Original Article

Improving the contrast of brain tomography Images using screened poisson equation

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ABSTRACT

Background and Objective: medicine is one of the applied areas of image processing that is currently widely applied in the analysis of images obtained from medical imaging devices, CT-scan and MRI included. Slight differences in an image's contrast can bring about considerable effects on the image quality. The present study attends to the improvement of medical images' contrast as one of the necessary preprocessing stages. Study Method: the algorithm proposed in the present study tries to reduce the effect of uneven light so that the maximum details of an image can be preserved. The algorithm proposed in the current research paper has been simulated using MATLAB. The dataset pertaining to brain CT-scan and MRI has been utilized herein. A sample of a brain MRI image is the input to the proposed algorithm. The image has been analyzed by the use of Poisson relations and equations and the final improved image will be exhibited. Then, the proposed algorithm will be compared with neural network and genetic algorithm. Findings: according to the results of comparing the efficiency of the proposed algorithm with those of the genetic algorithm and back-propagation neural network, it can be clearly discerned that, besides the notable speed of the proposed algorithm, it also offers defendable results versus back-propagation neural network but it is found not much successful in contrast to genetic-based algorithm. Conclusion: screened Poisson equation is an effective and, in the meantime, fast method for improving the contrast of the medical images, especially tomography images of the soft tissues like the cerebral tissue.

Keywords: contrast improvement, Poisson equation, Fourier transform, CT-scan

Introduction

Various imaging methods like computed tomography scan (CT-scan) and magnetic resonance imaging (MRI) extensively help to the medical research and diagnosis [1,2]. But, the essential problem lies in the idea that the images obtained from these devices feature low contrast following automatic extraction and the existence of different artefacts severely diminishes the image quality and prevents the extraction of useful information from them [3,4].

Using low radiation dosage during examination, image transferring and storage process in imaging devices and various kinds of image reconstruction algorithms cause the reduction of the contrast in these images [5,6]. On the other hand, the use of noise reduction filters causes degradation of the contrast when trying to reduce the noises [7,8].

Image quality improvement is a very important area in digital image processing [9]. The main objective of processing the medical images obtained from various imaging methods is making diagnosis and examining the medication images in a more effective and more precise manner. This goal can be obtained in a process of image quality improvement [10].

Image contrast is defined by its dynamic domain that is the ratio between the lightest to the darkest pixels' intensities and it can be influenced by the tissue thickness and density, electron density in tissue, X-ray energy (kV), X-ray spectrum, scatter trace, CT window level, digital subtraction angiography, film characteristics and screen play properties [11]. To reduce the incorrect diagnosis risk related to low-contrast CT-scan images, there is a need for the improvement of visual details of CT images so that the radiologists can make more informed diagnosis and interpretation [1,12].

The most common technique that has drawn a large deal of attention in numerous studies is histogram integration. In fact, the graphical image is the intensity of the image points' brightness along X-axis and the total number of pixels along Y-axis. One shortcoming of the method is its inability in

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improving all the parts of an image as well as its calculation time [13,14].

Another well-known algorithm for improving the contrast of the digital images is lossless compression method. Compression is carried out via calculating the dynamic domain considering the brightness intensity differential between the brightest and the darkest points. This dynamic domain is compressed using logarithmic transform operator. One disadvantage of the method is its very large dynamic domain and complicated mapping (Sang and Huang, 2015).

The next algorithm is gamma correction that performs nonlinear brightness regulation of the images based on gamma values. In various studies, the method has been only applied to the images with irregular brightness and it cannot be used for quality improvement of all digital images [15] .

Another algorithm that has been investigated in various studies is called contrast stretching integration. The algorithm reduces the contrast in very dark and very bright regions by a histogram featuring integrated distribution. But, the pitfall of this algorithm is in that the offered image quality is intensively weak for images with low contrast [16] .

According to the fact that image contrast enhancement before image reconstruction has been the key idea in Retinex theory during the recent years, the algorithms have been designed so to eliminate the brightness indicators with lower frequencies whereas the high-frequency reflective components are increased. In fact, the algorithm tries to model the human visual system by making use of random high-pass filters [17] .

The present study aims at using Poisson image editor, a new technique, for changing the image gradient's vector field so that the images can be retrieved with a gradient close to this modified gradient field, therefore, to increase small gradient in the image and more details can be revealed of the imaged tissue.

