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EVALUATION OF THE ENTROPY BASED CONTRAST ENHANCEMENT METHODS FOR MRI IMAGES

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Abstract: This paper presents the significant methods used for grayscale images quality enhancement. The contrast and entropy are among the principal attributes of the brain MRI images. We investigate which method works better for image enhancement without any loss of the important information. The proposed study is validated on 80 images (40 proton density and 40 T2w). They encompass images from healthy patients, and patients with Alzheimer, Pick and cerebral calcinosis degenerative disease. The images show a wide range of the gray level values and hence various contrast levels. For a comprehensive study, a comparison between processed vs. unprocessed image has been performed.

Keywords: image processing, contrast enhancement, MRI.

1. INTRODUCTION

Image contrast enhancement is carried out by using various techniques specific to the digital image processing field. These techniques aim to improve the visual display and clarity of an image and to preserve the information in the image. The representative parameters that can be manipulated to improve the image quality are variance, kurtosis, entropy, contrast, sharpness, average gradient, and edges intensity (Moraru and Moldovanu, 2012; Sudhavani, *et. al.*, 2015). Our study focuses on the contrast and entropy.

Contrast is an important attribute of the image. It is defined as the separation between the darkest and brightest areas of an image and it is suitable to improve the visibility of the details into image without generating unwanted artifacts (Sudhavani, *et. al.*, 2015; Saleem, *et. al.*, 2012). Basically, the contrast enhancement consists of increasing the separation between dark and bright areas. The well known image enhancement methods deal with either local or global contrast enhancement methods or a fusion between them (Saleem, *et. al.*, 2012). However, the used method should not be excessively and uniformly concentrate on a particular area of an image because a possible loss of information occurs.

Various algorithms for contrast enhancement in both two approaches of spatial domain and transformed domain are available. Most of the spatial domain techniques manipulate the intensities of pixels and are based on maps the intensity values in original grayscale image (MIV) (Kotkar and Gharde, 2013; Maini and Aggarwal, 2010), histogram equalization (HE) (Maini and Aggarwal, 2010) or adaptive histogram equalization (AHE) (Gonzalez and Wintz, 2008). However, these histogram manipulation techniques are inappropriate to enhance the complex image such as brain MR images where various artifacts are induces by the scanners (Toet and Wu, 2015)

The MIV method maps the pixel intensity values in image and modifies the pixels distribution by clipping the lower and higher pixel values. If higher pixel values are less than the lower values, the output intensity is reversed. This process is similar to negative images in photography and is particularly useful for enhancing the white or gray details embedded in a large dark region (Kotkar and Gharde, 2013).

The histogram equalization (HE) is the most popular technique for contrast enhancement of images. As a simple image enhancement technique it is integrated in a global operation but it not preserves the image brightness (Raju, *et. al*., 2013; Kim and Paik, 2008). Also this technique introduces artefacts such as the loss of contrast in those image regions showing less frequent gray levels, and produces over enhancement those regions with more frequent gray levels (Kim and Chung, 2008).

The AHE method redistributes the intensity distribution corresponding to a distinct section of the image. It divides the image into several non-overlapped domains, runs an equalizing histogram task, and modifies the intensity levels so that they match across boundaries (Sharma, 2013; Al-amri, *et. al.*, 2010). AHE over amplifies the noise in homogeneous regions of an image.

Entropy measures the energy content (or the amount of disorder) in an image and is stronger correlated to the local contrast (Sezgin and Sankur, 2004; Gonzalez, *et. al.*, 2003). The higher values of the entropy indicate an information-rich image whilst a close to zero entropy value shows a little variation in pixel values. The histogram entropy information and more specifically the Shannon entropy has been used to define various thresholding function (Sezgin and Sankur, 2004). Entropy also characterizes the texture of an image (Sezgin and Sankur, 2004; Gonzalez, *et. al.*, 2003). This parameter has been considered in the present paper because it helps to evaluate the texture of the input image from the point of view of the pixels randomness. An older reference (Skilling and Bryan, 1984) used the entropy to evaluate the astronomic images, and more recent researches (German, *et. al*., 2005; Raju, *et.al*., 2013) have used the entropy to analyze the pixels' content of high dynamic range images.

We test the algorithmic solutions on two types of MR images: proton density and T2w in sagittal plane of the brain.

2. THEORETICAL APPROACHES

We present a brief overview of the existing image processing techniques used to evaluate the efficacy of the contrast enhancement operation.

The MIV method is modeled as $g(x,y)=T[f(x,y)]$, where $f(x,y)$ is the input image and $g(x,y)$ is the processed image by using T operator. This operator works on each pixel (x,y) that belongs to a square or rectangular sub-image area centered at (x,y). This process is operable only when the operator T acts on the pixels belonging to the selected. T can becomes a transformation function of the form of the gray-level into intensity mapping (Maini and Aggarwal, 2010; Gonzalez and Wintz, 2007).

