented and tested on MATLAB R2017a on HP desktop having configuration 4-GB RAM, Intel (R), Xeon (R), E3, 3.4 GHz processor and 64 bits windows operating system.

5.2 Performance Metrics

We have compared rgb2gray, PCA, MSMO, CLAHE, and their various combinations statistically using signal to noise ratio (SNR) and contrast to noise ratio (CNR) values.

SNR: It is a performance metric used to compare the quality of images. It is defined as follows:

$$SNR = \frac{\mu}{\delta} \tag{5}$$

where,

$\mu \rightarrow$ mean of an image

$\delta \rightarrow$ standard deviation of that image

CNR: It is a performance metric used to compare the quality of images. It is similar to the metric SNR, but subtracts a term before taking the ratio. It is defined as follows:

$$CNR = 20 \times \log 10 \frac{signal}{noise} \tag{6}$$

where,

signal $\rightarrow$ mean of reference image - mean of obtained image

noise $\rightarrow$ standard deviation of obtained image

5.3 Result Analysis

The proposed approach has been implemented and tested on large number of images of various medical image datasets such as HRF, DRIVE, STARE, MRI and Ultrasound. The outcomes of several methods on these datasets are shown in the Tables 1, 2, 3, 4 and 5. If we observe these tables, then we can see that SNR and CNR values for the proposed approach (PCA+MSMO+CLAHE) are highest among all the methods. We have computed the CNR value by considering grayscale image generated by rgb2gray as a reference image for other methods. Figures 3 and 4 show the images enhanced by different methods [26] [27] [28]. If, we observe these two figures then we can see that images enhanced by the proposed method have quality better than others. The proposed method is compared with different methods of this field in Table 6. Obtained results and enhanced images demonstrate that quality of medical images processed by the proposed approach has significantly improved and better than existing methods of this field [34] [36] [39].

Table 1: SNR and CNR values of different methods for DRIVE images

Img.	rgb2gray	PCA		PCA+CLAHE		PCA+MSMO		Propsd. med.	
	SNR	SNR	CNR	SNR	CNR	SNR	CNR	SNR	CNR
01_test.tif	1.565	2.181	49.776	3.104	54.102	2.167	49.703	3.21	54.047
02_test.tif	1.549	2.141	50.983	3.018	55.266	2.126	50.913	3.158	55.411
03_test.tif	1.628	2.363	47.667	3.074	51.59	2.35	47.6	3.239	51.719
04_test.tif	1.496	2.158	50.173	3.029	54.42	2.141	50.092	3.156	54.443
05_test.tif	1.578	2.219	49.474	3.137	53.62	2.204	49.4	3.267	53.649
06_test.tif	1.575	2.184	49.305	3.012	53.453	2.167	49.225	3.102	53.455
07_test.tif	1.512	2.158	50.183	2.999	54.477	2.144	50.112	3.121	54.555
08_test.tif	1.539	2.179	50.221	3.069	54.365	2.164	50.151	3.208	54.464
09_test.tif	1.556	2.144	50.701	3.087	55.148	2.128	50.63	3.209	55.243
10_test.tif	1.556	2.24	48.891	3.199	53.073	2.225	48.817	3.259	52.873
11_test.tif	1.513	2.141	50.777	3.02	55.102	2.126	50.706	3.157	55.215
12_test.tif	1.567	2.181	50.264	3.119	54.591	2.164	50.188	3.188	54.528
13_test.tif	1.541	2.142	50.289	3.047	54.54	2.13	50.226	3.18	54.704
14_test.tif	1.576	2.227	50.404	3.168	54.756	2.208	50.32	3.282	54.746
15_test.tif	1.46	2.223	49.022	3.194	53.174	2.209	48.946	3.274	52.91
16_test.tif	1.561	2.147	50.546	3.002	54.79	2.132	50.475	3.334	54.905
17_test.tif	1.564	2.13	50.925	2.964	55.269	2.113	50.852	3.091	55.421
18_test.tif	1.553	2.134	50.76	3.033	55.152	2.12	50.694	3.172	55.303
19_test.tif	1.581	2.263	48.314	3.069	52.083	2.247	48.232	3.127	51.886
20_test.tif	1.571	2.195	49.938	3.168	54.101	2.181	49.871	3.309	54.17
Avg. val.	1.552	2.187	49.931	3.076	54.154	2.172	49.858	3.202	54.182

