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A Resolution Enhancement Technique in Digital Images

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A RESOLUTION ENHANCEMENT TECHNIQUE IN DIGITAL IMAGES

by

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ABSTRACT

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Image enhancement is the processing of images to increase their usefulness. The image enhancement methods and objectives vary with the application. When images are enhanced for human viewers, as in television, the objective is mostly to improve perceptual aspects: image quality, intelligibility, or visual appearance. The aim of this research work is to make the processed image better in the visual sense than the unprocessed image. An image can often be enhanced by modifying its contrast or dynamic range, increasing the sharpness of edges, reducing the noise, or reducing the blurring. The most commonly used contrast enhancement technique is histogram modification. In many cases, the subjective contrast of an image is improved if one equilizes the histogram of the gray levels of the picture elements (pixels). In this thesis a method for reducing noise and enhancing edges and thus enhancing the resolution of the image is presented. Noise removal is done through vector median filtering. The median filter performs a nonlinear filtering operation where a window moves over an image. At each location the pixel with the smallest norm with respect to other pixels within the window is chosen as the vector median and the output value of the pixel at that location. The edge enhancement procedure is done through increasing the sharpness of edges by a nonlinear procedure that uses shape invariant properties of edges across scale and utilizes Laplacian transform and Laplacian pyramid image representation.

The experiments performed on various images captured at low and non uniform environment show promising results. The details of the high frequency regions of the images are improved significantly by the proposed method. Research work is progressing to adapt the algorithm to make it suitable for enhancing images based on the statistical characteristics of the objects to be recognized.

To

My wife and son

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CHAPTER 1

INTRODUCTION

Image enhancement refers to accentuation, or sharpening, of image features such as edges, boundaries, or contrast to make a graphic display more useful for visual perception and analysis. The goal in image enhancement is to improve the visual perception of an image, or to convert an image to a form that is better suited for analysis by human or machine. Methods and objectives of image enhancement vary with the application. When images are enhanced for human viewers, as in television, the objective may be to improve perceptual aspects: image quality, intelligibility or visual appearance. Three important tasks in image enhancement are: contrast enhancement, noise reduction, and edge sharpening. The most commonly used contrast enhancement technique is histogram modification. In many cases, the subjective contrast of an image is improved if one equilizes the histogram of the gray-levels of the picture elements (pixels), in other words one should make the histogram of the brightness of the pixels uniform. One way of noise reduction is to use Wiener (linear least squares) filters. An alternative way is to use Kalman filters. In order to reduce noise but keep the edges in the image sharp, one has to use linear shift-varying or nonlinear filters. The linear shift varying filters include adaptive Wiener of Kalman filters. The nonlinear filters include median filters. Edge sharpening can be done by raising the amplitudes of the high spatial frequencies of an image relative to those of the lower spatial frequencies, or by using nonlinear methods. In this work the main objective is to enhance the resolution of digital images in order to improve the visual perception of the image so that it seems sharper to the human observer. The enhancement process does not increase the inherent information content of the image data. The enhancement process in this work consists of enhancing the resolution of an image by sharpening the edges in the image. In order to not enhance noise components in the image a nonlinear noise removal procedure is applied to the image. The noise components within the image are of impulse type which are one of the most found types in digital images.

There is no general theory of image enhancement. When an image is processed for visual interpretation, the viewer is the ultimate judge of how well a particular method works. Visual evaluation of image quality is a subjective process. When the image is enhanced by any of the methods described above, together with the edges the noise components are also enhanced. First applying impulse noise removal procedures to the image and then applying enhancement methods gives a better visual perception of the image. The goal of this thesis is to improve the visual perception of digital images by enhancing resolution of digital images. Since edges are one of the most effective factors in identifying the sharpness of an image, the enhancement procedure aims to increase the sharpness of edges. Both noise components and edges correspond to high frequencies of images. When edges are enhanced the noise components are also enhanced. In order to remove spiky noise components the image is first gone through a preprocessing stage of spiky noise removal, and then the enhancement procedure is applied. So this research aims to remove the impulse type noise components of the image first and then enhance the resolution of the image.

Since the basic goal is to enhance the resolution by augmenting the sharpness of edges, a noise removal procedure that does not affect the edges is needed. The method for impulse noise removal utilizes the vector median filtering. The median filter suppresses the impulse noise while preserving the edges. The median filter performs a nonlinear operation where a window moves over an image and at each point the median value of the data within the window is taken as the output for that point. When dealing with multichannel or color images the median operation is extended to vector-valued operation. The vector filtering is used in order to preserve the inherent correlation that exists between color components.