Histogram equalization is a global spatial operation. It uniformly redistributes the pixel values in order to obtain a linear cumulative histogram. Let f be an image represented as a matrix of integer pixel intensities ranging from 0 to $L-1$. L is the number of possible gray levels or intensity values, usually 256. p_n denotes the normalized histogram of f with a bin for each possible intensity. So

$$p_n = \frac{number\ of\ \ pixels\ with\ \ \text{intensity}\ \ n}{total\ \ number\ \ of\ \ \ pixels} \quad (1)$$

where $n = 0, 1, ..., L-1$

The output image g provided by histogram equalized operation will be:

$$g_{i,j} = floor\left((L-1)\sum_{n=0}^{f_{i,j}} p_n \right) \quad (2)$$

Here the operator floor() rounds down to the nearest integer (Gonzalez and Wintz, 2007; Toet and Wu, 2015).

Adaptive histogram equalization separates the input image into several rectangular domains and acts as a local operation. For each non-overlapping domain, an equalization histogram operation is performed in order to enhance the pixels density value. This adaptive algorithm modifies each pixel intensity value based on the pixel values that belong to the selected region surrounding this pixel. This region represents the contextual region. If *(x,y)* is a pixel having the intensity i, then $m_{+,-}$ denotes the mapping of the right upper x_+, $m_{+,+}$ is the mapping of right lower x_+; $m_{-,+}$ the mapping of left lower x_- and $m_{-,-}$ the mapping of left lower x_-. The interpolated adaptive histogram equalization is compute as:

$$m(i) = a\left[bm_{-,-}(i) + (1-b)m_{+,-}(i)\right] + (1-a)\left[bm_{-,+}(i) + (1-b)m_{+,+}(i)\right] \quad (3)$$

where

$$a = \frac{y - y_-}{y + y_+}, \quad b = \frac{x - x_-}{x + x_+} \quad (4)$$

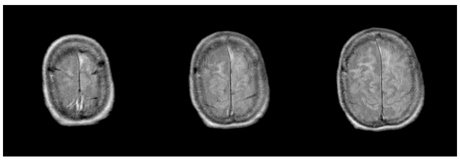
The main drawback of using the adaptive histogram equalization method is that it enhances not only the image, but also it enhances the noise in the image (Sharma, 2013; Sharma, 2013).

Shannon defines the entropy of an image as a measure of uncertainty associated with information contained in that image. Entropy is a statistical measure of randomness used to characterize the texture of an image. For an image *I* having a total number of the pixels *N*, the image histogram is denoted by h_I and entropy of the image is computed as (Gonzalez, *et. al.*, 2003; Sabuncu, 2016)

$$H(I) = \sum_i h_I(i) \log N / h_I(i) \quad (5)$$

3. DATASETS AND SOFTWARE

To evaluate the proposed methods for image enhancement a set of 80 brain MR images encompassing both images of degenerative diseases and of healthy patients has been used. The images are acquired in two specific ways: PDw (proton density) (40 images) and T2w (40 images). In this case, an important variation of the intensity and contrast exists in dataset so, it is suitable to assess of the contrast enhancement. The images belong to the Whole Brain Atlas (WBA) database. Each sub-set of 40 images includes 10 images of healthy patients, 10 images of patient with Alzheimer, 10 Pick and 10 with cerebral calcinosis diseases. The processing operations have been implemented using Image Processing toolbox for MATLAB R2016a software. An example of the sequential brain PDw-MRI images is shown in figure 1.



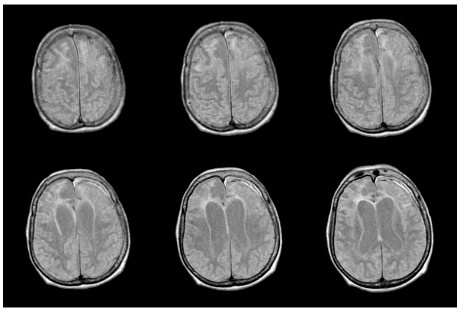
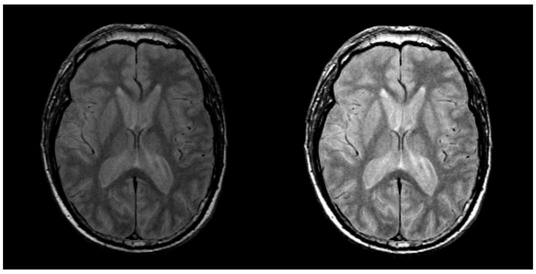