Table 2: SNR and CNR values of different methods for HRF images

Img.	PCA		PCA+CLAHE		PCA+MSMO		Propsd. med.	
	SNR	CNR	SNR	CNR	SNR	CNR	SNR	CNR
01_h	2.355	51.149	2.877	54.360	2.349	51.104	2.967	54.480
02_h	2.368	51.069	2.860	54.307	2.362	51.025	2.941	54.427
03_h	2.334	50.185	2.878	53.288	2.327	50.132	2.979	53.403
04_h	2.305	49.965	2.765	53.059	2.296	49.908	2.809	53.067
05_h	2.347	49.611	2.779	52.858	2.338	49.559	2.844	52.966
01_dr	2.377	49.970	2.821	53.418	2.370	49.919	2.902	53.549
02_dr	2.371	49.047	2.751	52.557	2.361	48.986	2.810	52.600
03_dr	2.368	50.596	2.740	54.418	2.361	50.549	2.811	54.513
04_dr	2.354	49.029	2.755	52.431	2.349	48.989	2.825	52.474
05_dr	2.341	49.861	2.816	53.093	2.335	49.820	2.876	53.210
01_g	2.406	49.892	2.972	53.380	2.390	49.814	3.332	53.403
02_g	2.377	49.414	2.799	52.630	2.370	49.368	2.895	52.784
03_g	2.376	49.802	2.872	53.191	2.369	49.758	2.947	53.324
04_g	2.374	50.054	2.867	53.377	2.368	50.010	2.936	53.497
05_g	2.361	49.276	2.844	52.546	2.354	49.229	2.926	52.698
Avg. val.	2.361	49.928	2.826	53.261	2.353	49.878	2.920	53.360

