Enhancement of Ultrasonic Image Based on the Multi-Scale Retinex Theory*

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Abstract. Liver ultrasonic images enhancement processing is studied based on Retinex theory in this paper. Characteristic parameters extracted based on Retinex theory algorithm are compared to that of histogram equalization and homomorphic filtering. The experiment data show that Multi-Scale Retinex enhancement algorithm can improve image brightness, increase contrast and enlarge image information entropy. Then the statistical feature parameters abstracted based on MSR are applied for texture classification by the Probabilistic Neural Network (PNN) and it achieve good effects.

Keywords: Retinex Theory, Image Enhancement, Dynamic Range Compression, Texture Analysis.

1 Introduction

Ultrasonic imaging has become one of the most popular tools used in diagnosis and prognostication of human abdominal organs such as liver, spleen and kidneys, due to its ability to visualize human tissue without deleterious effects. The ultrasonic liver images have various granular structures describe by texture [1], therefore the analysis of ultrasonic liver images can be viewed as the problem of texture analysis. A considerable number of image texture analysis techniques were developed over the years, such as the gray histogram statistics, gray level difference statistic, gray level co-occurrence matrix, the fractal dimension texture analysis, the gray run length statistics [2], the Fourier power spectrum and wavelet transformed analysis [3][4]. Each of the above methods has its own peculiarity in performance.

Edwin Land firstly proposed theory of Retinex color constancy in 1977[5]. The word "Retinex" is a portmanteau formed from "retina" and "cortex", suggesting that both the eye and the brain are involved in the color perception processing. Retinex theory is mainly introduced as follows: the visual system of human being could practically recognize and match colors under a wide range of different illuminations. Color constancy is a feature of the human color perception system which ensures that

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the perceived color of objects remains relatively constant under varying illumination conditions. Retinex theory was used in image enhancement and got good effects over the years, which is widely used in digital image processing [6][7][8].

Image quality will be greatly affected in gathering, conversation and transmission with interference of image equipment. Ultrasonic images have abundant texture details, wide dynamic range and low contrast; therefore image pre-processing must be done before feature extraction. Image pre-processing broadly include de-noising and enhancement. In this paper, we study the enhance methods based on Retinex theory, and apply them to ultrasonic images.

The paper is organized as follows: Firstly, image enhancement method based on Retinex theory is introduced. Then histogram equalization, homomorphic filtering enhancement, Single-Scale Retinex (SSR) algorithm and Multi-Scale Retinex(MSR) algorithm are applied on image enhancement of ultrasonic images, texture feature parameters are extracted after image enhancement. Subsequently, The PNN is employed as a classifier in our methods. Feature parameters extracted from MSR are chosen as the input of PNN to make automatic classification to two kinds of images.

2 Methods

According to Retinex theory mode, the available image *I(x,y)* can be decomposed into two different images, the illumination image *L(x,y)* and the reflectance image *R(x,y)*:

$$I(x,y) = L(x,y) * R(x,y) \tag{1}$$

Where *L(x,y)* is the spatial distribution of the source illumination and *R(x,y)* is the distribution of scene reflectance. *L(x,y)* describes brightness of surrounding environment and the low frequency information of *I(x,y)*, while *R(x,y)* describes object reflection ability and corresponds to the high frequency information of *I(x,y)*. That is to say, *L(x,y)* represents the approximation of the *I(x,y)*, and *R(x,y)* represents the details of *I(x,y)*. *L(x,y)* describes dynamic range of the image pixel value; *R(x,y)* decides image's inner detail characteristics.

The essence of the Retinex theory is to abtain object's true face by discarding effects of illumination from given image and extracting object reflection, that is to say, *R(x,y)* should be obtained from *I(x,y)* by excluding the impact of *L(x,y)*, thus kinds of Retinex algorithms are derived from the mode.