In this thesis the consideration for multichannel image dimension is two and for the number of color channels is three that are **R**ed, **G**reen, and **B**lue. A 3×3 matrix is used as the filter window. The window is moved to every point in the image. The point at the center of the matrix (2, 2) determines the position of the filter window. Before beginning of the procedure the columns and rows at the borders of the image are replicated so that the pixel values at the borders are processed. Each point in the image is considered as a 3- point vector. For each point the sum of the vector distance to other points within the filter window is calculated. The pixel with the smallest distance is considered as the median vector and constitutes as the output for the center pixel. Thus the noise component is suppressed without affecting the edges.

The edge enhancement algorithm increases the frequency content of the image by using shape-invariant properties of edges across scale. The procedure utilizes the Laplacian transform and the Laplacian pyramid representation. The shape-invariant properties of edges across scale is used to create new high spatial frequencies to augment the resolution. The augmentation procedure is based on multiresolution image representation and this procedure can be described by using scaling theorems for zero crossings. The procedure includes an extrapolation representation method across scale that generates phase coherent higher harmonics. The result is visually pleasing in enhanced images.

The experiments related to this work are done by using MATLAB 6.5. It is a simple and efficient programming language especially used for engineering purposes. It is very efficient at handling matrices which all digital images are represented by. The algorithm is expected to do the following:

1) Removal of spiky noise from image by blurring the image with vector median filtering.

2) Sharpening the visual appearance of the image by a resolution enhancement procedure that increases the sharpness of edges with the utilization of scale-space properties of edges across scale and the transform of Laplacian and Laplacian pyramidal representation.

The thesis is organized as follows. Chapter 2 contains a background information on digital image enhancement methods and resolution enhancement procedures. It gives an idea of broad categories of image enhancement approaches. Various ways of image enhancement procedures are discussed. The enhancement procedures are applied to various digital images. The chapter aims to make an understanding of applying different methods to different types of images. Chapter 3 first describes a nonlinear impulse noise reduction method called vector median filtering in order to not enhance noise components by edge sharpening method and then describes the image resolution enhancement technique by using a nonlinear method in frequency domain. This method utilizes Gaussian and Laplacian pyramidal representations of digital images. The formation of Gaussian and Laplacian pyramids with some examples will be explained. The parts of the image that make the image seem sharper will be explained and a method of sharpening one of the parts which is the most important (edge) will be discussed. Chapter 4 deals with the results of the experimentation. The advantages and disadvantages of the proposed method are discussed. The results will be compared with results of other image enhancement methods with some examples. In Chapter 5 the algorithm is summarized and the use of the new method in real life applications is discussed. Further work for this research is also briefly described.

CHAPTER 2

THEORETICAL BACKGROUND AND LITERATURE REVIEW

2.1 Introduction

Image processing is a considerably growing field with the increased utilization of imagery in many applications coupled with improvements in size, speed, and cost effectiveness of digital computers and related image processing techniques. Image processing has found a significant role in scientific, industrial, biomedical, space, and in many other application areas. Images with high resolution are often required and desired in most image processing applications. High resolution means that pixel density within an image is high, and therefore a high resolution image can offer more details that may be critical to various applications[1]. The images with enhanced resolution show more details that are very helpfull in most applications. Since being used in many fields, resolution enhancement is one of the most active research areas. Being an important topic in image processing fields, resolution enhancement has attracted many researchers and it has been approached from different points of views. The subject of this thesis is a combination of impulsive noise removal procedure and one of the approaches to resolution enhancement.

The resolution enhancement procedure in this thesis consists of two parts. Noise removal and resolution enhancement. Noise removal deals with removal of impulse noise. The resolution enhancement method contains the enhancement of edges. Since edges and noise in an image are both represented by high frequency components in the frequency domain, noise components within an image are also enhanced by the edge enhancement method. To avoid enhancing noise it will be better to apply a noise removal procedure before applying the edge enhancement algorithm.

The impulsive noise removal algorithm in this thesis utilizes vector median filtering algorithm[2].

