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A Fuzzy Sharpness Metric for Magnetic Resonance Images

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ABSTRACT

A fuzzy-based sharpness metric for the objective measurement of sharpness of Magnetic Resonance (MR) images is proposed in this paper. In the proposed metric, Quadratic Index of fuzziness (QIF) is used to quantitatively express image sharpness. The proposed metric is found to be superior to Maximum Local Variation (MLV) metric, Perceptual Sharpness Index (PSI), Second order Derivative based Measure of Enhancement (SDME), Blanchet's Sharpness Index (BSI) and Roffet's Blur Metric (RBM) in terms of correlation with subjective quality ratings and computational time.

1. Introduction

In computerized analysis of Magnetic Resonance (MR) images, automated localization of structures is possible only if they have well-defined and sharp boundaries [1–3]. State of art techniques for image sharpening includes Unsharp Masking (UM) [4], shock filters [5] *etc*. Development of customized sharpening techniques suitable for MR images [6–8] is one of the hot areas of research in medical image computing. Need for objective quality metrics for the performance evaluation and comparison of state of art sharpening techniques is the major motivation of this paper. Another concern is that, majority of the sharpness metrics are developed for panoramic images, rather than medical images like MRI. Sharpness metrics with good correlation with subjective fidelity ratings, which are computationally feasible too, are rare. Apart from mere performance evaluation of sharpening techniques, these objective metrics have other applications as well. Sharpness metrics are usually used as objective functions while computing the optimum values of the operational parameters of the sharpening algorithms. Sharpness metrics are extensively used in quality control to compare the quality of images produced by different makes of MR equipment.

Quantitative indices meant for measuring image sharpness are Maximum Local Variation (MLV) metric [9], Perceptual Sharpness Index (PSI) [10], Second order Derivative based Measure of Enhancement (SDME) [11], Blanchet's Sharpness Index (BSI) [12] and Roffet's Blur Metric (RBM) [13]. In the MLV metric [9], MLV at each pixel was computed from the maximum of intensity difference among that pixel and its eight-connected neighbors. The tail end of MLV distribution was amplified through nonlinear weighting, considering that human visual perception is comparatively more sensitive to regions of high contrast in the image. Eventually, image sharpness was computed from the standard deviation of weighted distribution of MLV. In PSI, image sharpness was considered as a function of thickness and slope of the edges. Edges were detected via gradient based threshold. SDME is the average of contrast at distinct blocks of arbitrary size. Blanchet's Sharpness Index was metric computed from the global phase coherence. In Roffet's Blur Matric, extent of blur was calculated from the dispersion of local gray level values in the original image and its Gaussian-blurred version.

The sharpness indices available in literature have serious demerits. The magnitude of Maximum Local Variation can better describe the sharpness than its standard deviation used in MLV metric [9]. The concordance of PSI [10] and SDME [11] with subjective fidelity ratings purely depends on the arbitrary threshold used for detecting the edges and the block size, respectively. Repeated computation of 2D discrete Fourier transform is the demerit of Blanchet's Sharpness Index [12]. As mentioned above, metrics like PSI [10] and SDME [11] used for measuring either do not have a finite range or their performance depend on arbitrarily defined parameters.

The organization of the paper is; mathematical formulation of the fuzzy-based sharpness metric and procedure for simulation of standard MR images with different degrees of sharpness used for

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analyzing the performance of the proposed metric are explained in Section 2. In Section 3, the performance of the fuzzy-based sharpness metric is compared against available state of art sharpness metrics like MLV metric, PSI, SDME, BSI and RBM in terms of correlation with Mean Opinion Score (MOS) and computational time. The contribution of this paper and highlights of the proposed metric are;

- A fuzzy-based sharpness metric for the objective measurement of sharpness of MR images is proposed in this paper.
- Major highlights of the proposed metric are its high correlation with subjective fidelity ratings and fast computation.
- The proposed metric is a bounded statistics with finite range between zero and one
- No reference image is required for its computation
- Formulation of the proposed metric does not include any manually selected parameters

2. Methodology

Mathematical formulation of the fuzzy-based sharpness metric and procedure for simulation of standard MR images with different degrees of sharpness used for analyzing the performance of the proposed metric are explained in this section.

2.1. Fuzzy Sharpness Metric

In the proposed metric for measuring image sharpness, Quadratic Index of fuzziness (QIF) is used. Fuzzy membership function in QIF is modified such that QIF quantitatively accounts for sharpness of the input image.