2.1 SSR Enhancement Algorithm

Jobson proposed SSR algorithm according to the Retinex theory [9]. To obtain the reflectance image, the key factor is how to estimate the illustration component accurately. The first step is to take logarithm on both side of (1), so that the product in (1) is turned into summation operator, then:

$$\log R(x,y) = \log I(x,y) - \log L(x,y) \tag{2}$$

$$\text{Suppose } \tilde{L}(x,y) = I(x,y) * F(x,y) \tag{3}$$

$\tilde{L}(x,y)$ denotes the estimation of *L(x,y)*, *I(x,y)* is the input image, * means convolution operation, *F(x,y)* is a low pass filter. Normally *F(x,y)* is a normalized surround function and $\iint F(x,y)dxdy=1$. From (2) and (3) we can have that:

$$\log \tilde{R}(x,y) = \log I(x,y) - \log[I(x,y) * F(x,y)]$$

$\tilde{R}(x,y)$ denotes the estimation of $R(x,y)$, i.e. the estimation of the reflectance image which indicates image's inner detail characteristics. $\tilde{R}(x,y)$ is what we want to get.

The core of the method is the estimation of illustration component $\tilde{L}(x,y)$, there are many ways to get $\tilde{L}(x,y)$, $\tilde{L}(x,y)$ is determined in our case by applying a low pass filter *F(x,y)* to the *I(x,y)*. The most common LPF is the Gaussian function $F(x,y) = K \cdot e^{-\left(x^2+y^2\right)/2c^2}$, where *c* is the standard deviation about surrounding field. "*c*" determines the type of information that the Retinex provides. The smaller *c* provides more dynamic range compression, and the larger *c* provides more color constancy. That is to say, standard deviation "*c*" affects the result of image enhancement and it controls that how many details can be maintained in the image.

In fact, a distinct trade-off controlled by the scale of the surround function exists between dynamic range compression and tonal rendition, and one can be improved only at the cost of reducing the other. Usually, equilibrium point need to be found between dynamic range compress and color sense consistency.

2.2 MSR Theory Algorithm

The SSR can provide dynamic range compression or tonal rendition, but not synchronously. MSR algorithm is an image enhancement method, which can not only fulfill image dynamic compress but also ensure color sense consistency. The algorithm is described as:

$$\log \tilde{R}(x,y) = \sum_{n=1}^{N} W_n \cdot \{\log I(x,y) - \log[F_n(x,y) * I(x,y)]\}$$

where N is the number of spectral bands, i.e. the number of scales. $N=1$ means gray image, $N=3$ means color image. $F_n(x,y)$ is the surround function, and W_n is the associated weighting coefficient.

Regarding to medical image, experiments show that three scales: big, middle and small, should be selected. Each scale's weight is determined according to the need of focus on dynamic range compress or color sense consistency.

The pixel value of image processed by MSR method may be negative and it will exceed the display range of monitor. Therefore it needs to be corrected to make translation and compression in the display range of monitor [7].

2.3 Correction to R(x,y)

The paper adopts adaptive linear tensile method to do amendment processing to images [8] [9]. For normal random variables in Gaussian distribution, it is almost certain that the value falls in interval $[\mu-3\sigma,\mu+3\sigma]$ (μ is image mean, and σ is standard deviation), that is the called 3σ rules. According to 3σ rules, pixel values whose distance to image mean μ is larger than 3σ to the image quality can be neglected. Thus, low saturation point $d_{low}=\mu-3\sigma$ and high saturation point $d_{high}=\mu+3\sigma$ are taken out to do linear tensile processing to enhance images according to the formula below:

$$G=\begin{cases} 0; R<d_{low} \\ \dfrac{R-d_{low}}{d_{high}-d_{low}}; d_{low}<R<d_{high} \\ 255; R>d_{high} \end{cases}$$

In which R is the output of three-scale Retinex algorithm processing, and G is the output image after amendment.

3 Experiments

Ultrasonic images of normal and fatty liver are shown as Fig.1. Enhancement processing is carried out to the region of interest (ROI).

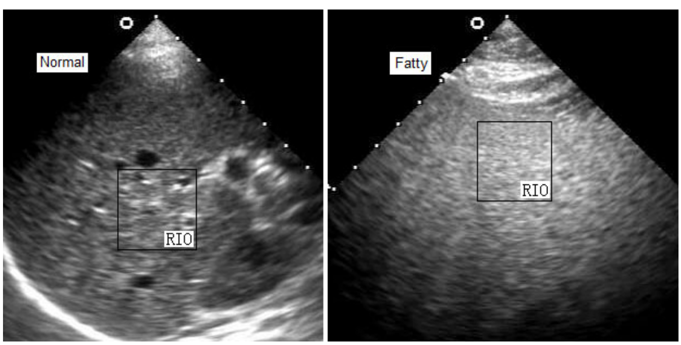

Fig. 1. Ultrasonic normal and fatty images

Histogram equalization enhancement (Hist-Enhance), homomorphic filtering enhancement, SSR method and MSR method are carried out to ROI respectively. Three texture characteristic parameters are abstracted: image brightness, contrast and Shannon information entropy. When image entropy is much bigger, information is much more and image details are much richer. Data records are shown as Table 1.