2.2 Noise Removal and Vector Median Filtering

Noise reduction filters are preprocessing method which image quality depends on in many applications [2]. There are two basis approaches for noise filtering, namely, spatial methods and frequency methods. The term spatial domain refers to the description of image at its spatial cooordinates. The operations based on this approach are performed on the pixels of the image. Frequency domain techniques are based on modifying the fourier transform of an image [3]. The use of median operation in signal processing was introduced by Tukey as a tool in time series analysis [4],[5]. The median filters are nonlinear spatial filters based on order-statistics theory (also called rank filters) whose response is based on ordering the pixels contained in an image neighborhood with the value determined by the ranking result [6]. In [7] Astola et. al introduced the well-known class of vector median filters (VMF), which are derived as maximum likelihood (ML) estimates from exponential distributions. In the vector median filters the samples of the vector valued signal are processed as vectors. The vector median filters exhibit properties similar to those of the median filter, including the suppressing of impulses and the preserving of edges in the signal [7]. Vector based filters are mostly used in multichannel structures, especially in color image processing, because of the inherent correlation that exists between the image channels [8], [9]. In vector approaches each pixel value is considered as an m-dimensional vector [m is the number of image channels; in the case of color channels m=3 and colors are Red, Green, and Blue) whose characteristics are examined. The magnitude and direction are examples of vector characteristics used in image processing. In direction-magnitude approach the vectors' direction signifies their chromaticity while their magnitude is a measure of their brightness [10]. Since this method is very well suited for the elimination of noise [8], [11]-[13], and other tasks, such as restoration [14], [15], edge enhancement [16], edge detection [17], [18], and segmentation [19]. The vector median filters (VMF) perform accurately when the noise follows a long-tailed distribution(e.g exponential or impulsive), moreover, any outliers in the image data are easily detected and eliminated by VMF's [10]. Vector directional filters (VDF) process the color image data using directional information which are effective in preserving the chromaticity of the image vectors [20], [21]. VDF's have a drawback of not considering the magnitude of the image vectors. In [10] D.G. Karakos and P.E. Trahanias introduced a new filter type called directional distance filters(DDF's) which take advantage of both VMF's and VDF's. Directional-distance filters are very useful in color image processing, since they inherit the properties of VMF's and VDF's.

A new class of VDF's called adaptive VDF's [22] that combines fuzzy membership functions, average filters and angle-based distances was introduced in order to have a good performance over VDF's without requiring any a priori knowledge about the signal and noise characteristics. Some other noise suppression filters are introduced [23]-[30].

2.3 Overview of Image Enhancement Techniques

Image enhancement approaches fall into two broad categories: Spatial domain methods and frequency domain methods[3]. The term spatial domain refers to the description of image at its spatial cooordinates. The operations based on this approach are performed on the pixels of the image. Frequency domain techniques are based on modifying the fourier transform of an image.

2.3.1 Spatial Image Enhancement Techniques

Spatial domain methods consist of procedures that operate directly on pixels of images. Spatial domain process can be expressed as

$$g(x,y) = T[f(x,y)] \tag{2.1}$$

where f(x,y) is the input image, g(x,y) is the processed image, and T is an operator on f, defined over neighbourhood of (x,y). Here f(x,y) is a two dimensional light intensity function where x and y denote spatial coordinates and the value of f at any point (x,y) refers to the brighness (or gray level) of the image at that point. In spatial domain digital image may be characterized as a matrix whose row and column indices identify a point in the image and corresponding matrix element value identifies the gray level at that point. The elements of such an array are called image elements, picture elements, pixels or pels. Most commonly used are pixels. The principal approach in defining a neighborhood about a point (x,y) is to use a square or rectangular subimage area centered at (x,y). The center of subimage is moved from pixel to pixel and applying the operator T at each location to produce an output pixel for that point. The T operator is the desired function to be applied to the pixel to produce the desired resultant pixel. For example T can be a transformation that produces a higher contrast image by darkening the levels below some value and brightening some levels above the value known as contrast stretching and so on. Enhancement in spatial domain includes

- Gray level transformations
- Histogram Processing

- Enhancement using arithmetic/logic operations
- Spatial Filtering

2.3.1.1 Gray Level Transformations

The gray level transformation can be expressed as,

$$s=T(r) \tag{2.2}$$

where T is the transformation that maps the pixel value r into the pixel value s. Three basic types of functions used for gray level transformations used for image enhancement are: linear(negative and identity transformations) , logarithmic (log and inverse log transfomations), and power-law (nth power and nth root transformations).

Image Negatives: The negative of an image with gray levels in the range [0,L-1] is obtained by using negative transformation which is given by the expression

$$s=L-1-r \tag{2.3}$$

Reversing the intensity of an image by this way produces the equivalent of a photographic negative. This type of processing is particularly used for enhancing white or gray detail embedded in dark regions of an image, especially when the black areas are dominant in size.

Log Transformations: The general form of log transdformation is expressed as

$$s=c*\log(1+r) \tag{2.4}$$

where c is a constant and it is assumed that r>=0. This type of transformation is used to expand the values of dark pixels in an image while compressing the higher-level values. It is generally used for spreading/compressing of gray levels in an image.

Power-law transformations: Power law transformations have the form

$$s=cr^{\gamma} \tag{2.5}$$

where c, and γ are positive constants. Power-law curves with fractional values of γ map a narrow range of dark input values into a wider range of output values.

