A SURVEY OF MRI ENHANCEMENT TECHNIQUES

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Abstract: Enhancement of medical images is a requisite for increasing the accuracy of computer aided diagnosis in radiology. The research issue in medical image enhancement is to enhance the visual appearance without compromising with the intrinsic image features as they are crucial for diagnosis. This paper presents a short overview of different image enhancement techniques. The impact of different techniques for T1 C+ MRI brain ring enhancing lesions are evaluated based on Peak Signal to Noise Ratio.

Index Terms - Medical image enhancement, Histogram Equalization, Bilateral filter, Wiener filter, Homomorphic filtering

INTRODUCTION

The quality of medical images are deteriorated during image acquisition and illumination conditions. Image enhancement apply mathematical transformation on images to improve the visual appearance for assisting radiologists for diagnosis and surgical planning. Different techniques are proposed to solve this issue based on spatial methods, wavelet methods, histogram methods and contrast improvement to enhance the appearance of images for better visual interpretation, understanding and image analysis[1].

Medical image enhancement technologies have gained attention since advanced medical equipments were put into use in the medical field[2]. As intensity levels, edge details, enhancement pattern plays a crucial role for medical image analysis, the enhancement methods should be chosen without affecting this details in images. Also, in case of real time image processing, enhancement techniques should be less time consuming even in case of bulk volume MRI. MRI poses certain challenges like intensity non-uniformity, high visual similarity between normal and abnormal tissues.

Several techniques for enhancement based on histogram, contrast stretching, tone mapping are proposed[3]. The spatial domain methods operate directly on image pixels. It considers the pixel neighborhood information for image enhancement. Frequency based method transforms image into its fourier representation for applying the filtering techniques and then revert the image by its inverse fourier transform. Histogram Equalization techniques can be used to improve the contrast of images. Contrast techniques can be local, global, partial in images. The following section discusses the seven different types of image enhancement techniques.

ENHANCEMENT TECHNIQUES

2.1. Histogram Equalization and Local Histogram Equalization

Histogram equalization manipulates the image histogram to uniformly distribute the pixel intensity resulting in a uniform histogram. For each pixel in the image the 3X3 window is extracted and the histogram equalization is used to compute the enhanced pixel value. The process of Local Histogram equalization[4] is that:

1. Compute the probability distribution function, \( p(X_k) \):

\[
p(X_k) = \frac{nk}{n} \quad (1)
\]

2. Compute the cumulative distribution function \( c(X) \) for each pixel value

\[
c(X) = \sum_{i=0}^{k} p(X_i) \quad (2)
\]

3. The centre pixel is replaced with the \( c(X) \) value.

<table>
<thead>
<tr>
<th>Image</th>
<th>Abcess</th>
<th>Gliblastomultiforme</th>
<th>Metastasis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Histogram Equalization and Local Histogram Equalization</td>
<td><img src="image1.png" alt="Image" /></td>
<td><img src="image2.png" alt="Image" /></td>
<td><img src="image3.png" alt="Image" /></td>
</tr>
<tr>
<td>PSNR</td>
<td>77.26</td>
<td>75.25</td>
<td>73.28</td>
</tr>
</tbody>
</table>

2.2. Non Local Means Filter

The pixel value is estimated based on the pixel similarity and the weighted average of all the pixels in the image. For the intensity image \( v = \{ v(i) | i \in I \} \), the estimated value \( NL[v](i)[5] \), for a pixel \( i \), is computed as a weighted average of all the pixels in the image and is given by,

\[
NL[v](i) = \sum_{j \in I} w(i, j) v(j) \quad (3)
\]

Weights \( w(i, j) \) depend on the intensity similarity between the pixels \( i \) and \( j \), and in the range \( 0 \leq w(i, j) \leq 1 \) and \( \sum \_j w(i, j) = 1 \).
2.3. Bilateral Filter

Tomasi and Manduchi [6] proposed bilateral filter as an alternative to anisotropic diffusion filter. Bilateral filter combines domain and range filtering. The similar neighborhood pixels are isolated and the weighted average is used for estimating the enhanced pixel value. For the intensity image \( v = \{v(i) \mid i \in I\} \), the estimated value \( BL[v](i) \) is computed as

\[
BL[v](i) = \frac{1}{W_p} \sum_{x \in \Omega} v(x_i) f_r(\|v(x_i) - v(x)\|) g_s(\|x_i - x\|)
\]

(4)

where, \( \Omega \) is the neighborhood window, \( f_r \) is the range kernel for smoothing intensity differences, and \( g_s \) is the domain kernel for smoothing spatial coordinate differences.

\[
W_p = \sum_{x \in \Omega} f_r(\|v(x_i) - v(x)\|) g_s(\|x_i - x\|)
\]

(5)

Table III Results of Bilateral Filter with normalization \( w=5 \)

