Correction of Intensity In-Homogeneity of MR Image Based on Average Median Intensity Value Method

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Abstract:

The Magnetic Resonance Image (MRI) may be valuable techniques for learning the structural property of the human brain. However, the reproducibility of imaging results, that arises from swish intensity variation happens the entirety MR image, named as Intensity in-homogeneity or non-uniformity. The intensity in-homogeneity may be a hurdles encountered in human and computer interpretations and analysis of MRI. Automated methods for MRI non-homogeneity correction could fails as a result of resolution because solution for them need identification regions on behalf of an equivalent tissue for a a varietyof various tissue, regardless of the approach could fails this job. Normally, MRI brain image contain intensity in-homogeneity. Therefore accurate process of brain image may be a terribly trouble some task. Thus will use one amongst the correction technique could useful for proper diagnosis for clinical purpose and conjointly segmentation of the image process or segmentation primarily based fusion process. During this paper, we tend to project a brand new technique on the Average Median Intensity Value. This algorithm initial to ascertain the background and foreground voxels then estimate the intensity value of foreground and replacement all the values of background voxels by average median intensity value. This computation time is quick and best compared with the prevailing algorithms, analysis primarily based results is nice for than the source image.

Keywords: *MRI, in-homogeneity, Average Median Intensity.*

I. INTRODUCTION

The Magnetic Resonance Imaging (MRI) technology has been frequently used for clinical diagnosis. However, MR images occasionally suffer intensity in-homogeneity, which is usually caused by imperfection within the radio frequency coils or inhomogeneous coil sensitivities within the receiving coils. During this issues talk to slow intensity variations a similar tissue over the image region, which may have impact on clinical diagnosis or automatic analysis such as registration, segmentation and segmentation primarily based fusion [1]. A range of algorithms has been proposed to correct the intensity in-homogeneity of the MR images, a best vision of the image analysis. A review of these correction methods was bestowed by Mohammad Ali Balafar [2]. Supported these review the foremost well-liked ways are Fitting methods, filtering methods, segmentation based correction methods and histogram based correction methods.

In intensity primarily based surface fitting methods [3] turn out sensible results when pixels of a principal tissue are distributed over the image and might be choose. However estimation of the in-homogeneity field from one tissue and blindly distributes it over the image. Thus another approach is gradient based surface fitting methodology is yields sensible results once a images contains giant homogenous areas. However in these methodologies assume there are distinctive and enormous homogeneous areas in image and should integrate unwilling image information. To calculate the partial derivative of the intensity in- homogeneity gradient using 1D polynomial fitting [4] on each x-coordinates and y-coordinates. However, the gradient based algorithms are intensity gradient is very tremendously to noise and image boundaries that it can initiate giant estimation errors.

In filtering methods, each homomorphic filtering and homomorphic un-shape mask [5] are a straightforward and quick, however it would eliminate low frequency image information and that they turn out a streak artifact on the edges called as edge impact.. In non-pharametric segmentation based methods like max shift and mean shift [6] are more general and don't concerning any earlier information about tissue distribution, at the similar time is more expensive and complexity.

In histogram based methods like high frequency maximization approach [5] use solely the information that's gift in an image while not creating assumptions on spatial and intensity distribution. However they have a constraint to preserve contrast in image and therefore the non-linear log computations of entropy difficult. Another approach is histogram matching method [7] desires no initialization and previous data creating these totally these fully automatic and general. Therefore these strategies wiped out sub volumes of images have constant in-homogeneity.

II. MATERIALS AND METHODS

In Filtering contemplate in-homogeneity a low-frequency artifact and use low-pass filter to in-homogeneity field detection [8]. If there have been any low frequency image information, these methods may eliminate them. Different shortcoming of those strategies is manufacturing a streak artifact on edges referred to as edge impact that causes distortion of homogeneous tissues close to the edges. Homomorphic filtering [9] and -homomorphic unsharp masking (HUM) method are two most vital filtering in-homogeneity correction methods. In homomorphic filtering, subtraction of log transformed of input image from log-transformed of its low-pass filtered is taken into account corrected image [10].

Homomorphic filtering produces edge effect on boundary between tissues. Guillemaud proposed to use filter just to object to shrink this artifact [11]. In-homomorphic un-sharp masking (HUM), the in-homogeneity correction field is obtained by low-pass filtering of the input image, divided by the constant to preserve mean or median intensity. In mean filter is is employed as low-pass filter and and therefore the background are masked out from HUM input for reducing edge artifact. In [12], a algorithm uses multiplication in Fourier domain for low-pass filtering and uses average intensity value to replace background pixels from HUM input for reducing edge artifact. Also in [13], average intensity value replaces background pixels for sinking edge artifact.

Histogram Based mostly Methods like High-Frequency Maximization methods doesn't use any knowledge regarding image and iteratively, estimate in-homogeneity by maximizing the high frequency information of tissue distribution. This method assumes in-homogeneity as low frequency and image information as high frequency, and maximizes high frequency information. Therefore, it's going to eliminate low frequency information of image. In [14], a non-parametric none-uniform intensity normalization (N3) method is proposed which models in-homogeneity field as a Gaussian distribution with tiny variance to constrain the solution area. N3 estimates the in-homogeneity field by maximizing the frequency content of the image intensity distribution. Information Minimization: These methods consider in-homogeneity as extra information and minimizing information for in-homogeneity correction [15]. They use distribution entropy or log of it to measure information. In [16], a nonparametric course to fine approach is proposed which in each scale estimates in-homogeneity using entropy minimizing. If entropy in two scales does not change, interpolate in-homogeneity estimation to original scale.