Inherently, pixel intensities in images follow nondeterministic pattern and considerably high level of ambiguity. Hence, fuzzy set theory [14–15] is more applicable to image processing than ordinary set theory. According to the fuzzy set theory, an image 'X', with dimensions $M \times N$ and dynamic range of grey levels between 0 and L-1 can be possibly viewed as a vector of fuzzy singletons each with a membership value within the range of 0 to L-1. According to the fuzzy notations, image set 'X' can be represented as [14],

$$X = \left\{ \mu_x\ (x_{mn}) = {}^{\mu_{mn}}\!/\!_{x_{mn}},\ m = 1, 2 \ldots M,\ n = 1, 2 \ldots N \right\} \quad (1)$$

or

$$X = \bigcup_m \bigcup_n \mu_{mn}/x_{mn},\ m = 1, 2 \ldots M,\ n = 1, 2 \ldots N \quad (2)$$

where μ, is the fuzzy subset or membership function. If 'x_{mn}' denotes pixel intensity at the coordinates, (m,n) in the image 'X' and 'μ_x' denotes membership function corresponding to the X and then membership value at the pixel 'x_{mn}' can be denoted as $\mu_x(x_{mn})$. Here, $\mu_x(x_{mn})$ or μ_{mn}/x_{mn} lies in the interval [0,1]. Fuzzy subset 'μ' of the image 'X', is in fact a mapping of the pixel intensities in 'X' into a bounded closed interval [0,1]. In general, fuzzy membership value, '$\mu_x(x_{mn})$' represents the degree of possessing a particular image property like randomness, brightness or homogeneity by the pixel 'x_{mn}'.

As mentioned already, in the proposed sharpness metric, QIF is used to quantitatively express image sharpness. Quadratic indices of fuzziness for an image set 'X' are computed using (3).

$$\gamma_q\ (X) = \frac{2}{\sqrt{MN}} \left[\sum_{i=1}^{M} \sum_{j=1}^{N} min \left\{ \mu_x(x_{mn}),\ 1 - \mu_x(x_{mn}) \right\}^2 \right]^{1/2} \quad (3)$$

where M and N, indicates the number of rows and columns in the image. The term, 1- $\mu_x(x_{mn})$ is the complement of fuzzy membership value $\mu_x(x_{mn})$.

In the proposed fuzzy-based sharpness metric, normalized local gradient is considered as the fuzzy membership value $\mu_x(x_{mn})$. It is a known fact that gradient magnitude has significant dependency on image sharpness. The grey level difference between adjacent pixels will increase when the image becomes sharper. Local value of the gradient magnitude increases with respect to the increase in the grey level difference between the contextual pixel and its neighbors. These two aspects imply the scope of the gradient to account for the image sharpness. Gradient vector of the image X can be calculated from (4).

$$\nabla = \sqrt{{\nabla_h}^2 + {\nabla_v}^2}\ Given\ \nabla_h = S_h * *X\ and\ \nabla_v = X * *S_v \quad (4)$$

In (4), ∇_h and ∇_v denote gradient along horizontal and vertical directions, respectively. The symbol '**' in (4) stands for 2D convolution. S_h and S_v are Sobel masks along horizontal and vertical directions, respectively.

$$S_h = \begin{matrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{matrix} \qquad S_v = \begin{matrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{matrix}$$

As mentioned already, normalized local gradient is used as the fuzzy membership value. Thus, the fuzzy membership value at the pixel 'x_{mn}',

$$\mu_x(x_{mn}) = \frac{\nabla_{mn}}{\nabla_{max}}\ where\ \nabla_{max} = \sqrt{20}(L-1) \quad (5)$$

∇_{max} in (5) is the maximum possible gradient value. Four different pixel combinations at which the gradient value becomes maximum are,

L-1	L-1	0	0	0	L-1	L-1	L-1	L-1	0	0	0
L-1	0	0	0	0	L-1	L-1	0	0	0	0	L-1
L-1	0	0	0	L-1	L-1	0	0	0	L-1	L-1	L-1
	(a)			(b)			(c)			(d)	

Upon normalization, range of the normalized gradient and thereby, the range of fuzzy membership values become bounded within the closed interval [0,1]. The term in (3), min{$\mu_x(x_{mn})$, 1-$\mu_x(x_{mn})$} will be maximum only when $\mu_x(x_{mn})$ = 0.5. Hence, QIF will reach its maximum *ie.* unity, when all membership values are equal to 0.5. This implies that maximum value of the normalized local gradient, ∇_{mn} should be 0.5. Hence, the normalization factor, '∇_{max}' in (6) is modified as $2\nabla_{max}$. So that (5) become,

$$\mu_x(x_{mn}) = \frac{\nabla_{mn}}{2\nabla_{max}} = \frac{\nabla_{mn}}{\sqrt{80}(L-1)} \approx \frac{\nabla_{mn}}{9(L-1)}$$
$$where\ \nabla_{max} = \sqrt{20}(L-1) \quad (6)$$

Largest challenge in developing sharpness metric for MR images is the absence of a standard database comprising images of known level of sharpness. Hence, as a primary step for designing the sharpness metric, a repository of MR images with different levels of sharpness are simulated. Unsharp masking is used in this paper to simulate standard MR images with different degrees of sharpness.

2.2. Unsharp Masking

In UM, to increase its sharpness of the input image, a fraction of difference of the input image and its low-pass filtered version or low-frequency content is added back to the input image itself. Low frequency content of the input image is obtained by convoluting it with a Gaussian kernel. Difference between the input image and its low-frequency content is obviously high- frequency content of the input image. In UM, sharpened image [16],

$$Y = X + \lambda [X - (X * *H_G)] \quad (7)$$