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Evaluation of Basic Noise Removal and Image Enhancement Techniques for Iris Database

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Abstract: ***Automated person identification is very important to improve the security level especially in highly sensitive areas. Human retina provides a reliable source for biometric based system which is almost impossible to forge. Here, we evaluate the performance of two basic stages of automated iris recognition, noise removal and image enhancement. Performance of various basic noise removal algorithms and image enhancement algorithms is evaluated on iris datasets. The performance of noise removal techniques is evaluated using PSNR,RMSE and correlation of coefficient. The performance of image enhancement is evaluated using Absolute mean difference, RMSE and Entropy. The work will provide a baseline for the researchers working in iris recognition for choosing the best noise removal and image enhancement technique.***

Keywords: iris recognition, noise removal, image enhancement, PSNR, RMSE, Entropy, Absolute mean difference

1. Introduction

Biometric iris recognition utilizes pattern recognition techniques based on high resolution and distortion-free images of the irises of the human eyes.Iris is an organ whose structure remains stable throughout life. Thus it serves as a very good biometric for establishing identity of an individual.

Several hundred million persons in several countries around the world have been enrolled in iris recognition systems for convenience purposes such as passport-free automated border-crossings and some national ID programs. A key advantage of iris recognition, besides its speed of matching and its extreme resistance to false matches is the stability of the iris as an internal and protected, yet externally visible organ of the eye. Iris recognition is divided in five major stages, image noise removal, image enhancement, image segmentation, image features extraction and recognition. Among these, in this paper first two stages are considered for various iris datasets.

The proposed work in this paper has been carried out in two sub tasks

A. Task 1: Analyzing the performance of various noise removal techniques

Following basic noise removal algorithms are evaluated on the iris dataset under consideration.
1) Median Filter
2) Average Filter
3) Weiner Filter
4) Noise Removal by FFT and IFFT

The performance is evaluated using PSNR, RMSE and Correlation of coefficient.

B. Task 2: Analyzing the performance of image enhancement techniques

Following basic image enhancement algorithms are evaluated on the iris dataset under consideration.

Basic Intensity Transformation Functions
1) Negative Transformation
2) Thresholding
3) Logarithmic Transformation
4) Power Law Transformation
5) Contrast Stretching
6) Intensity Level Slicing

Histogram Processing
1) Histogram Equalization
2) Adaptive Histogram Equalization
3) Contrast Limited Adaptive Histogram Equalization

The performance is evaluated using Absolute Mean Difference, RMSE and Entropy.

1.1 Noise Removal Techniques

Image noise is the random variation of brightness or color information in images produced by the sensor and circuitry of a scanner or digital camera. Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detector [1].Image noise is generally regarded as an undesirable by-product of image capture. Although these unwanted fluctuations became known as "noise" by analogy with unwanted sound they are inaudible and such as dithering. The types of Noise are Amplifier noise (Gaussian noise), Salt-and-pepper noise, Shot noise (Poisson noise), Speckle noise.

Image de-noising is very important task in image processing for the analysis of images. Ample image de-noising algorithms are available, but the best one should remove the noise completely from the image, while preserving the details. Broadly speaking, De-noising filters can be classified in the following categories:

a) Median Filter

The median filter is a nonlinear digital filtering technique, often used to remove noise from an image or signal [2]. Such noise reduction is a typical pre-processing step to improve the results of later processing (for example, edge detection on an image). Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise (but see discussion below), also having applications in signal processing. The main idea of the median filter is to run through the signal entry by entry, replacing each entry with the median of neighboring entries. The pattern of neighbors is called the "window", which slides, entry by entry, over the entire signal [3]. For 1D signals, the most obvious window is just the first few preceding and following entries, whereas for 2D (or higher-dimensional) signals such as images, more complex window patterns are possible (such as "box" or "cross" patterns). Note that if the window has an odd number of entries, then the median is simple to define: it is just the middle value after all the entries in the window are sorted numerically[4].

b) Weiner Filter

The goal of the Wiener filter is to compute a statistical estimate of an unknown signal using a related signal as an input and filtering that known signal to produce the estimate as an output. For example, the known signal might consist of an unknown signal of interest that has been corrupted by additive noise. The Wiener filter can be used to filter out the noise from the corrupted signal to provide an estimate of the underlying signal of interest. The Wiener filter is based on a statistical approach, and a more statistical account of the theory is given in the minimum mean square error (MMSE) estimator article.