Study Method

The following problem is going to be solved:

$$\begin{cases} \lambda u - \Delta u = -\Delta f & \text{in } \Omega \\ \frac{\partial u}{\partial n} = 0 & \text{in } \partial\Omega \end{cases} \quad (1)$$

Where, $\lambda > 0$.

The screened Poisson equation (1) can be solved using discrete Fourier transform. Newman boundary condition is implicitly exerted via symmetrical stretching of the initial image towards its edges in such a way that the stretched image, that is four times more enlarged, becomes symmetric and periodic. Discrete Fourier Transform (DFT) enables the direct calculation of *(J, L)*-periodic function's Fourier coefficient in terms of the limited band, *u*, from u_{jl} samples on a *JL* grid. The algorithm outputs an image that is the result of exerting screened Poisson equation onto every color canal in separate and the subsequent simplification of color balance in a 0.2% saturation rate. So, the screened Poisson equation takes the following form in Fourier domain:

$$\left(\lambda + \left(\frac{2\pi m}{J}\right)^2 + \left(\frac{2\pi n}{L}\right)^2\right)\hat{u}_{mn} = \left(\left(\frac{2\pi m}{J}\right)^2 + \left(\frac{2\pi n}{L}\right)^2\right)\hat{f}_{mn} \quad (2)$$

The solution takes the following form in Fourier domain:

$$\hat{u}_{mn} = \frac{\left(\left(\frac{2\pi m}{J}\right)^2 + \left(\frac{2\pi n}{L}\right)^2\right)}{\left(\lambda + \left(\frac{2\pi m}{J}\right)^2 + \left(\frac{2\pi n}{L}\right)^2\right)}\hat{f}_{mn} \quad (3)$$

Exerting inverse discrete time Fourier transforms, the solution for *u* is obtained.

In 8-bit digital images, the domain is in [0, 255] span. As it has been shown in [3], the best results are obtained when a small percentage of pixels are saturated in 255 and 0. The aforesaid algorithm is run for the results obtained from color balance simplification with a 0.2-percent saturation rate and the final result is eventually obtained by reimplementation of the simplest color balance on the previous stage's results. The point is that the algorithm is run on the monochromatic images that have been made symmetrical. FFTW library[1] is used for Fourier transform. Figure (1) illustrates the flowchart related to the proposed method.

The proposed algorithm has been simulated using MATLAB and CT-scan and MRI brain images dataset has been employed. The dataset includes researches about the investigation of the brain structural differences in children with affective disorders and attention deficits. The studied population incorporated the hyperactive children and adolescents who had depression and attention deficit. Each image existent in the dataset was inputted to the proposed algorithm of the present study to be converted to a gray scale image in the first stage. To be able to perform mathematical and computational operations on the images, the input image should be transformed to double-type data following which an initial matrix is created with zero values and image size. Then, the entries of each line and column of the matrix are assigned with values. In other words, the entire remaining stages of the proposed algorithm that encompasses mathematical and computational operators, as well, will be conducted using the foresaid matrix. Each entry of the matrix will be the differential of each pixel with its adjacent one and such an operation is employed for getting the mathematical calculations done. Put differently, all of the remaining stages of the proposed algorithm that embraces the computational and mathematical operators will be undertaken using this matrix. As a result, the normalization processes are performed in practice on the image. Then, Poisson algorithm is recalled parallel to the image quality improvement.

At the same time with implementing Poisson algorithm, Laplace formula is firstly run on the input data, i.e. the very normalized image. In this state, each pixel is assumed with four neighbors in the form of upper, lower, left and right neighbors and this is done for each of the aforementioned neighbors, as

[1] M. Frigo and S.G. Johnson, FFTW package, http://fftw.org

well, so that the differences can be calculated; then, the eigenvalues of the image are calculated following its being subjected to Fourier transform and the result can be displayed after implementing inverse Fourier transform.

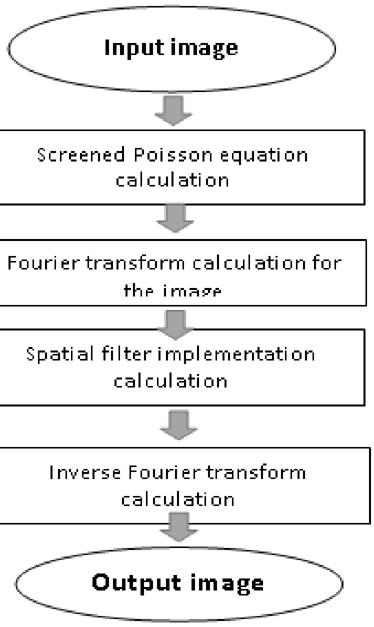

Figure 1. flowchart of the proposed algorithm

Findings

A sample of a brain MRI image was inputted into the proposed algorithm. The image was analyzed using Poisson relations and equations and the improved final image can be seen in figure (2). Figure (3) displays and compares both the input and output image alongside one another. The differential points of the input and output image can be clearly identified in the figure.