Histogram matching methods, in these methods, image is divided into sub volumes. These methods assume sub volumes have constant in-homogeneity and use histogram of image to initialize a finite Gaussian mixture model and fit the model to histogram of sub volume to estimate local in-homogeneity. The estimated local in-homogeneity is checked for outliers. At last, the result is interpolated to produce the final in-homogeneity field of input image. In [17], a histogram matching in-homogeneity correction method proposed which divides the image into small sections with relatively constant intensity in-homogeneity. In order to estimate local intensity in-homogeneity, the intensity histogram model (a finite Gaussian mixture) is fitted to the actual histogram of a section by least square fitting. The ultimate in-homogeneity is produced by interpolation of local estimates in section.

A review of the different approaches, histogram based techniques is a smaller amount complicated and quicker and a lot of complexness. In this paper, we tend to projected a new novel approach is histogram based on estimate the average median intensity value.

Average Median Intensity Value:

Intensity in-homogeneity is one in every of the important issues happens in MR imaging. Once those drawback to be corrected that helps to will increase the image readability, image segmentation and segmentation based image fusion. In supported literatures, most of those methods are computationally stringent that is requires above 1 minute for a 2D image. Here, we tend to design and implementing the proposed to new technique named as average median intensity value, it is faster and less complexity, whose results isn't in correct absolutely however can it helps the segmentation process [18]. The intensity in-homogeneity correction methods are as follows.

1. Assume, MR Images consists of two layers such as the foreground and the background. The values of intensity I(x,y) of the input MR images are linearly scaled to the range of [0..256].
2. Calculate the histogram as

$$H(i) = \sum_{x,y} h(x,y) \quad for\ 0 \le i \le 256$$

$$where, h(x,y) = \begin{cases} 1, & when\ i - 0.5 \le I(x,y) \le i + 0.5 \\ 0, & otherwise \end{cases}$$

3. Derivative H' from H then find the initial index i_0 , here, $H'(i_0)>0$ as the Threshold value.
4. If $I(x,y) < I_0$ then we classify of as a background voxel, otherwise it as a Foreground voxel.
5. In foreground voxels, estimate the average median intensity values AM_f immediately construct a foreground image I_f by replacing all the intensity values of the background voxels by AM_f.
$$I_f(x,y) = \begin{cases} M_f, & if\ I(x,y) \in [0, I_0] \\ I(x,y), & otherwise \end{cases}$$
6. The foreground image I_f is blurred to I_b by convolving, whose σ is set to one half of the image size in the X – Y plane. Now se set $\sigma = 128$ (eg., 256 x 256).
7. Then the corrected image of in-homogeneously I_c is derived by normalizing the input I with the blurred foreground I_b.
$$I_c(x,y) = \frac{I(x,y)}{I_b(x,y)}$$

III. RESULTS AND DISCUSSIONS

It has been developed with MATLAB 15a for simulation, several versions procurable. However, in version of MATLAB 15a additional features of the present work like, sub-versions offer supply management integrations, advanced graphics systems etc., In general, MATLAB is associate degree interactive program for numerical computations and information image to supported to different operating systems such as UNIX, Windows etc., Here a few reasons to choosing the MATLAB 15a throughout the analysis work as a results of, provides quite a lot of functions allows to form numerical preciseness at intervals conclusion, mathematical and geometrical support for the implementing of this algorithm, helpful to matrix and vectors formulations of the present work.

In MRI causes intensity in-homogeneity, its incredibly difficulties in image segmentations and can't to understanding the MR images. Before quantitative analysis of MR images or additional processing, that image must be correct on intensity in-homogeneity value. In intensity in-homogeneity occurs in real images such as CT and MR images, it is the significant troubles for the bring MR image segmentation. In Fig. 1. Represents the Intensity inhomogeneity in MR brain image.

Original Image In-homogeneity Field Corrected Image

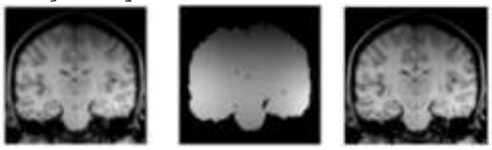

Fig. 1. Intensity inhomogeneity in MR brain image

Various methods were studied and compared the analysis, new approach is a lot of advantage of the some processing like, increase the standard deviation, reduce the mean square error and reduce the computational time and space complexity in Table 1.

Table 1. Evaluation Parameter

	Average Mean Intensity	SD
Input MR Image	425.16	214.38
Corrected Image	172.17	83.43

IV. CONCLUSION

In-homogeneity degrades medical diagnosis and image segmentation. In that downside correction is a necessary stage to boost the accuracy of the results. This field may be a analysis is a research area for several to plenty of researches has been done. In this paper, novel approach of the intensity in-homogeneity correction to improve the image quality to helps the image segmentation as well as medical diagnosis. However, during this approach is not a precise and not able to estimate the bias value. In future, get better those algorithms to estimate the bios and to develop the right algorithm.

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