Typical deterministic filters are designed for a desired frequency response. However, the design of the Wiener filter takes a different approach. One is assumed to have knowledge of the spectral properties of the original signal and the noise, and one seeks the linear time-invariant filter whose output would come as close to the original signal as possible. Wiener filters are characterized by the following:[5]

1) Assumption: signal and (additive) noise are stationary linear stochastic processes with known spectral characteristics or known autocorrelation and cross-correlation
2) Requirement: the filter must be physically realizable/causal (this requirement can be dropped, resulting in a non-causal solution)
3) Performance criterion: minimum mean-square error (MMSE)

1.2 Image Enhancement Techniques

Millions of people are visually impaired, with the number of people with disabling visual problems increasing with the growing aging population. A Louis Harris survey found that vision impairment affects 17% of Americans 45 and older, and 26% of those 75 and older [6]. A visual image is rich in information. Confucius said, “A picture is worth a thousand words.” [7] Medical imaging uses IE techniques for reducing noise [8] and sharpening details to improve the visual representation of the image [9]. Visually impaired people have difficulties reading small print, watching television, recognizing faces, etc. While much research and rehabilitation effort has been aimed at improving the reading ability of low-vision patients [10,11]. Image enhancement to improve video images for the visually impaired was first proposed by Peli and Peli[12] applying an adaptive enhancement algorithm, and Peli, Arend, and Timberlake[13] investigated the use of a number of common image enhancement algorithms. Similar techniques were applied to the enhancement of text by Lawton[14] and by Fine and Peli [15]. While image enhancement was shown to modestly improve reading rate and may improve mobility.

Images provide visual representation of the content that is to be examined and allow the users to reflect on them later. They are a powerful data collection medium [16], [17] that is stored easily and used indefinitely. With the advent of digital imaging, a whole new set of possibilities have opened up for professional and amateur users. The amateur users can now easily snap, store, edit and share images [18], while researchers and professional users rely on them to identify areas of interest and present their findings effectively.

Image Enhancement (IE) transforms images to provide better representation of the subtle details. For example forensic images/videos employ techniques that resolve the problem of low resolution and motion blur while medical imaging benefits more from increased contrast and sharpness. To cater for such an ever increasing demand of digital imaging, software companies have released commercial softwares [19], [20] for users who want to edit and visually enhance the images. Low vision can be caused by an accident, a disease, a condition existing from birth (or early childhood) or due to aging. The most common causes of low vision are macular degeneration, cataracts, glaucoma, retinal detachment, diabetic retinopathy or retinitis pigmentosa [21]. Students with visual impairments encounter many difficulties in exploring interesting articles and attending seminars and, thus, may miss opportunities to learn. The result can be a far less effective learning experience and thus a hindrance to their education. Hence there arises a need for a low cost, portable system which assists to read not only the close up materials but also far away objects in a class room environment. This system also needs facility to combine different techniques depending on their personal needs.

a) Basic Intensity Transformation Functions

When you are working with gray-scale images, sometimes you want to modify the intensity values. For instance, you may want to reverse black and the white intensities or you may want to make the darks darker and the lights lighter. An application of intensity transformations is to increase the contrast between certain intensity values so that you can pick out things in an image. For instance, the following two images in figure 1 show an image before and after an intensity transformation. Originally, the camera man's jacket looked black, but with an intensity transformation, the difference between the black intensity values, which were too close before, was increased so that the buttons and pockets became viewable.

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Figure 1: Intensity level Transformation

Generally, making changes in the intensity is done through Intensity Transformation Functions.

b) Negative Transformation

The Photographic Negative is probably the easiest of the intensity transformations to describe. Assume that we are working with grayscale double arrays where black is 0 and white is 1. The idea is that 0's become 1's, 1's become 0's, and any gradients in between are also reversed. In intensity, this means that the true black becomes true white and vise versa. MATLAB has a function to create photographic negatives—imcomplement (f). Given a=0:.01:1, the below figure 2 shows a graph of the mapping between the original values (x-axis) and the imcomplement function.

