CHAPTER 7

IMAGE ENHANCEMENT

7.1 INTRODUCTION

The term image enhancement means the alternation of the appearance of an image. Image enhancement is among the simplest and most appealing areas of digital image processing. The idea behind enhancement is to bring out detail that is obscured, or simply to highlight some features of interest in an image. A familiar example of enhancement is when we increase the contrast of an image because “it looks better”. The principle objective of image enhancement is to process an image so that the result is more suitable than the original image for specific application. There are two major approaches. First one depends on statistics of gray values of the pixels or spatial domain and other depends on spatial frequency content of the image or frequency domain. The wavelet domain techniques take advantages of both the approaches. Image enhancement includes the following options: Contrast Manipulation, Edge Detection, Histogram Equalization, Negative, and Filters. When taking a picture, blur (attenuation of high-frequency components) occurs because of the point spread function in the observation system or for some other reasons. A blurred image does not offer clear contours, which impairs recognizability, so it is necessary to transform blurred image into clear ones. Edges may be enhanced, generally, by amplifying high frequency components. Methods have been proposed to enhance these high frequency components by means of unsharp masking or Lapalacian subtraction **[Gonzalez 2005]**, however noise component is also amplified. There are algorithms that differentiate noise and information components.

This chapter presents a wavelet-based technique for enhancing the perceptual sharpness of an image. The sharp variation points are often among the most important features for analyzing properties of transient piecewise smooth signals. To characterize singular structures of a signal, Holder exponent **[Mallat 1992b]** provides a pointwise measure of a function over a time interval. Due to pioneer work by Jaffard and Meyer, it can be shown that local signal singularities of a function are characterized by the decay of its wavelet coefficients amplitude across scales **[Jaffard 2005]** and **[Meyer 1992]**. The goal of enhancement is not in complete reconstruction, but rather in augmenting image sharpness, as perceived by a human observer. This goal, which is intrinsically comprised of more subjective constraints, is of importance in a variety of application domains. One such scenario, for example, is when a given input image is blurred with no exact degradation model known. If a degradation model does in fact exist, restoration techniques can be applied, together with other frequency enhancement techniques. The enhancement scheme described in this chapter can then be applied as an additional enhancement utility.

Given a blurred image, the classic problem of image enhancement is to recover completely lost high-frequency components so that the processed image looks sharper and more pleasing to human observers. Traditionally this was performed by so-called un-sharp filters, which are linear processors. It is well known that linear shift invariant (LSI) filters can modify only the existing frequencies but can not generate new frequency components, and thus can not recover the lost high-frequency component in principle. Non-linear filtering methods **[Liew 1997]**, **[Sattar 1997]**, **[Jin 2002]**, **[Oktem 2002]**, **[Sindelarova 2002], [Jinzhu 2005]**, **[Russo 2005]**, **[Temizel 2005],** and **[Temizel 2006]** were also studied by several authors**.** However, so far there are only ad hoc solutions and designing general purpose non-linear filters remains difficult.

Recently, several multi-scale image enhancement approaches have been proposed with interesting results **[He 2002]**. It is inspired by human visual system which processes and analyzes image information at different scales. All of these approaches attempt to utilize the inter-scale dependency (mainly the dependency among edges) to extrapolate lost high frequency components. Greenspan **[Greenspan 2000]** used zero-crossings of the second derivative of smoothed images to locate edges, and based on the ideal step edge model they estimated the inter-scale relations of edges. Then they used these relations to estimate edges in finer scales from those of the low-frequency subbands. Klnebuchi **[KInebuchi 2001]** assumed a different approach: they first used a HMT model to infer the probability of each hidden state and corresponding variances. Image enhancement in a multi-scale context can be considered as the estimation of coefficients in high frequency subbands based on those in lower-frequency subbands. The multiscale image enhancement scheme is shown in Fig. 7.1. The detail (highpass filtered) component $\hat{x}_d$ is estimated by a given lowpass filtered signal x_l subsequently x_l and $\hat{x}_d$ are combined to give the enhanced signal.