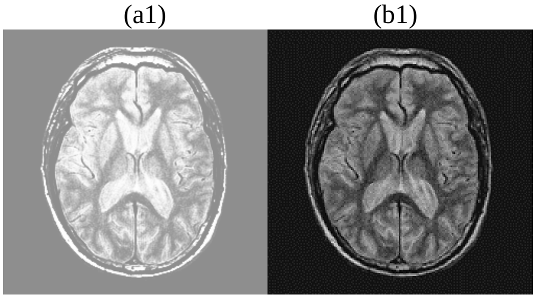
Fig.1. Sequential PDw-MRI image of patients with Pick’s disease from WBA dataset. (www.med.harvard.edu/aanlib/home.html)

4. EXPERIMENTAL RESULTS AND DISCUSSION

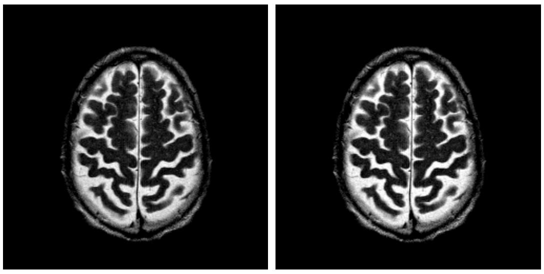
As the final goal is to evaluate the contrast enhancement, the images were processed using three methods. These method were tested on low- and high- contrast images. Some examples of MR images are presented in figure 2 in order to illustrate the effectiveness of the analysed methods. An image consisting of 256 x 256 pixels that shows different gray levels and contrast sensitivity is of interest as it is typically of the image processing. Thus, an unprocessed image (the first column), and the results of the MIV method (the second column), HE method (the third column) and AHE method (the forth column) are shown. Slightly visual contrast amplification is observed for images processed using MIV but HE method better preserve the details into image.



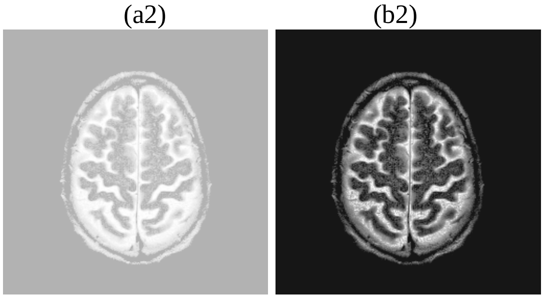
(a1) (b1)



(c1) (d1)



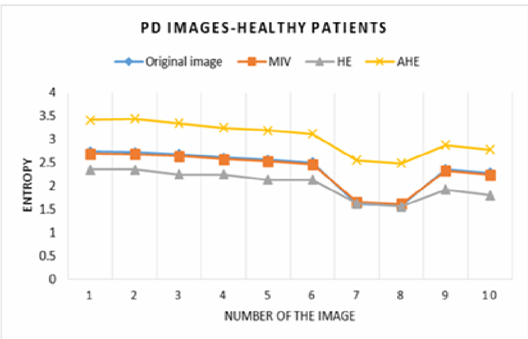
(a2) (b2)



(c2) (d2)

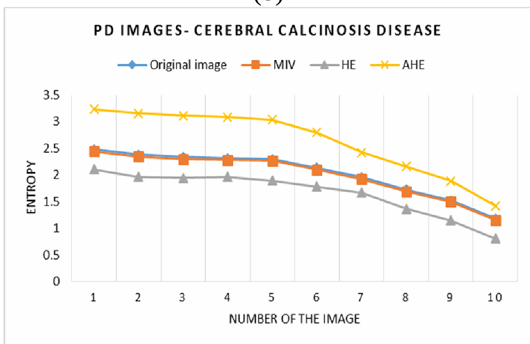
Fig.2. Contrast manipulation. The first row shows (a1) Original brain MR image acquisitioned in the PDw ways; (b1) PDw image processed with MIV method; (c1) PDw image processed with HE method; (d1) PDw image processed with AHE method. The second row shows (a2) Original brain MR image acquisitioned in T2w ways; (b2) T2w image processed with MIV method; (c2) T2w image processed with HE method; (d) T2w image processed with AHE method.

Figures 3 and 4 show the evolution of the entropy parameter for each image. The entropy has been computed after the images were processed using the MIV, HE and AHE methods.