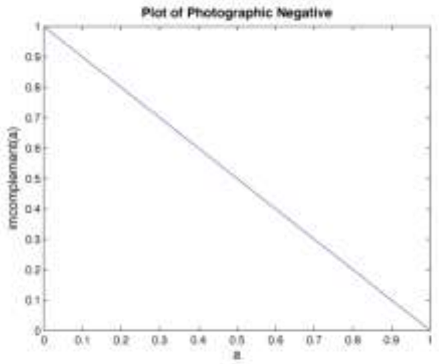

Figure 2: Graph of mapping

1) Thresholding

Thresholding is the simplest method of image segmentation. From a grayscale image, thresholding can be used to create binary images

The simplest thresholding methods replace each pixel in an image with a black pixel if the image intensity {\displaystyle I_{i,j}} is less than some fixed constant T or a white pixel if the image intensity is greater than that constant. In the example image on the right, this results in the dark tree becoming completely black, and the white snow becoming completely white.

2) Logarithmic Transformation

Logarithmic Transformations can be used to brighten the intensities of an image (like the Gamma Transformation, where gamma < 1). More often, it is used to increase the detail (or contrast) of lower intensity values. They are especially useful for bringing out detail in Fourier transforms (covered in a later lab). In MATLAB, the equation used to get the Logarithmic transform of image f is:

g = c*log(1 + double(f))

The constant c is usually used to scale the range of the log function to match the input domain. In this case c=255/log(1+255) for a uint8 image, or c=1/log(1+1) (~1.45) for a double image. It can also be used to further increase contrast—the higher the c, the brighter the image will appear. Used this way, the log function can produce values too bright to be displayed. Given a=0:.01:1, the plot below shows the result for various values of c. The y-values are clamped at 1 by the min function for the plot of c=2 and c=5 (teal and purple lines, respectively).

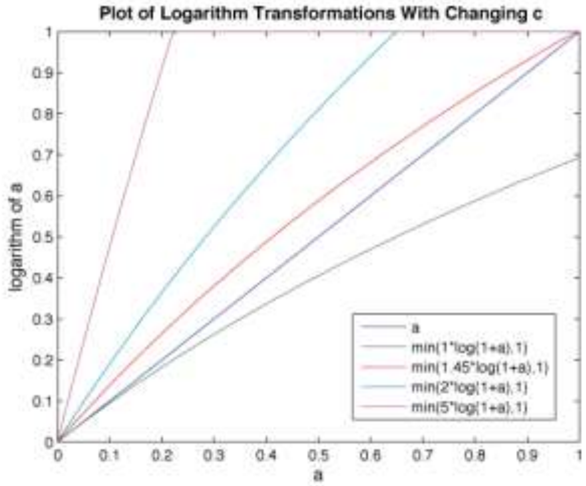

Figure 3: Logarithmic Transformations

3) Power Law Transformation

Power Law transformation is an image enhancement technique widely used in digital image processing. It has the functionality of increasing contrast of an image by controlling the value of gamma and a constant c.

For a gray scale image, let r be the intensity of input low contrast image and s is the intensity of high contrast output/processed image. Power law transformation is stated as

$$s=c.r^{\gamma}$$

Here , **c** is a constant and **gamma** can be

$$\gamma>0$$

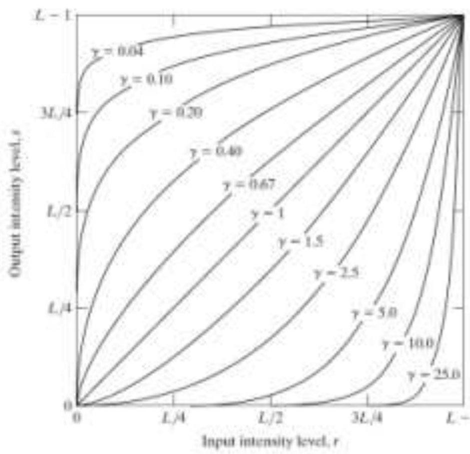

Figure 5: Power Law transformation curves for various gamma values and c = 1

4) Contrast Stretching

Contrast-stretching transformations increase the contrast between the darks and the lights. In lab 1 we saw a simplified version of the automatic contrast adjustment in section 5.3 of the textbook. That transformation kept everything at relativelt similar intensities and merely stretched the histogram to fill the image's intensity domain. Sometimes you want to stretch the intensity around a certain level. You end up with everything darker darks being a lot darker and everything lighter being a lot lighter, with only a few levels of gray around the level of interest. To create such a contrast-stretching transformation in MATLAB, you can use the following function:

g=1./(1 + (m./(double(f) + eps)).^E)