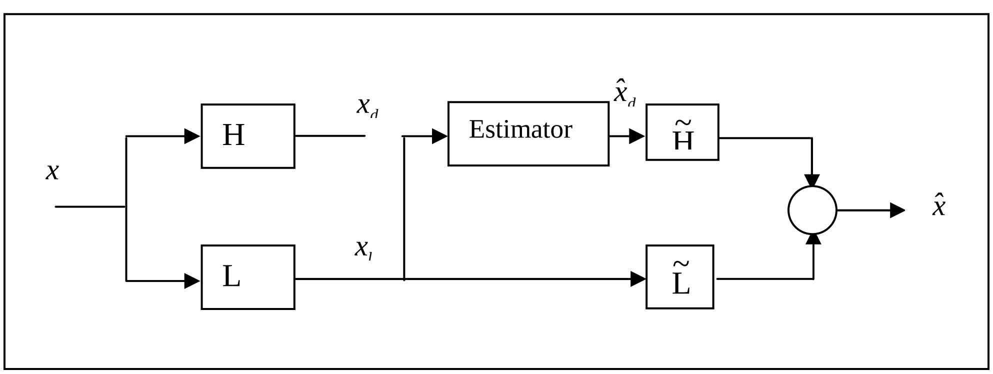

Fig. 7.1 Multi-scale Image Enhancement

Then a Gaussian mixture model (GMM) (corresponding to the hidden states) is used for each coefficient and wavelet coefficients in the highest subband are generated randomly. In estimating variances the property of exponential decay of variances was assumed with roughly estimated exponents **[Carey 1999]**. In this chapter, Wavelet-based multi-scale framework is tried to enhance image. Specifically, Mallat-Zhong wavelet transform has been used, which is an approximate multi-scale Canny edge detector **[Canny 1986]**. Like, we will treat the image enhancement as edge enhancement, as smooth areas of an image are well preserved in the approximation low frequency part of the wavelet transform, which often does not need to be enhanced. The local maxima of first-order derivatives are used to detect edges (instead of zero-crossings of second order derivatives in) since the first-order derivative are more robust to noise. In the following sections we will first introduce the basics of enhancement in wavelet domain and then describe our enhancement approach which is based on regularity measures followed by experimental results and discussion.

7.2 WAVELETS BASICS IN ENHANCEMENT

Image enhancement in the wavelet domain can be treated as the estimation of wavelet coefficients in the highest frequency subband from coefficients in the lower frequency subbands. This can be explained with the help of the high resolution image is at the input to a filter bank. The low-pass filter, L, represents the effects of the image acquisition system, which is generally modeled by a Gaussian function. If we were able to filter the original high-resolution image I with the high-pass filter H to obtain the detail signal, x_d, and if we had a perfect reconstruction filter bank, it would then be possible to reconstruct the original image perfectly. In image enhancement problems we clearly do not have access to the detail signal, x_d, so we have to estimate it. The signal is estimated by wavelet-based multi-scale framework.

7.2.1 Regularity Measurement

To characterize singular structures, it is necessary to precisely quantify the local regularity of a signal. Holder spaces and Holder exponents provide a uniform regularity measurement over time intervals, as well as at a particular point.

Definition 1: Let $I \subseteq R$ and f be a continuous function from I to R. f is said to belong to a global Holder space $C^{\alpha}(I), \eta > 0$ if and only if for any $v \in I$ there exists a positive constant c and a polynomial P_v of degree $m = \lfloor \eta \rfloor$, $\lfloor \eta \rfloor$ denotes the largest integer $m \leq \eta$, such that

$$\left| f(x) - P_{x0}(x - v) \right| \leq c \left| x - v \right|^{\eta}, \forall x \in I \tag{7.1}$$

Definition 2: f is said to belong to a pointwise Holder space $C^{\eta}(x_0), \eta > 0$ if and only if there exists a positive constant c and a polynomial P_{x0} of degree $m = \lfloor \eta \rfloor$ such that

$$\left| f(x) - P_{x0}(x - x_0) \right| \leq c \left| x - x_0 \right|^{\eta}, \forall x \in I \tag{7.2}$$

Definition 3: A function f is said to have Holder exponent η at a point x_0 if there exists a polynomial P_{x0} of degree $m = \lfloor \eta \rfloor$ and f satisfies

For any θ

$$\lim_{\Delta \to 0} \frac{\left| f(x_0 + \Delta) - P_{x0}(\Delta) \right|}{\left| \Delta \right|^{\theta}} = 0 \tag{7.3}$$

For $\eta < +\infty$, and any $\theta > \eta$

$$\lim_{\Delta \to 0} \frac{\left| f(x_0 + \Delta) - P_{x0}(\Delta) \right|}{\left| \Delta \right|^{\theta}} = +\infty \tag{7.4}$$

The vanishing moment property of a wavelet function is crucial to measuring the local regularity of a signal. If a wavelet $\psi(.)$ has *n* vanishing moments, i.e.,

$$\int_{-\infty}^{\infty} t^k \psi(t)dt = 0, \quad 0 \le k < n \tag{7.5}$$

It can be shown that a wavelet transformation is actually a multiscale differential operator of order *n* **[Mallat 1999]**. This property relates the differentiability of f with its wavelet transform decay at fine scales.

