MR IMAGE ENHANCEMENT BY NONLINEAR TECHNIQUES

K. N. Bhanu Prakash

Dept. of Electrical Engg.
IISc, Bangalore-560012
bhanu@ee.iisc.ernet.in

A. G. Ramakrishnan

Dept. of Electrical Engg.
IISc, Bangalore-560012.
ramkiag@ee.iisc.ernet.in
Ph: 080-3092556

ABSTRACT

We propose two weighted nonlinear (WN) methods and a third degree polynomial based method for enhancing MR images. The WN methods are based on expressions similar to those of Shannon and Renyi's entropy measures. Neuroradiologists, who evaluated 120 sets of images, voted the polynomial based enhancement as the best technique.

Index Terms: MRI; nonlinear; enhancement; polynomial; GMM.

1. INTRODUCTION

Magnetic Resonance Imaging (MRI) is widely used for anatomical imaging of the brain. Excellent soft-tissue contrast and high spatial resolution can be obtained by this imaging modality. Segmentation of the MR image into different tissues, i.e. gray matter, white matter, cerebrospinal fluid and background is an important prerequisite for a number of applications like brain morphometry, surgical planning and abnormality detection.

In MRI, intensity of the image is not standardized [1]. The signal intensity of an MR image can represent a mixture between T1-, T2- and $\rho-$ values, flow, diffusion, perfusion and other factors influencing the signal emitted by structures within a volume element. More information is encoded in MR images compared to other imaging modalities. This makes the contrast behaviour of MRI more complex than that of any other medical imaging modality. In medical imaging, contrast is defined as the relative difference between the intensities of two adjacent regions within an examined object. The numerous factors influencing contrast can be divided into two groups: the *intrinsic* and the *extrinsic* parameters. Some of the intrinsic factors are proton density, T1- relaxation, T2- relaxation, physiologic motion and changes in tissue composition. Extrinsic factors that influence contrast are magnetic field strength, magnetic field inhomogeneity, hardware and software parameters and pulse sequence parameters. Many *extrinsic* factors directly influence the *intrinsic* factors. For the clinical application of MRI, it is necessary to be aware of the influences and interactions of the above factors, if one is to react rapidly and efficiently in a diagnostic question.

One of the main advantages of MRI is the possibility of changing the contrast by choosing special pulse sequences and their parameters. By emphasizing one factor or mixing several factors in a specific way, the contrast behaviour of a certain morphologic region or pathological lesion can be highlighted.

While analyzing the brain MR images obtained in a study of normal subjects in a neurocentre, some of the images were found to be of very low contrast. It was found difficult to differentiate the various tissue regions in the images. Samples of such low contrast images and their histograms are shown in Fig.1. Thus, the enhancement of the contrast between the different tissue types was formulated as an objective in our study. This enhancement can also be used as a prelude to segmentation. Various enhancement methods, based on linear and nonlinear transformations, were explored. We have formulated techniques based on entropy

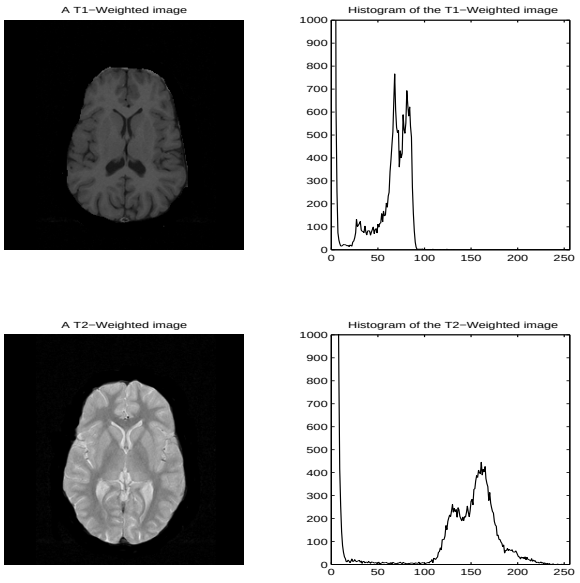

Figure 1: Samples of MR images used in the study and their histograms

measures and polynomial transformation.