E controls the slope of the function and m is the mid-line where you want to switch from dark values to light values. eps is a MATLAB constant that is the distance between 1.0 and the next largest number that can be represented in double-precision floating point. In this equation it is used to prevent division by zero in the event that the image has any zero valued pixels. There are two plot/diagram sets below to represent the results of changing both m and E. The below plot in figure 6 shows the results for several different values of Egiven a=0:.01:1 and m=0.5.

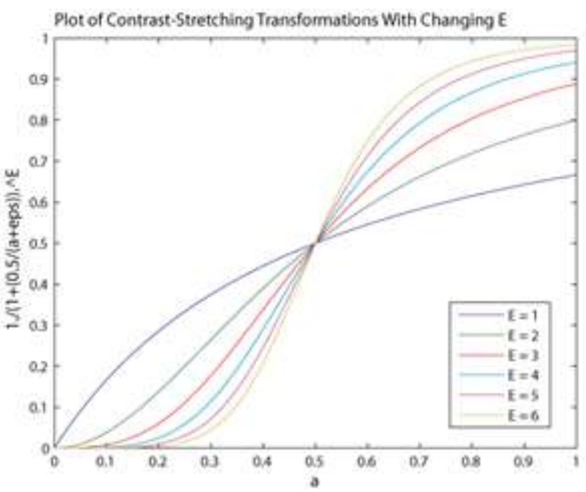

Figure 6: Contrast Stretching

5) Intensity Level Slicing

In this method, a range of intensity values from point A to point B present in image is brightened or unchanged and rest of image pixels is set zero in general and vice versa. It can segment out the region of interest (ROI) in an image.

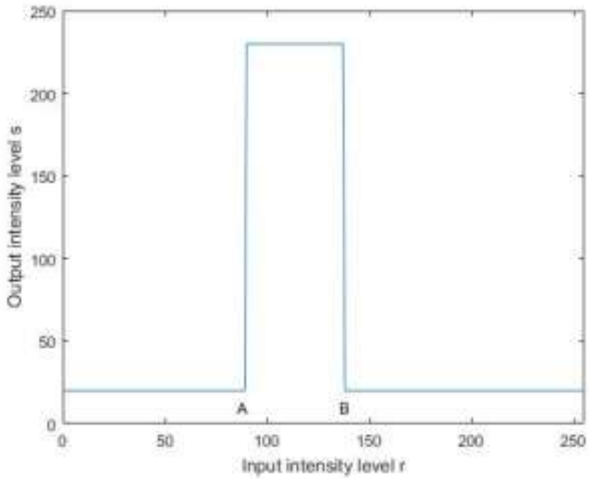

Figure 7: Intensity Level Slicing

c) Histogram Processing

1) Histogram Equalization

Histogram equalization is a method in image processing of contrast adjustment using the image's histogram.

The Histogram Equalization algorithm enhances the contrast of images by transforming the values in an intensity image so that the histogram of the output image is approximately flat.

```
I = imread('pout.tif');
J = histeq(I);
subplot(2,2,1);
imshow( I );
subplot(2,2,2);
imhist(I)
subplot(2,2,3);
imshow( J );
subplot(2,2,4);
imhist(J)
```

2) Adaptive Histogram Equalization

Adaptive histogram equalization (AHE) is a computer image processing technique used to improve contrast in images. It differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. It is therefore suitable for improving the local contrast and enhancing the definitions of edges in each region of an image.

However, AHE has a tendency to overamplify noise in relatively homogeneous regions of an imageThe size of the neighbourhood region is a parameter of the method. It constitutes a characteristic length scale: contrast at smaller scales is enhanced, while contrast at larger scales is reduced.