Table 3: SNR and CNR values of different methods for STARE images

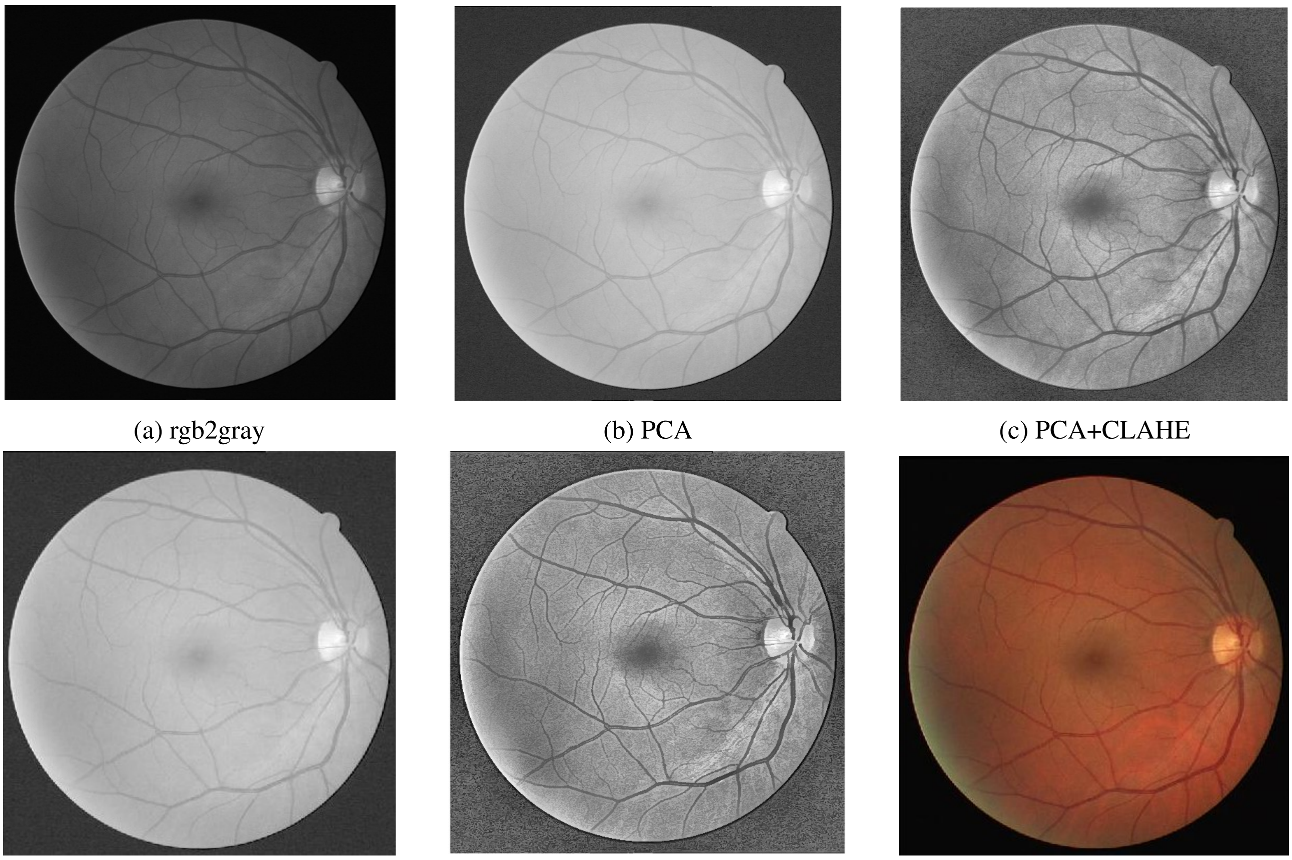
Img.	PCA		PCA+CLAHE		PCA+MSMO		Propsd. med.	
	SNR	CNR	SNR	CNR	SNR	CNR	SNR	CNR
im0001.ppm	3.428	53.351	4.474	56.519	3.406	53.313	4.473	56.908
im0002.ppm	3.200	52.146	4.377	55.869	3.190	52.124	4.437	56.403
im0003.ppm	3.307	53.977	4.346	57.452	3.283	53.932	4.371	57.891
im0004.ppm	3.138	51.652	3.663	54.678	3.122	51.620	3.723	54.616
im0005.ppm	2.877	52.702	3.704	56.220	2.861	52.662	3.731	56.395
im0044.ppm	3.510	56.223	3.595	58.017	3.485	56.178	3.992	58.077
im0077.ppm	2.769	52.882	3.681	56.376	2.755	52.848	3.742	56.584
im0081.ppm	3.264	52.145	3.856	54.884	3.240	52.101	3.878	55.156
im0082.ppm	2.706	52.553	3.672	56.288	2.693	52.519	3.750	56.410
im0139.ppm	3.652	53.081	4.422	54.936	3.627	53.034	4.443	55.763
im0162.ppm	2.775	52.377	3.853	56.221	2.760	52.341	3.907	56.398
im0163.ppm	2.579	52.468	3.708	56.941	2.568	52.439	4.381	56.922
im0235.ppm	2.512	52.097	3.617	56.194	2.503	52.071	4.412	56.381
im0236.ppm	2.585	52.215	3.676	56.087	2.575	52.189	3.744	56.380
im0239.ppm	2.859	53.495	3.780	57.051	2.846	53.466	3.834	57.190
im0240.ppm	3.308	50.600	3.744	53.125	3.286	50.563	3.753	53.393
im0255.ppm	3.244	52.208	4.175	54.694	3.218	52.156	4.194	55.390
im0291.ppm	3.164	52.482	3.957	55.927	3.144	52.444	3.986	56.060
im0319.ppm	2.754	52.854	3.666	56.980	2.743	52.828	3.733	56.730
im0324.ppm	2.769	52.897	3.547	56.803	2.757	52.870	3.615	56.487
Avg. val.	3.020	52.720	3.876	56.063	3.003	52.685	4.005	56.277