2. PROPOSED ENHANCEMENT METHODS

Entropy is a measure of the average amount of information present or the degree of uncertainty of a random variable. The Shannon's [2, 3] entropy of a source such as an image I is defined as the average information generated by the source, i.e.

$$E_S(I(x_k)) = -\sum_{k=1}^{N} p(x_k)\ \log\left(p(x_k)\right) \qquad (1)$$

Another entropy measure, which is also quite useful, is Renyi's entropy measure [4], is defined as

$$E_R(I(x_k)) = \frac{1}{1-\alpha}\ \log\ \sum_{k=1}^{N} p(x_k)^{\alpha},\ \ \alpha > 1 \qquad (2)$$

Any entropy measure is a global feature and is given as a single number for the image. The nonlinear transformations proposed on the lines of Shannon's and Renyi's entropy measures for the enhancement of MR images are described in the following subsections.

2.1. Weighted Nonlinear Method -1

This method is based on the Shannon's entropy relation. We have made use of the pixel intensities as the variable instead of the probability measures of the pixels. The method is a point based global method, since it operates similarly on each pixel intensity of the image. The enhanced value of the pixel $Y_s(x_k)$, corresponding to an input pixel value x_k is given by,

$$Y_s(x_k) \ = \ x_k \ \ \log\ (x_k) \qquad (3)$$

The processed pixels are then normalized to have the gray values between 0 and 255. The pixels having *zero* intensity value are replaced by a small value ϵ, for the purpose of computing the logarithm. Enhancement can be controlled by suitably changing the base of the logarithm. Significant enhancement is obtained if the gray values of the original image do not occupy the entire gray scale. This method has worked better with T1-weighted images than T2-weighted ones. This is due to the fact that in T2- weighted images, CSF has intensity values close to the upper limit of the gray scale and the background has values near the lower limit of the scale.

2.2. Weighted Nonlinear Method-2

This method is based on a 3×3 neighbourhood. This is also a global method, as each pixel is processed in a similar fashion. The transformation is based on Renyi's entropy relation. The enhanced intensity, $Y_r(x_k)$ is defined as,

$$Y_r(x_k) = \frac{1}{1-\alpha}\ \ \log\ \ \sum_{k=1}^{9} {x_k}^{\alpha},\ \ \alpha > 1 \qquad (4)$$

2.3. Polynomial Based Method

Polynomial methods are useful for enhancing the image contrast, when histogram stretching is to be carried out around a particular value of the input intensity. Given a range of input intensities, $x \in [x_{min}, x_{max}]$, and output intensities, $y \in [0, y_{max}]$, and the point $x \ = \ x_c$, at which the histogram is to be stretched, a third-order polynomial [5] can

be specified to meet this criteria, according to,

$$y(x) \;=\; Ax^3 + Bx^2 + Cx + D \qquad (5)$$

where $A \;=\; \dfrac{1-m}{x_{max}^2 - 3x_c x_{max} + 3x_c^2}$

$B \;=\; -3Ax_c \quad C \;=\; m + 3Ax_c^2 \quad D \;=\; 0$

The values of A, B, C and D can be obtained from the following initial conditions :

$$\begin{aligned} y(0) &= 0, \quad \text{the lowest intensity value} \\ y(x_{max}) &= y_{max} \;=\; x_{max} \\ \dot{y}(x_c) &= \frac{dy}{dx} \;=\; m \\ \ddot{y}(x_c) &= \frac{d^2y}{dx^2} \;=\; 0 \end{aligned} \qquad (6)$$

where m is the slope in the region of the histogram transformation around x_c.

When the output intensity values produced by the mapping function exceed y_{max}, the output must be clipped at y_{max}. The severity of clipping can be reduced by a gradual tapering toward upper and lower bounds; this is achieved by a ramp function of the form

$$\text{lower bound: } y_{lower}(x) \;=\; kx \qquad (7)$$

$$\text{upper bound: } y_{upper}(x) \;=\; k(x - x_{max}) + y_{max} \qquad (8)$$

where k is the slope of the ramp (adjustable parameter). The severity of clipping is reduced when k is increased from zero. However, as k approaches one, the range of contrast enhancement is narrowed, and the overall effect of the transformation is diminished, eventually leaving the image unaltered. A typical value of k is 0.2. Taking into account the tapered bounds, the mapping function may be defined in the following form:

$$y = \begin{cases} y_{lower}(x) & : \; y(x) < y_{lower}(x) \\ y_{upper}(x) & : \; y(x) > y_{upper}(x) \\ y(x) & : \; otherwise \end{cases} \qquad (9)$$

The mapping function is shown in Fig. 2 for low, medium and high values of x_c with $m = 2$.