- Due to the nature of histogram equalization, the result value of a pixel under AHE is proportional to its rank among the pixels in its neighbourhood. This allows an efficient implementation on specialist hardware that can compare the center pixel with all other pixels in the neighbourhood. An unnormalized result value can be computed by adding 2 for each pixel with a smaller value than the center pixel, and adding 1 for each pixel with equal value.

- When the image region containing a pixel's neighbourhood is fairly homogeneous regarding to intensities, its histogram will be strongly peaked, and the transformation function will map a narrow range of pixel values to the whole range of the result image. This causes AHE to overamplify small amounts of noise in largely homogeneous regions of the image.

3) Contrast Limited Adaptive Histogram Equalization

A variant of adaptive histogram equalization called contrast limited adaptive histogram equalization (CLAHE) prevents this by limiting the amplification.

Ordinary AHE tends to overamplify the contrast in near-constant regions of the image, since the histogram in such regions is highly concentrated. As a result, AHE may cause noise to be amplified in near-constant regions. Contrast Limited AHE (CLAHE) is a variant of adaptive histogram equalization in which the contrast amplification is limited, so as to reduce this problem of noise amplification.

In CLAHE, the contrast amplification in the vicinity of a given pixel value is given by the slope of the transformation function. This is proportional to the slope of the neighbourhood cumulative distribution function (CDF) and therefore to the value of the histogram at that pixel value. CLAHE limits the amplification by clipping the histogram at a predefined value before computing the CDF. This limits the slope of the CDF and therefore of the transformation function. The value at which the histogram is clipped, the so-called clip limit, depends on the normalization of the histogram and thereby on the size of the neighbourhood region. Common values limit the resulting amplification to between 3 and 4.

It is advantageous not to discard the part of the histogram that exceeds the clip limit but to redistribute it equally among all histogram bins.

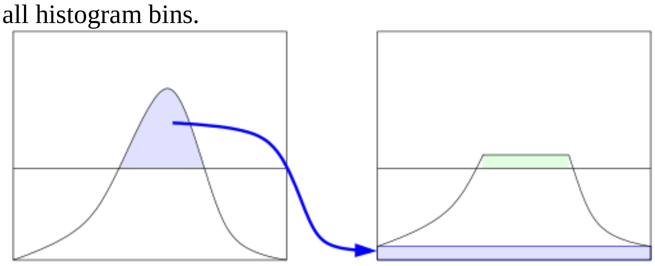

Figure 8: Contras Limited Adaptive Histogram Equalisation

d) Iiris datasets

1) Digital Retinal Images For Vessel Extraction: DRIVE Database

The DRIVE database[22] has been established to enable comparative studies on segmentation of blood vessels in retinal images. The photographs for the DRIVE database were obtained from a diabetic retinopathy screening program in The Netherlands. The screening population consisted of 400 diabetic subjects between 25-90 years of age. Forty photographs have been randomly selected, 33 do not show any sign of diabetic retinopathy and 7 show signs of mild early diabetic retinopathy. Each image has been JPEG compressed.

2) High Resolution Fundus (HRF) Image Database

This database [23] has been established by a collaborative research group to support comparative studies on automatic segmentation algorithms on retinal fundus images. The public database contains at the moment 15 images of healthy patients, 15 images of patients with diabetic retinopathy and 15 images of glaucomatous patients.

e) DRIONS Database

The DRIONS database [24] consists of 110 colour digital retinal images. Initially, it were obtained 124 eye fundus images selected randomly from an eye fundus image base belonging to the Ophthalmology Service at Miguel Servet Hospital, Saragossa (Spain). From this initial image base, all those eye images (14 in total) that had some type of cataract (severe and moderate) were eliminated and, finally, was obtained the image base with 110 images.

f) Real Time Images From hospital Dataset

We have obtained real time retinal images of 65 patients from the hospital

2. Performance Evaluation

A. Task 1: Analyzing the performance of various noise removal techniques

Dataset

Datasets used for evaluating the noise removal techniques are

1) DRIVE Dataset (40 Instances)
2) DRIONS Dataset (110 Instances)
3) High Resolution Fundus Dataset (45 Instances)
4) Real Time Hospital Images Dataset (65 Instances)

Evaluations and Results

Following basic noise removal algorithms are evaluated on the iris dataset under consideration.