Due to the pioneering work by Mayer and Jaffard, it can be shown that a local signal singularity is characterized by the decay of its wavelet transform amplitude across scales **[Meyer 1992]** and **[Jaffard 2005]**.

Theorem 1: Let $\psi(.)$ be a wavelet with n vanishing moments, $f \in L^2(R)$ and $Wf(.,.)$ denote its wavelet transform. Suppose f has a Holder exponent $\eta < n$ at x, then there exists a constant A such that

$$\forall (u,s) \in R \times R^+, \left|Wf(u,s)\right| \le As^{\eta+\frac{1}{2}}\left(1+\left|\frac{u-x}{s}\right|^{\eta}\right) \tag{7.6}$$

Conversely, if $\eta < n$ is not an integer and there exists a constant A and $\eta' < \eta$ such that

$$\forall (u,s) \in R \times R^+, \left|Wf(u,s)\right| \le As^{\eta+\frac{1}{2}}\left(1+\left|\frac{u-x}{s}\right|^{\eta}\right) \tag{7.7}$$

then f has Holder exponent η at x.

7.2.2 Estimation of Holder Exponent

The global Holder exponent of a function can be measured by means of the Fourier transform; such a measurement is not very useful for analyzing transient signals since it cannot provide information regarding the location and spatial distribution of singularities. By taking advantages of the compactly supported wavelet frames and bases, the information about local Holder exponent at a certain point can be provided since the wavelet can provide localization in both spatial and frequency domains. Mallat and Hwang **[Mallat 1992b]** proposed to estimate the Lipschitz exponent of a singularity by tracing its wavelet transform modulus maxima (WTMM) curves across scales inside the cone of influence (COI). They demonstrated that the local regularity of certain types of nonisolated singularities in the signals could be characterized by using the WTMM. However, as pointed out by Hsung, there may be some errors and ambiguities in tracing the maxima curves in scale space **[Hsung 1999]**. The accuracies of the estimated Lipschitz exponents will be affected when the singularities are not isolated, which means that the COIs of these singularities have common support. **Hsung** proposed a simpler but also efficient way to estimate the Lipschitz exponent through the interscale ratio of the WTMS within a COI, in particular, for 2-D images, the Lipschitz exponent was estimated from the interscale ratio of WTMS within a DCOI. In the WTMS algorithm, the DCOI of a point (x_0, y_0) at scale 2^j is defined as follows:

$$DCOI_{(x_0,y_0)} = \{(x,y) : (x-x_0)^2 + (y-y_0)^2 \le k2^{2j}\} \text{and } \frac{y - y_0}{x - x_0} = \tan(A_{2^j} f(x_0, y_0)) \qquad (7.8)$$

where $A_{2^j} f(x_0, y_0)$ is defined in Eq. (7.7), but in numerical calculations, to determine the DCOI for each point, the linear interpolation has to be performed within a disk region since not all wavelet coefficients lie on the direction indicated by $A_{2^j} f(x_0, y_0)$ **[Hsung 1999]**. By thresholding the interscale ratio of WTMS within a DCOI, wavelet coefficients at each scale are classified into two categories, one corresponds to the irregular coefficients and the other corresponds to the edge-related and regular coefficients.