Table 1. Feature Extracted by Different kinds of Enhancement Methods

Methods	Normal Image			Fatty Image		
	Bright	Contrast	Entropy	Bright	Contrast	Entropy
Original-Image	88.7549	23.3488	6.4989	126.8721	25.1680	6.6509
Hist-Enhance	127.3994	74.9104	5.9081	127.5956	74.7842	5.9504
Homomorphic	91.0046	29.7128	6.8945	123.4016	39.2642	7.3116
SinglScalRetinex	121.2947	60.2167	7.5137	119.7425	55.5961	7.2892
MultiScalRetinex	123.1676	69.2715	7.6283	122.9156	67.2474	7.5458

From Table 1, entropy comes down which show that information has been lost although contrast ratio is higher by histogram equalization method. Contrast and entropy value are all improved by homomorphic filtering method. But image's contrast and entropy value are much higher after Retinex algorithm processing and they are further improved by MSR algorithm rather than SSR algorithm.

Ten normal and ten fatty liver images are taken out. Brightness, contrast and entropy are abstracted out from images before and after processing respectively. Data records are shown as Fig. 2.

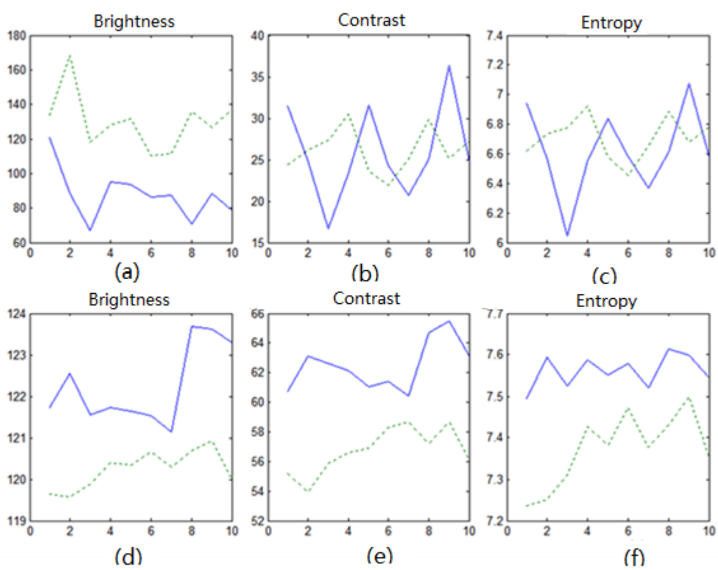

Fig. 2. Feature parameters derived normal and fatty image by MSR method

Real line indicates normal liver images and dashed line is fatty liver images. Fig. 2.(a) (b) (c) show the data records derived from normal and fatty original image before MRS enhancement processing. Fig.2. (d) (e) (f) show the data records derived from normal and fatty images after MSR processing.

The experimental results show that: to images without MSR enhancement processing, their brightness values have some difference but contrast and entropy value are almost coincided, so they can't be distinguished. On the contrary, after MSR enhancement processing, the three parameters of normal and fatty liver images have marked difference.

PNN is used to differentiate ultrasonic normal liver from fatty liver image [10]. Firstly feature parameters of eighty sample images are extracted based on MSR, then parameters as learning sample to train the neural network. Another twenty images are taken out as testing sample. Recognition rates of fatty and normal liver are above 85%.

4 Conclusion

In this paper, Retinex theory is applied to enhance ultrasonic normal and fatty images. Comparing the result to that of the usual enhancement methods, experimental results show that MSR enhancement algorithm can improve image brightness, increase contrast and enlarge image information entropy. Using feature parameters extracted from MSR algorithm method could distinguish the fatty images from normal images effectively by PNN. Concerning different images, some problems need to be analyzed according to specific problems such as how to select surround function (LPF), how to select standard deviation.

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