1) Median Filter
2) Average Filter
3) Weiner Filter
4) Noise Removal by FFT and IFFT

The performance is evaluated using PSNR, RMSE and Correlation of coefficient. Figure 9 shows the noise removal performance for the sample image from DRIONS dataset.

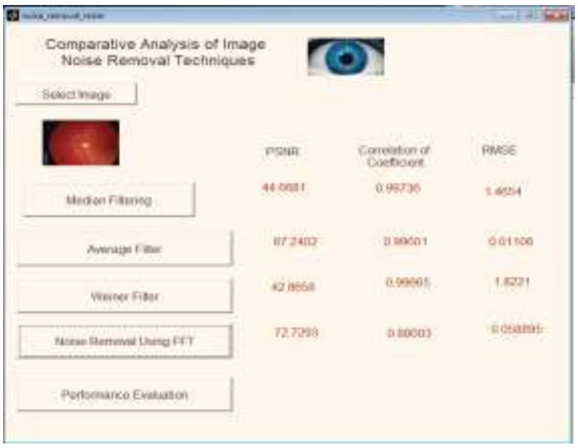

Figure 9: Performance Evaluation of Various Noise Removal Techniques

The performance of various noise removal techniques is depicted in table 1

Table 1: Performance Evaluation of Various Noise Removal Techniques

Performance of Various Noise Removal Techniques			
DRIVE Dataset	40 Instances		
	PSNR	Correlation of Coefficient	RMSE
Average Filter	56.44596021	0.999045283	0.389146865
Noise Removal Using FFT	69.97412802	0.920987943	0.082301985
Median Filter	92.06260637	0.99950674	0.006374121
Weiner	90.13496853	0.999248289	0.007959245
DRIONS Dataset	110 Instances		
	PSNR	Correlation of Coefficient	RMSE
Average Filter	59.24523559	0.996671198	0.280886552
Noise Removal Using FFT	72.51201159	0.894872857	0.060776171
Median Filter	89.25793825	0.997611968	0.008911324
Weiner	88.688005	0.997423854	0.009466675
High Resolution Fundus Dataset		45 Instances	
	PSNR	Correlation of Coefficient	RMSE
Average Filter	5703529	0.9981	0.3476
Noise Removal Using FFT	73.4406	0.932	0.0547
Median Filter	96.2688	0.9996	0.004
Weiner	91.8949	0.999	0.0066
Real Time Images From hospital Dataset		65 Instances	
	PSNR	Correlation of Coefficient	RMSE
Average Filter	57.69665752	0.999617615	0.347112591
Noise Removal Using FFT	57.69665752	0.960510537	0.047552212
Median Filter	96.16220045	0.999666419	0.003994798
Weiner	95.46105548	0.999616437	0.004330375

As shown in table 1, the median filter is found to give the best performance in terms of PSNR, RMSE and Correlation of Coefficient.

B. Task 2: Analyzing the performance of image enhancement techniques

Dataset

Datasets used for evaluating the image enhancement techniques are

1) DRIVE Dataset (40 Instances)
2) DRIONS Dataset (110 Instances)
3) High Resolution Fundus Dataset (45 Instances)
4) Real Time Hospital Images Dataset (65 Instances)

Evaluations and Results

Following basic image enhancement algorithms are evaluated on the iris dataset under consideration.

Basic Intensity Transformation Functions

1) Negative Transformation
2) Thresholding
3) Logarithmic Transformation
4) Power Law Transformation
5) Contrast Stretching
6) Intensity Level Slicing

Histogram Processing

1) Histogram Equalization
2) Adaptive Histogram Equalization
3) Contrast Limited Adaptive Histogram Equalization

The performance is evaluated using Absolute Mean Difference, RMSE and Entropy. Figure 10 shows the performance evaluation of various image enhancement techniques for the sample image from DRIONS dataset.

