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Adaptive Enhancement Technique for MRI Imaging

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Abstract:-. This research deals with some methods for medical image disparity enhancement. Objective is to provide the fast automatic enhancement technique, which may be easy to implement and results are enhanced image as an output. Although many enhancement techniques available for medical imaging but this may found suitable for specifically medical images. In this research, standard MRI image has been used.

Keywords*:* Image enhancement, image disparity, auto contrast, MRI image

I. INTRODUCTION

"Output of the previous step will be the input for next step" this is the method image processing believe. In image processing Contrast enhancement is an important area for both human and computer vision[1]. It is widely used for medical image processing and as a preprocessing step in speech recognition, texture synthesis, and many other image/video processing applications. Many images, such as medical images, remote sensing images, electron microscopy images and even our real-life photographic pictures, suffer from poor contrast[1, 2]. This affects the identification and verification / matching process. Therefore, it is very necessary to enhance the contrast of such images before further processing or analysis can be conducted.

Magnetic resonance imaging (MRI) is a non-ionizing technique[3] that uses radio frequency(200MHz–2 GHz) electromagnetic radiation and large magnetic fields (around 1–2 tesla(T), compared with the Earth's magnetic field of about (0.5 × 10–4 T)[3]. The large magnetic fields are produced by superconducting magnets, in which current is passed through coils of superconducting wire whose electrical resistance is virtually zero.

MRI images provide anatomical and physiological details, i.e. structure and function, with full three-dimensional capabilities, excellent soft tissue visualization, and high spatial resolution (~1mm). Like x-ray CT, it is a tomography imaging modality. Image reconstruction [3], while conceptually equivalent to that in CT, is obtained from the raw signals collected in frequency space[3]. With sufficient slice images, the image data is practically three-dimensional and it is possible to reconstruct the data in different two-dimensional planes. Scans last several minutes, rather than a few seconds as in x-ray CT[3], so that patient motion can be a problem. Furthermore, MRI scanners are several times as costly as a CT scanner because of the expensive superconducting magnet required.

There have already been many techniques for enhancing image contrast[1]. The most widely used methods include various contrast manipulations and histogram equalization [1, 2]. Classic contrast manipulation [1,7] is usually based on a globally defined stretching function (or called transfer function in the following). Traditionally histogram equalization is also a global technique in the sense that the enhancement is based on the equalization of the histogram of the entire image. However, it is well recognized that using only global information is often not enough to achieve good contrast enhancement (for example, global approaches often cause an effect of intensity saturation). To remedy this problem, some authors proposed localized (or adaptive) histogram equalization [1, 3], which considers a local window for each individual pixel and computes the new intensity value based on the local histogram defined in the local window. The adaptivity can usually improves the results but it is computationally intensive even though there are some fast implementations for updating the local histograms [6]. Furthermore, adaptive histogram equalization is a uniform local operator in the sense that all the pixels within the local window equally contribute to the determination of the new value of the center pixel being considered. Sometimes, like Gaussian filter[1,2] vs. evenly averaging filter for image smoothing, a weighted contribution of all the neighbors to the center pixel is more desired.

This paper proposed a fast method for image contrast enhancement. The basic idea of our method is to design a transfer function for each pixel based on the local statistics.

Organization of this paper as follows. first it describe the details of proposed approach. Then presented several examples of medical images and show the contrast-enhanced results by proposed approach. Finally conclusion.

II. AUTO - CONTRAST ADJUSTMENT

Automatic contrast adjustment [7] ("auto-contrast") is a point operation whose task is to modify the pixels such that the available range of values is fully covered. This is done by mapping the current darkest and brightest pixels to the lowest and highest available intensity values, respectively, and linearly distributing the intermediate values.

Let us assume that a_{low} and a_{high} are the lowest and highest pixel values found in the current image, whose full intensity range is $[a_{min}, a_{max}]$.