7.3 PROPOSED METHOD

The proposed method is based on a manipulation of the Hölder regularity of the input signal. The basic idea is as follows: any signal that has at least some amount of regularity has positive Hölder exponents **[Mallat 1992]**. In contrast, it can be shown that the wide sensed stationary white noise creates singularities whose regularity is negative. It is proved that Holder exponent of any signal will reduce when noise is added **[Vehel 2001]**, **[Vehel 2003]**. In image denoising using multifractal analysis, the Hölder regularity of the input signal is manipulated so that it is close to the regularity of the desired signal. The holder exponent of observed image is defined as:

$$\eta_{f'} = \eta_f + \eta_n \tag{7.9}$$

where $\eta_{f'}, \eta_f$ and η_n are Holder exponent of noisy image, noise free image and noise respectively. In general, the *estimated* Holder exponent of enhanced image $\hat{f}$ is "in between" those of f and f'. A plausible denoising procedure is then to look for image that would minimize the risk subject to the constraint that its regularity is close to one of f. Usually the regularity of f is not known. We will thus be content with imposing equalities of the form:

$$\text{regularity of } \hat{f} = \text{regularity of } f' + \text{shift} \tag{7.10}$$

where shift is some positive parameter. For various reasons, it is much easier to consider regularity in the sense of local Holder exponents.

To allow for simple algorithms, the method is wavelet-based, i.e. we estimate regularity with the help of wavelet coefficients. Then coefficients are modified and the updated coefficients are used to reconstruct the smoothed image. It is well adapted to the case where the image to be recovered is very irregular and nowhere differentiable, a property relevant to fractal or self-similar structures.

7.4 METHODOLOGY

The Lena image and single band remote image are taken as test images. The original image is contaminated by additive zero-mean additive white Gaussian noise with known variance and remote image is contaminated by speckle noise. The noisy image is transformed to the wavelet domain, $w_{i,j}^{s,o}$ denote the wavelet coefficients where $s = 1,2......J$ and $o \in [A, H, V, D]$. For the wavelet coefficients in Approximate (A), Horizontal (H), Vertical (V), and Diagonal (D) subbands, wavelet transform module maxima (WTMM) is found. WTMM is used as a mask and remaining wavelet coefficients are threshold by universal threshold. For enhancement, the most obvious way to increase the local Holder regularity by an amount δ is simply to multiply all the wavelet coefficients which are masked. The multiplication factor δ depends on noise level and type of noise which are not known in practical cases. It is decided by types of application and visual inspection. The image is reconstructed by modified coefficients to get the denoised image.

7.5 EXPERIMENTAL RESULTS AND DISCUSSION

This technique is analyzed using MATLAB (version 6) software. The Gaussian noise with a known variance (0.05) is added with Lena image. The Speckle noise is added with remote sensing image. Wavelet transform coefficients are calculated for three scales. There is no as such quantitative evaluation parameter. The qualitative evaluation is done by visual interpretation; the viewer is the ultimate judge of how well a particular

Fig. 7.2 a) Original Image b) Noisy Image c) Enhanced Image

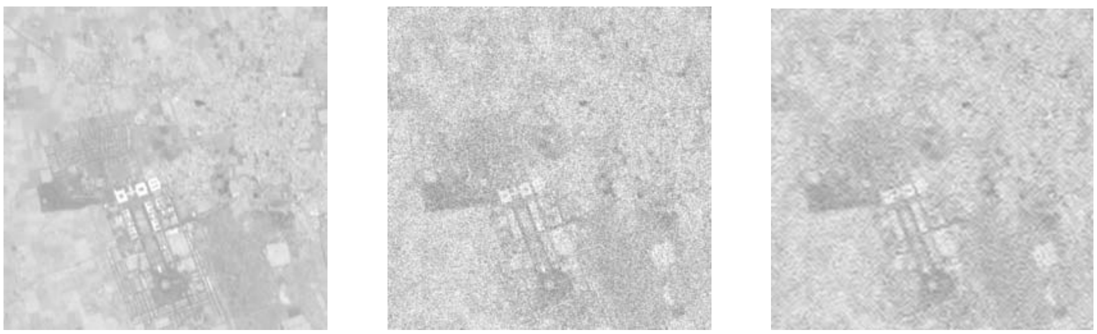

Fig. 7.3 a) Original Image b) Noisy Image c) Enhanced Image

image is improved. It is highly subjective process. Fig. 7.2 and Fig. 7.3 show the output of the the enhanced algorithm in Lena and remote sensing image.

7.6 SUMMARY

When the noise characteristics of the image are unknown, denoising by multifractal analysis has proven to be the best method. The algorithm performance is well for images that are highly irregular and are corrupted with noise of complex nature. A wavelet based procedure is used for estimating and controlling the Holder exponent. It is to be noted that regularity is an abstraction and is valid only asymptotically. So the true value of Holder regularity is not the point of interest but only a resultant value that is greater than that of the input signal is of interest.