The control point (x_c) was estimated by analyzing the input images themselves, without the need for user interaction. The histograms of the sample images shown in Figure 1 have two distinct regions. The peaks correspond to the background region of the MR image and the brain region. The background has gray values in the range 0 to 20. By selecting a threshold of 20, the background was removed. The histogram of the modified image is modelled by a gaussian mixture model (GMM)[6]. The overall density function (histogram) is the sum of two unimodal densities. The mixture probability density function is defined as

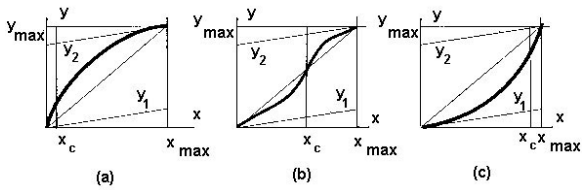

Figure 2: Polynomial mapping function to enhance (a) low intensities (b) middle intensities and (c) high intensities

$$p(z) \;=\; w_1\, p_1(z) \;+\; w_2\, p_2(z) \qquad (10)$$

and for the Gaussian case,

$$\begin{aligned} p(z) \;=\; & \frac{w_1}{\sqrt{2\pi}\sigma_1} \exp\left[-\frac{(z-\mu_1)^2}{2{\sigma_1}^2}\right] \\ & + \frac{w_2}{\sqrt{2\pi}\sigma_2} \exp\left[-\frac{(z-\mu_2)^2}{2{\sigma_2}^2}\right] \end{aligned} \qquad (11)$$

where μ_1 and μ_2 are the mean values of the two brightness levels of the histogram, σ_1 and σ_2 are the standard deviations about the means, and w_1 and w_2 are the weights with which the two gaussian functions are combined with the condition;

$$w_1 \;+\; w_2 \;=\; 1 \qquad (12)$$

The value of x_c is calculated as follows:

$$x_c \;=\; \frac{\mu_1\sigma_2 \;+\; \mu_2\sigma_1}{\sigma_1 \;+\; \sigma_2} \qquad (13)$$

The parameters of the GMM were estimated using the Expectation-Maximization [7] technique.

3. RESULTS AND DISCUSSION

The images used in our study were acquired at National Institute of Mental Health and Neuro-Sciences, from 1.5 Tesla Siemens machine. The imaging protocol included spin-echo (SE), T1 - weighted sequences [TR / TE = 650 / 15 / 1] and turbospin echo (TSE), T2-weighted sequences [TR / TE / 1 = 5500 / 22, 90 / 1] in axial planes. An inversion recovery sequence FLAIR (Fluid Attenuated Inversion Recovery) [TR / TE = 9000 / 120 / 1] was also performed in axial plane. A field of view (FOV) of 230-250 and a matrix of 256×256 were employed for these sequences. The flip angle for TSE-T2 and FLAIR sequences was 180° and 70° for T1-weighted sequence.

A total of 120 images were used to evaluate the proposed methods. The data set contained axial slice images at various depths and varying contrast. The results obtained by all the proposed techniques are presented for some sample images in Figs. 3 and 4. The enhanced images were evaluated by two neutral observers trained in MR image analysis who were blinded to the data sets. The evaluators rated the images on a scale of 1 (best contrast) to 4 (poor contrast). The outcome of their evaluation is given in Table 1. The 4 parts of the table correspond to evaluation on original, WNM-1, WNM-2 and polynomial enhanced images, respectively. All the methods have given good enhancement in terms of the contrast, especially for T1-weighted images which is evident from the figures. This is because, in most T1-weighted images, the gray values are distributed in the low range of the gray scale, giving room for enhancement. However, in the case of T2-weighted images, the histogram extends up to the maximum gray level. Thus, the logarithm based methods, which basically stretch the low gray level region of the histogram, are less effective with T2 images.