Figure 2. the improved final image

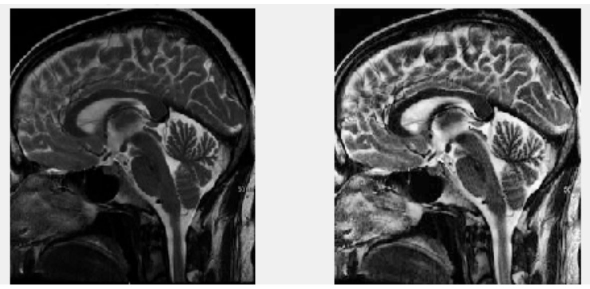

Figure 3. the initial input image (left) and the final image (right)

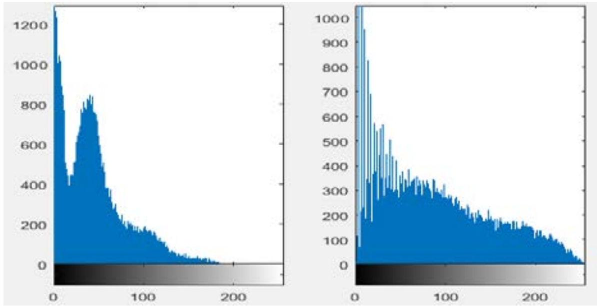

Figure 4. the histogram of the initial image (left) and the improved image (right)

In the following, we intend to investigate the evaluation criteria for the proposed algorithm and the two other methods. Improvement process has been examined using neural network in the first method and using genetic algorithm in the second one.

Table 1. investigating the evaluation criteria for the proposed algorithm and some of the other existing methods

Method used	Implementation time	PSNR	SSIM
Proposed method	3.82637	17.9652	46.6322
Neural network	17.43673	12.9573	39.572
Genetic algorithm	12.67394	19.0838	48.7364

The results of table (1) show that the proposed algorithm in the present study performs the quality improvement process in a shorter time than the other methods existent for doing so which is a big advantage of the proposed method. On the other hand, the proposed algorithm can offer larger PSNR and SSIM values than the methods that use back propagation for image quality improvement; however, the comparison of the proposed algorithm with the method that uses genetic algorithm for image quality improvement is indicative of smaller PSNR and SSIM values for the proposed algorithm. In other words, the proposed algorithm process optimizes the implementation time in comparison with the genetic algorithm but it has failed offering better PSNR and SSIM values.

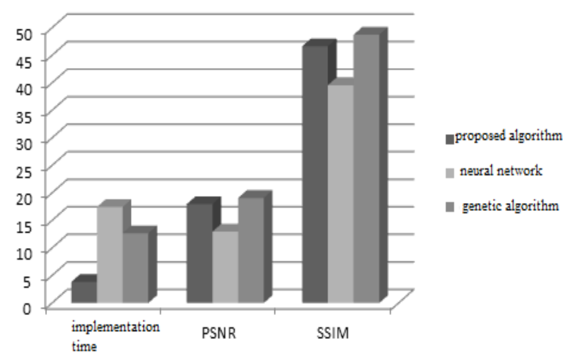

Figure 5. investigating the evaluation criteria in the proposed algorithm and other methods

Figure (5) demonstrates the weak and strong points of the proposed algorithm as abovementioned in such a way that according to the screened Poisson equation, the biggest advantage of the proposed algorithm is its speed of action indicating that it performs image contrast improvement and processing in a significantly lower time ($P<0.05$) based on t-test method as compared to the other two methods.

Discussion and Conclusion

The results were suggestive of the idea that the proposed method causes the expansion of the images' histogram and the various components of the image are displayed in a higher precision and resolution and this is largely helpful in an increasingly more exact investigation of the brain tomography images by the physicians and facilitates the fast and accurate diagnosis of the cerebral diseases. The rapid and on-time diagnosis of brain problems is deemed as one of the urgent needs for the fact that they can expose the patients to critical conditions as repeatedly emphasized by the medical society.