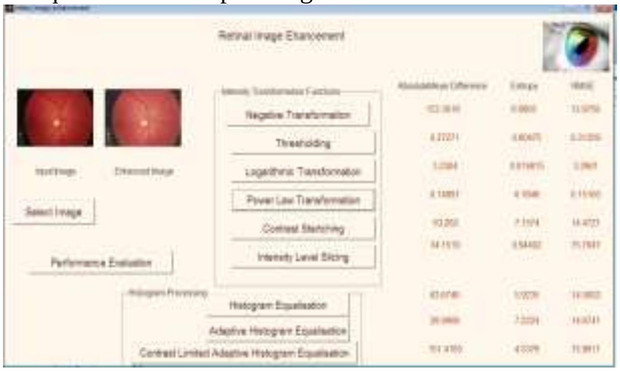

Figure 10: Evaluating the Performance of Various Image Enhancement Techniques

The performance of various image enhancement techniques is depicted in table 2

Table 2: Image Enhancement techniques

Image Enhancement			
DRIVE Dataset		40 Instances	
	Absolute Mean Difference	Entropy	RMSE
Negative Transform	151.2307	5.7678	13.8771
Thresholding	0.3245	0.9081	0.3892
Logarithmic Transformation	0.1895	6.2477	0.2289
Power Law Transformation	0.129	5.8024	0.1394
Contrast Stretching	47.6724	6.2081	13.4535
Intensity Level Slicing	83.9355	0.7791	124.0907
Histogram Equalisation	46.3071	5.2276	14.3277
Adaptive Histogram Equalisation	14.4948	6.8711	11.2596
Contrast Limited Adaptive Histogram	132.9495	4.856	15.7461
DRIONS Dataset		110 Instances	
	Absolute Mean Difference	Entropy	RMSE
Negative Transform	157.8318	6.5924	14.4183
Thresholding	0.2745	0.702	0.3296
Logarithmic Transformation	0.1627	7.111	0.1979
Power Law Transformation	0.1377	6.7628	0.1464
Contrast Stretching	51.1755	7.0849	14.1224
Intensity Level Slicing	42.549	0.9378	78.2485
Histogram Equalisation	66.1846	5.7337	15.1352
Adaptive Histogram Equalisation	25.5059	7.0267	13.9043
Contrast Limited Adaptive Histogram	154.3298	4.93	15.9479
High Resolution Fundus Dataset	45 Instances		
	Absolute Mean Difference	Entropy	RMSE
Negative Transform	166.6153	6.0207	13.6306
Thresholding	0.3223	0.569	0.3603
Logarithmic Transformation	0.1836	6.519	0.2243

Power Law Transformation	0.1222	6.0288	0.1378
Contrast Stretching	79.5902	6.5323	14.7511
Intensity Level Slicing	110.1358	0.9126	148.6801
Histogram Equalisation	50.9711	5.5223	14.052
Adaptive Histogram Equalisation	16.2388	6.5617	12.1882
Contrast Limited Adaptive Histogram	130.7267	4.6816	15.9047

Real Time Images From hospital Dataset	65 Instances		
	Absolute Mean Difference	Entropy	RMSE
Negative Transform	144.9635	6.1891	14.2403
Thresholding	0.4331	0.8587	0.5046
Logarithmic Transformation	0.1734	6.6421	0.2103
Power Law Transformation	0.1292	6.3815	0.1425
Contrast Stretching	36.4249	6.5199	14.3922
Intensity Level Slicing	39.8065	0.896	70.3091
Histogram Equalisation	52.8274	5.4855	14.2886
Adaptive Histogram Equalisation	15.1972	6.7659	11.2984
Contrast Limited Adaptive Histogram	149.4495	4.9602	15.9526

3. Conclusion

Image Noise removal techniques are used to improve image quality any removing unwanted data from the image. Various image noise removal techniques are analyzed for iris dataset. The performance is measured against PSNR, correlation of coefficient and RMSE. As depicted in results, median filter is proven to perform better as compared to other noise removal techniques. Image enhancement methods improve the image quality so that the resultant image is better than the original image for a specific application or set of objectives. In this paper different image enhancement schemes have been evaluated for iris dataset. The improvement in image enhancement is particularly effective in the case of very low contrast images. Spatial domain is good method for contrast enhancement however frequency domain is less effective method and histogram equalization is simple and efficient in terms of implementation.

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