The polynomial method has worked very well with both T1 and T2-weighted images. This is due to the fact that the enhancement is symmetric around x_c, which feature is missing in the other two methods. The choice of x_c gives an extra degree of freedom to select the region on the gray scale where enhancement is necessary. Excellent

Table 1: Evaluation Results on Original Images, Images enhanced by WNM-1, Images enhanced by WNM-2 and Polynomial enhanced images

		EVAL 1				
		1	**2**	**3**	**4**	**Total**
EVAL 2	**1**	0	1	1	1	3
	2	0	0	0	1	1
	3	0	1	1	4	6
	4	0	1	11	98	110
	Total	0	3	13	104	120

		EVAL 1				
		1	**2**	**3**	**4**	**Total**
EVAL 2	**1**	6	0	2	0	8
	2	6	36	16	1	59
	3	3	20	26	0	49
	4	1	1	2	0	4
	Total	16	57	46	1	120

		EVAL 1				
		1	**2**	**3**	**4**	**Total**
EVAL 2	**1**	4	5	1	0	10
	2	2	30	17	1	50
	3	2	19	32	1	54
	4	0	4	2	0	6
	Total	8	58	52	2	120

		EVAL 1				
		1	**2**	**3**	**4**	**Total**
EVAL 2	**1**	89	1	3	6	99
	2	3	1	2	3	9
	3	3	2	2	4	11
	4	1	0	0	0	1
	Total	96	4	7	13	120

differential tissue contrast can be obtained by appropriately choosing x_c. Further, the advantage with the polynomial method is that the slope of enhancement can be chosen depending on the need. A gaussian model was assumed for estimating x_c, as a linear combination of appropriate gaussian basis functions is capable of representing a large class of sample distributions and the observation from many MR brain images show that the dif-

ferent brain tissues approximately follow a normal distribution.

4. CONCLUSIONS

The details of tissues which were not clearly visible in the original image are enhanced by the proposed methods. The results of enhancement and validation indicate that the polynomial based enhancement is the best. The polynomial method selects x_c adapting to the input images, thus eliminating the need for user interaction in tuning the parameters for different classes of images. The polynomial based enhancement method works well both for T1- and T2-weighted images, and further, irrespective of the initial contrast.

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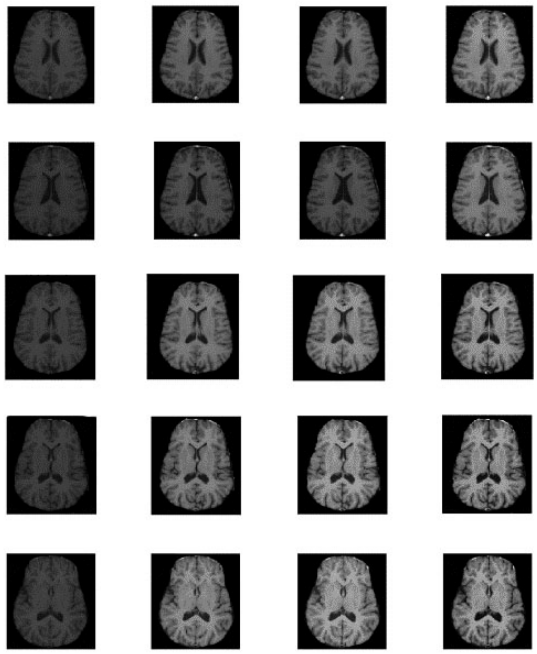

Figure 3: T1-weighted original images (first column) and the images enhanced using WNM-1, WNM-2 and the polynomial based method.

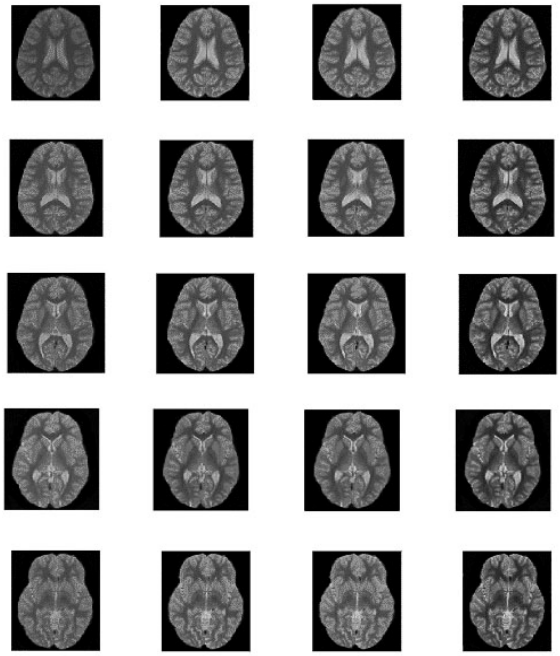

Figure 4: T2-weighted original images (first column) and the images enhanced using WNM-1, WNM-2 and the polynomial based method.