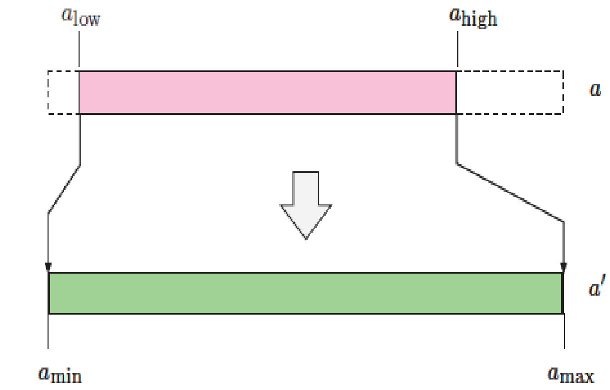


Figure 1 Auto-contrast operation according to Eqn. (a). Original pixel values a in the range [alow, ahigh] are mapped linearly to the target range [amin, amax].

To stretch the image to the full intensity range (see Fig. 1), we first map the smallest pixel value a_{low} to zero, subsequently increase the contrast by the factor $(a_{max}-amin)/(a_{high}-a_{low})$, and finally shift to the target range by adding amin. The mapping function for the auto-contrast operation is thus defined as

$$f_{ac}(a) = a_{min} + a - a_{low} \quad (\ amax-amin)/(ahigh - alow)) \qquad \ldots\ldots\ (a)$$

provided that ahigh≠ alow; i. e., the image contain at least two different pixel values.

For an 8-bit image with amin = 0 and amax = 255, the function in Eqn.(a) simplifies to

fac(a) = (a−alow) * 255/(ahigh−alow) ….(b)

The target range [amin, amax] need not be the maximum available range of values but can be any interval to which the image should be mapped. Of course the method can also be used to reduce the image contrast to a smaller range.

A. Dynamic Range and Contrast

The range of pixel values, defined as the difference between the maximum (amax) and the minimum (amin) pixel values found in the image, ignoring any obvious outliers, is known as the dynamic range[4] of the image. It can be expressed either as the difference in pixel values or (in decibels (dB)) as

$$\text{dynamic range of image} = 20 \log10 \text{ (amax - amin)} \qquad \ldots\ldots\ldots(1)$$

Thus a 12-bit deep CT image, spanning the full range of pixel values (or CT numbers!) available to it (i.e. 4096, from −1000 to +3095), has a dynamic range of 72 dB, while a typical 10-bit deep fluoroscopy image spanning its full range (i.e. 1024, from 0 to 1023) has a dynamic range of 60 dB.

Ideally, the dynamic range of the radiation from the scene being imaged should be close to the available dynamic range of the detector in the imaging system (2n for an n-bit system). In this case all the shades of gray in the scene are captured by the detector and represented in the image . If the dynamic range of the radiation from the scene is larger than the dynamic range of the detector, the image histogram has its low and/or high end cut off. Pixel values underflow or overflow into the values that mark the available limits, and information is irretrievably lost. Even if such underflow or overflow occurs at only one extreme of the histogram, and the pixel values are subsequently shifted away from that extreme, the information lost cannot be recovered. A more favorable situation is when the dynamic range of the object is smaller than the dynamic range of the detector. In this case, the dynamic range can be stretched to cover the whole range available , although the number of bins in the original histogram is maintained. The dynamic range of the detector and the display should also be matched. If they are not, for example a camera or scanner digitizing to 7 bits (128 levels) and the image displayed on an 8-bit display (256 levels), the recorded levels are spread out over the available display levels and the image histogram shows 128 levels each separated by an empty level. Thus the histogram often serves as an indicator to ensure the best image quality at the image acquisition stage.

A closely related concept to dynamic range is contrast. When the dynamic range of an image covers the available range of the imaging system (2n for an n-bit system), the image exhibits high contrast. Conversely, when the dynamic range is low, i.e. only a small range of closely spaced gray levels are present in the image, the image has low contrast and looks dull and washed out.