Table 4: SNR and CNR values of different methods for MRI images

Img.	PCA		PCA+CLAHE		PCA+MSMO		Propsd. med.	
	SNR	CNR	SNR	CNR	SNR	CNR	SNR	CNR
1	1.424	40.432	2.354	42.466	0.864	40.192	2.590	42.723
2	1.467	40.717	2.358	42.733	0.917	40.510	2.549	43.002
3	1.367	40.283	2.355	42.401	0.855	40.069	2.585	42.458
4	1.396	40.928	2.336	42.638	0.810	40.650	2.583	42.911
5	1.328	40.373	2.333	42.116	0.805	40.101	2.600	42.371
6	1.393	40.856	2.358	42.537	0.832	40.588	2.606	42.833
7	1.343	40.605	2.389	42.395	0.826	40.358	2.668	42.626
8	1.316	40.835	2.389	42.403	0.793	40.561	2.742	42.783
9	1.430	42.143	2.388	43.388	0.777	41.858	2.666	44.016
10	1.447	41.667	2.403	43.475	0.929	41.424	2.689	43.670
Avg. val.	1.391	40.884	2.366	42.655	0.841	40.631	2.628	42.939

Table 5: SNR and CNR values of different methods for Ultrasound images

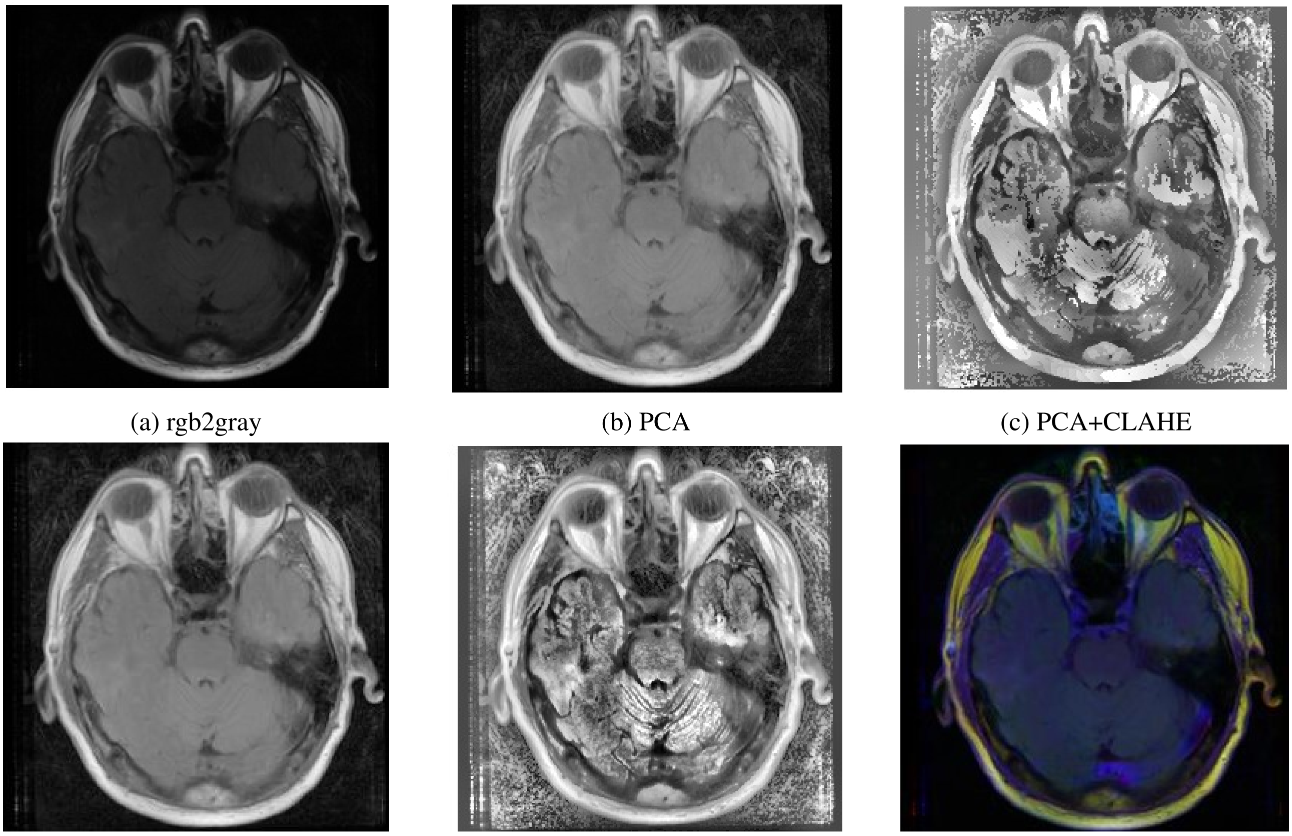
Img.	PCA		PCA+CLAHE		PCA+MSMO		Propsd. med.	
	SNR	CNR	SNR	CNR	SNR	CNR	SNR	CNR
1	1.875	45.409	2.075	45.452	1.686	45.075	2.121	47.611
2	1.593	44.568	2.011	45.722	1.469	44.316	2.069	46.815
3	1.939	45.668	2.172	45.762	1.754	45.337	2.161	47.957
4	1.878	45.312	2.143	45.507	1.694	44.964	2.145	47.596
5	1.690	43.501	2.030	43.864	1.551	43.220	2.145	45.981
6	1.447	41.858	1.927	43.316	1.354	41.662	2.034	44.341
7	1.179	41.461	1.627	42.727	1.119	41.288	1.722	43.593
8	1.302	43.180	1.744	44.783	1.228	42.986	1.903	45.404
Avg. val.	1.613	43.870	1.966	44.641	1.482	43.606	2.037	46.162



(a) rgb2gray (b) PCA (c) PCA+CLAHE

(d) PCA+MSMO (e) Proposed method (f) Original image

Figure 3: Enhanced Retina image by different methods