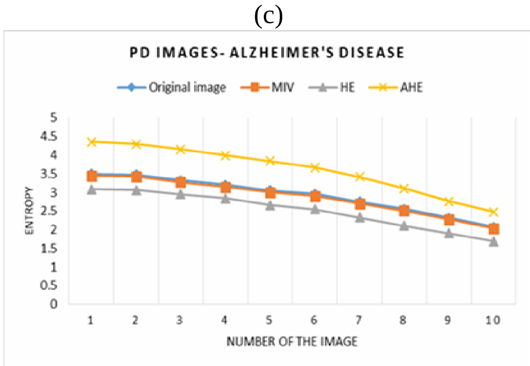


(a)

(b)

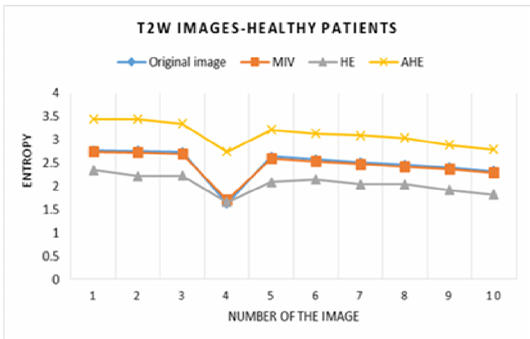


(c)

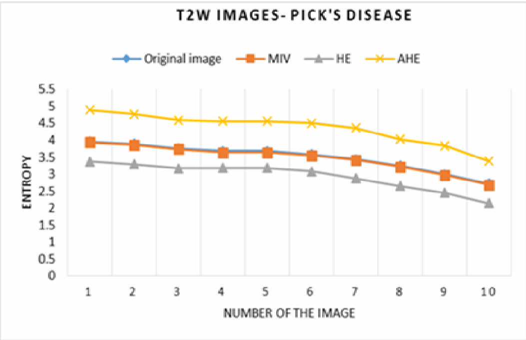


(d)

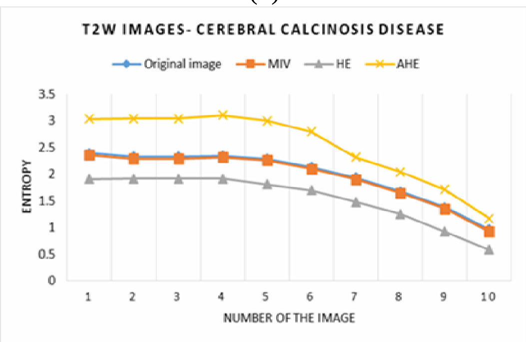
Fig.3. Entropy variation between processed and unprocessed brain MR PDw image. (a) healthy patients; (b) Pick's disease; (c) Cerebral calcinosis disease; (d) Alzheimer's disease.



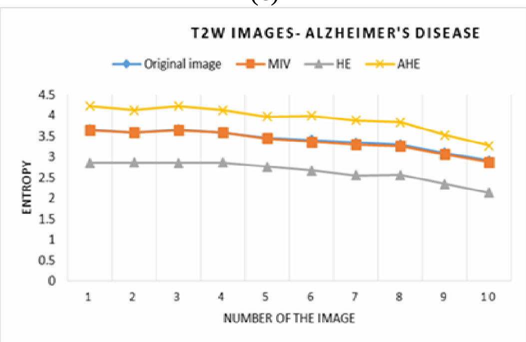
(a)



(b)



(c)



(d)

Fig.4. Entropy variation between processed and unprocessed brain MR T2w image. (a) healthy patients; (b) Pick’s disease; (c) Cerebral calcinosis disease; (d) Alzheimer’s disease.

The MR images have the technical advantage of changing the image contrast by changing the radio waves frequency and the strenght of the magnetic fields. Using the multiple radiofrequency pulses facilitates the emphasis of various types of tissue with different contrast levels. Among the selected methods we searched for that method which less degrade the initial image. According to the data in figures 3 and 4, the AHE method returned the higher entropy values compared to the unprocessed images, MIV and HE methods. As consequence, this method must be excluded from our analysis because it modifies the texture of the image and this is beyond of our goal.

As can be seen from figures 3 and 4, the entropy values computed for unprocessed images and those for images processed using MIV method are overlapped for all studied images. This means that the enhanced-based MIV images have an unmodified structure but an enhanced contrast.

The most popular enhancement techniques, namely the histogram equalization, returned the best results. The output images preserve the mean brightness value of the input image, whilst the separation between dark and bright pixels is increased. Also, the lesser entropy values were computed and this indicates that the image texture does not contain the random pixels.

Regarding the acquisition ways, it is observed that the low entropy values are obtained for T2w images and cerebral calcinosis disease. The entropy values are in the range 0.96 to 1.16 indicating an ordered texture. In the case of T2w image and Pick’s disease, the entropy has higher values from 3.96 to 4.88 indicating an information-rich image.

5. CONCLUSION

We have investigated the performance of three common methods used for contrast enhancement based on entropy parameter. Brain MR images retrieved from a publicly database were used because they provide a wide range of gray levels and contrast sensitivity. The entropy has been used as a measure of performance of proposed methods. HE has been resulted to be best method for enhancing images as it does not imply major lose of important information.

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