<table>
<thead>
<tr>
<th>Image</th>
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<tbody>
<tr>
<td><strong>Bilateral filter</strong></td>
<td><img src="Image" alt="Image" /></td>
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<tr>
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<tbody>
<tr>
<td>72.09</td>
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<tr>
<td>72.09</td>
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<tr>
<td>69.31</td>
</tr>
</tbody>
</table>

2.4. Anisotropic diffusion

Anisotropic diffusion is a multi-scale technique to detect edges [7]. The diffusion process performs smoothing in continuous regions and prevents smoothing in edges. The filter is based on constrained differential diffusion equation for the intensity image \( I \) with diffusion time \( t \),

\[
I_t = \text{div}(c(x, y, t) \nabla I) = c(x, y, t) \Delta I + \nabla c \cdot \nabla I
\]

(6)

Where, \( \text{div} \) is the divergence, \( \nabla \) is the gradient, \( \Delta \) is the Laplacian operator and \( c(x, y, t) \) is the diffusion strength. The diffusion strength is close to zero at edges having large gradients and maximum in homogeneous regions having small gradients.

Table IV Results of Anisotropic diffusion with iterations=2, delta=1/7, kappa = 30

<table>
<thead>
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<td>75.05</td>
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<tr>
<td>73.41</td>
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<tr>
<td>70.98</td>
</tr>
</tbody>
</table>

2.5. Contrast-limited adaptive histogram equalization (CLAHE)

CLAHE addresses the problem of noise amplification. It operates on small regions called tiles in image. For each tile, contrast is enhanced based on a distribution parameter. Artificial boundaries are prevented by combining the neighborhood tiles using bilinear interpolation [8].

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<tbody>
<tr>
<td><strong>Contrast-limited adaptive histogram equalization (CLAHE)</strong></td>
<td><img src="Image" alt="Image" /></td>
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<td>42.90</td>
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<td>42.41</td>
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<tr>
<td>Image</td>
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</tr>
<tr>
<td>Contrast-limited adaptive histogram equalization</td>
</tr>
</tbody>
</table>

PSNR

### 2.6. Wiener Filter

For each pixel, local statistics are measured from its 3X3 neighborhood η in the image I and the filtering is based on the following equation,

\[ w(n_1, n_2) = \mu + \frac{\sigma^2 - \nu^2}{\sigma^2} (I(n_1, n_2) - \mu) \]  

(7)

Where \( \nu^2 \) is the noise variance, \( \sigma^2 \) is the variance, \( \mu \) is the mean in \( \eta \).

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PSNR

### 2.7. Homomorphic Filtering

Homomorphic filtering [9] normalizes image brightness to increase contrast for enhancement. For uniform brightness the high frequency are amplified to contribute reflectance and low frequency components are attenuated to reduce illumination.

The illuminated image can be represented as,

\[ I_{out}(x,y) = i(x,y) \cdot r(x,y) \]  

(8)

Where \( i(x,y) \) is the illumination and \( r \) is the reflectance at the position \( (x,y) \). Taking log,

\[ \ln(I_{out}(x,y)) = \ln(i(x,y)) + \ln(r(x,y)) \]  

(9)

Applying Fourier transformation,

\[ \mathcal{F}(\ln(I_{out}(x,y))) = \mathcal{F}(-\ln(i(x,y))) + \mathcal{F}(\ln(r(x,y))) \]  

(10)

Or, \( M(u, v) = I(u, v) + R(u, v) \)  

(11)

\( u, v \) refer to the frequency domain transformation. Applying High pass filter \( H \) we get the filtered image \( N \),

\[ N(u, v) = H(u, v) \cdot M(u, v) \]  

(12)

![Fig.2. Homomorphic filtering process in frequency domain](image4.png)

Fig.2. a Abscess image 2.b Natural logarithm of abscess 2.c Fourier Transform 2.d Homomorphic filtering 2.e Inverse Fourier Transform 2.f Enhanced Image
MSE (Mean Square Error) is computed using the equation (14).

\[ \text{MSE} = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} [I(x, y) - I'(x, y)]^2 \]  

Where MSE is given by equation (14).

\[ \text{PSNR} = 10 \log_{10} \left( \frac{255^2}{\text{MSE}} \right) \]  

Where PSNR is given by equation (13).

### III. PERFORMANCE EVALUATION

The performance of the methods are analyzed visually and quantitatively using Peak Signal to Noise Ratio (PSNR). PSNR block computes the peak signal-to-noise ratio, in decibels, between two images. This ratio is often used as a quality measurement between the original and enhanced image. The higher the PSNR, better the quality of the estimated image. PSNR in decibels (dB) is computed by using the equation (13)

\[ \text{PSNR} = 10 \log_{10} \left( \frac{255^2}{\text{MSE}} \right) \]  

Where MSE is given by equation (14).

#### Table V Results of Homomorphic filtering

<table>
<thead>
<tr>
<th>Homomorphic filtering</th>
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<td>PSNR</td>
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#### REFERENCES