On the other hand, the comparison that was made between this method and the other existent method in terms of the required time for the implementation of the image contrast processing and improvement showed that the proposed method takes significantly shorter time for doing so and it is per se enumerated as one of its huge advantages because there is a very short time and golden chance in the diagnosis of the cerebrovascular disorders and /or cerebral infarctions the losing of which may cause irreparable damages to the patient and even loss of patient's life.

Poisson equation is intensively sensitive to the inhomogeneity and unevenness of the brightness in various spots of an image and tries to reduce the brightness inhomogeneity in a uniform manner so that the image details can be seen more clearly. Aiming at omitting the brightness inhomogeneity in various spots of the image, the algorithm reduces function variance and takes advantage of increasing the parameter λ for variance decrease.

References

1. Iwasokun GB, Oluwole CA. 2014. Image enhancement methods: a review. British Journal of Mathematics & Computer Science; 4(16):2251.
2. Tan TL, Sim KS, Tso CP, Chong AK. 2012. Contrast enhancement of computed tomography images by adaptive histogram equalization‐application for improved ischemic stroke detection. International Journal of Imaging Systems and Technology; 22(3):153-60.
3. Kofler JM, Yu L, Leng S, Zhang Y, Li Z, Carter RE, McCollough CH. 2015. Assessment of Low-Contrast Resolution for the ACR CT Accreditation Program: What is the Impact of Iterative Reconstruction? Journal of computer assisted tomography ;39(4):619.
4. Baker ME, Dong F, Primak A, Obuchowski NA, Einstein D, Gandhi N, Herts BR, Purysko A, Remer E and Vachani N. 2012. Contrast-to-noise ratio and low-contrast object resolution on full-and low-dose MDCT: SAFIRE versus filtered back projection in a low-contrast object phantom and in the liver. American Journal of Roentgenology; 199(1): 8-18.
5. Goenka AH, Herts BR, Obuchowski NA, Primak AN, Dong F, Karim W, Baker ME. 2014. Effect of reduced radiation exposure and iterative reconstruction on detection of low-contrast low-attenuation lesions in an anthropomorphic liver phantom: an 18-reader study. Radiology; 272(1):154-63.
6. Schindera ST, O D, Raza SA, Kim TK, Jang J, Szucs-Farkas Z, Rogalla P. 2013. Iterative Reconstruction Algorithm for CT: Can Radiation Dose Be Decreased While Low Contrast Detectability Is Preserved? Radiology; 239.
7. Jayaraman S, Esakkiranjan S, and Veerakumar T. 2015. Digital image processing. New Delhi: Tata McGraw Hill.
8. Ansari IA and Borse RY. Image Processing and Analysis. 2013. International Journal of Engineering Research and Applications; 3(4)1655-8.
9. Liu XS, Nie SD, and Sun XW. 2009. An enhancement method for small brain metastases in T1w MRI. Paper presented at the Fuzzy Systems and Knowledge Discovery 2009. FSKD'09. Sixth International Conference on.
10. Bai X, Zhou F, and Xue B. 2012. Image enhancement using multi scale image features extracted by top-hat transform. Optics & Laser Technology, 44: 328-336.
11. Foroughi AA, Ostad P, and Nazeri M. 2015. Brain Computerized Tomography Scan Findings in a Man After Inadvertent Intrathecal Ionic Contrast Agent Injection. Shiraz E-Medical Journal 16.
12. Zhou Y, Panetta K, and Agaian S. 2010. November. 3D CT baggage image enhancement based on order statistic decomposition. Technologies for Homeland Security, 287-291.
13. Santhi K, WahidaBanu RS. 2013. Contrast enhancement of bi-histogram equalization with neighborhood metrics. InComputing, Communications and Networking Technologies (ICCCNT), 2013 Fourth International Conference;1-5.
14. Wong CY, Liu S, Liu SC, Rahman MA, Lin SC, Jiang G, Kwok N, Shi H. 2016. Image contrast enhancement using histogram equalization with maximum intensity coverage. Journal of Modern Optics; 63(16):1618-29.
15. Rahman S, Rahman MM, Abdullah-Al-Wadud M, Al-Quaderi GD, Shoyaib M. 2016. An adaptive gamma correction for image enhancement. EURASIP Journal on Image and Video Processing; 2016(1):35.
16. Ramkumar M, Karthikeyan B. 2013. A survey on image enhancement methods. International Journal of Engineering and Technology;5(2):960-1012.
17. Morel JM, Petro AB, Sbert C. 2014. Screened Poisson equation for image contrast enhancement. Image Processing On Line; 4:16-29.