(a) rgb2gray (b) PCA (c) PCA+CLAHE

(d) PCA+MSMO (e) Proposed method (f) Original image

Figure 4: Enhanced MRI image by different methods

Table 6: Comparison of different image enhancement methods for DRIVE

Methods	SNR
Low pass filter	1.5916
High pass filter	1.4184
High boost filter	1.5493
Homomorphic LPF filter	1.7482
Homomorphic HPF filter	3.0932
Homomorphic HBF filter	1.8999
PCA	2.1875
PCA+CLAHE	3.0755
PCA+MSMO	2.1723
Proposed method	3.1922

6 Conclusion and Future Research Directions

Medical science is the largest and fastest growing field today. In modern medical science, diseases are identified and treated by observing the medical images. Generally, medical images are too dark, bright, unclear, and have poor contrast. Quality of medical images directly affects the treatment of various diseases. In this scenario, it becomes essential to design an appropriate method which enhances quality of these medical images better. In the proposed approach, we have used PCA, MSMO and CLAHE methods in a unique combination and sequence to enhance these medical images. We have tested and validated the proposed method on large number of images of various modalities. Obtained results demonstrate that quality of medical images processed by proposed method has significantly improved and better than other existing methods.

In future, proposed method can be tested on various types of and large number of non-medical images.

7 Conflict of Interest

The authors have no conflict of interest to declare regarding this article.

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