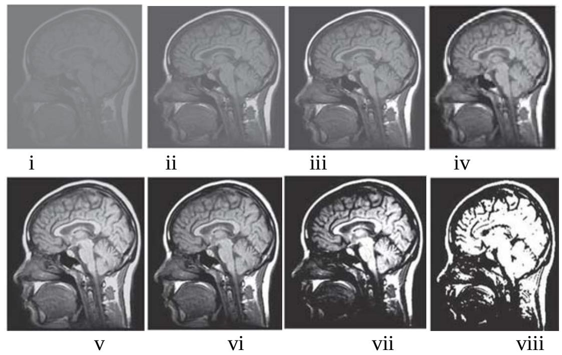


Figure 2 A series of images showing different contrasts. (The lowest contrast image is (i), and the highest contrast image is (viii).)

Look at the series of images in Figure2, each has the different contrast.

III. RESULT

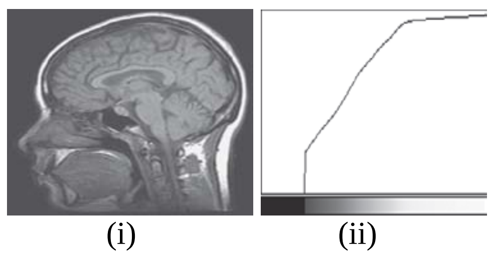


Figure 3 (i) Sagittal MRI image of a head,(ii) its cumulative distribution function

The integral of the normalized histogram/PDF is the distribution function or cumulative distribution function, CDF, of intensity in the image (Fig. 3(ii)), and indicates the probability of a pixel having a value equal to or less than a given value. The cumulative distribution function increases monotonically from 0 to 1 because the probability density function values are all positive. The cumulative distribution function value for a particular pixel value is obtained by adding the probability density function values for all the pixel values from zero up to the particular pixel value of interest. The minimum and maximum pixel values within the image can easily be obtained, either from the histogram/probability density function plot or from the cumulative distribution function plot; the median pixel value can be conveniently obtained from the cumulative distribution function plot by finding the pixel value corresponding to a cumulative probability of 0.5.

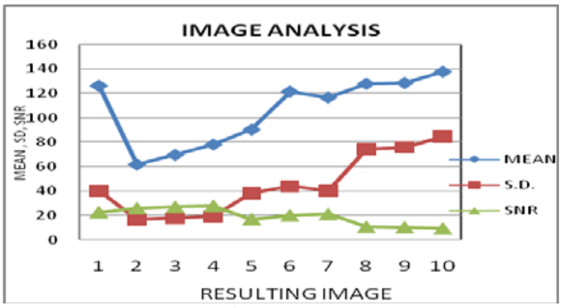
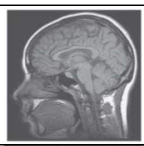
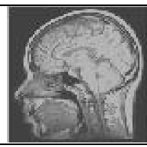
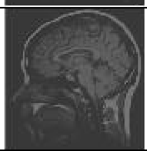
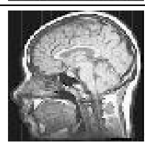
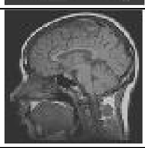
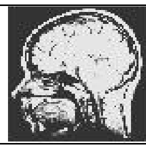


Figure.4 Performance Analysis Chart

IV. CONCLUSION

Proposed auto contrast enhancement technique found very well for medical image specifically for MRI images. After observing all eight images given in figure 2, the first and last are not clear in human vision. Visually and as per statistical measurements given in fig.4 both are not clear, but if consider middle images like 4th, 5th these are the clear and good quality images. This proves that middle value of the histogram may provide visually good quality image.

Table I. Experimental results and statistical measurements

SR.NO	RESULTING IMAGES	IMAGE	MEAN	S.D.	SNR	SR.NO	RESULTING IMAGES	IMAGE	MEAN	S.D.	SNR
1	Original image		126.22	40.19	22.88	**6**	Result image5		121.44	44.03	20.28
2	Result image1		61.98	16.89	25.99	**7**	Result image6		116.59	40.40	21.19
3	Result image2		69.78	18.05	27.04	**8**	Result image7		127.79	74.23	10.86
4	Result image3		78.27	19.35	27.95	**9**	Result image8		128.41	75.93	10.50
5	Result image4		90.51	38.48	17.10	**10**	Result image9		137.56	84.84	09.66

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