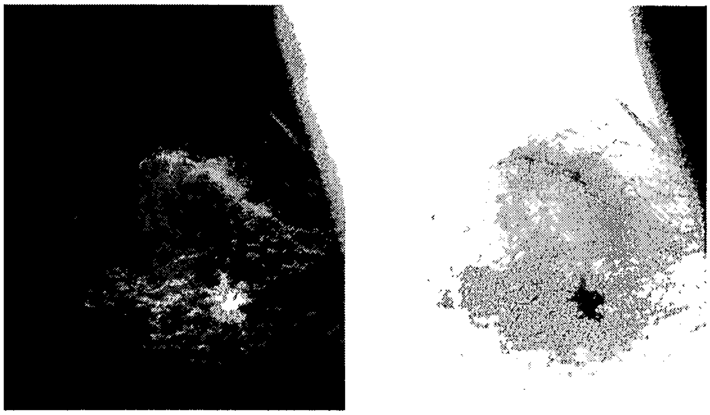
Piecewice-Linear Transformation functions:

Contrast stretching: Low contrast images ocur often due to poor or nonuniform lightning conditions or due to lack of dynamic range in the imaging sensor, or even wrong setting of a lens aperture during image acquisition. The idea behind contrast stretching is to increase the dynamic range of the gray levels in the image being processed.

Gray-level slicing: Gray level slicing is used for highlighting a specific range of gray levels in an image. Applications of this type include enhancing features such as masses of water in satellite imagery and enhancing flaws in X-ray images.

Bit-plane slicing: Instead of highlighting gray-level ranges, highlighting the contribution made to the total image appearance by specific bits might be desired. In this method the image is divided into bit planes. Seperating a digital image into bit planes is useful for analyzing the relative importance played by each bit of the image, a process that aids in determining the adequacy of the number of bits used to quantize each pixel.

An example of image enhancement by using gray-level transformation is shown in Figure 1. Here a small lesion in a breast is seen better by taking its negative.



(a) (b)

Figure 1. An example for a gray level transformation (a) Original digital mammogram image (b) Negative image of the original

2.3.1.2 Histogram Processing

The histogram of an image represents the relative frequency of occurence of the various gray levels in the image. Histogram modelling techniques modify an image so that its histogram has a desired shape. This is useful in stretching the low contrast levels of images with narrow histograms. Histograms provide useful image statistics. The histogram of a digital image with gray levels in the range [0,L-1] can be expressed as a discrete function $h(r_k)=n_k$, where r_k is the kth gray level and n_k is the number of pixels in the image having gray level r_k. Generally the histogram is normalized by dividing each of its values by the total number of pixels in the image, denoted by n, thus a normalized histogram is given by $p(r_k)=n_k/n$, for $k=0,1,2,..,L-1$. In a dark image the components of the histogram are concentrated on the low side of the gray scale while the components of the histogram of the bright image are biased towards the high side of the gray scale. An image with low contrast has a histogram that will be narrow and will be centered toward the middle of the gray scale. It can be concluded that an image whose pixels tend to occupy the entire range of the possible gray levels will have an appearance of high contrast and will exhibit a large variety of gray tones. The net effect of histogram processing will be an image that shows a great deal of gray-level detail and has high dynamic range.

Histogram Equilization: In histogram equilization, the goal is to obtain a uniform histogram for the output image.

$$s_k = T(r_k) = \sum_{j=1}^{k} p_r(r_j) = \sum_{j=1}^{k} \frac{n_j}{n} \quad \text{for k=1,2,...,L,} \tag{2.6}$$

where s_k is the intensity value in the output image corresponding to value r_k in the input image and $p_r(r)$ denote the probability density function of the image. The result of histogram equalization is an image with increased dynamic range, which tend to have higher contrast and thus enhanced image. Below is an electron microscope of pollen, magnified approximately 700 times and histogram equalization is applied in order to increase its dynamic range.

(a) (b)

Figure 2. A histogram processing example (a) Original image (b) Histogram equalized image.

Histogram Matching: In histogram equilization a transformation function is produced based on the histogram of a given image. Once the transformation function for an image has been computed, it does not change unless the histogram of the image changes. Histogram equilization achieves enhancement by spreading levels of input image over a wide range of the intensity scale. However in some applicaitons it is useful to specify the shape of the histogram. The method used to generate a processed image that has a specified histogram is called histogram matching.

2.3.1.3 Enhancement Using Arithmetic/Logic Operations

Arithmetic logic operations involving images are performed on a pixel-by-pixel basis between two or more images.

Image Substraction: The difference between two images f(x,y) and h(x,y), expressed as

$$g(x,y)=f(x,y)-h(x,y), \tag{2.7}$$

is obtained by computing the difference between all pairs of corresponding pixels from f and h. The key usefulness of subtraction is the enhancement of differences between images.

2.3.1.4 Spatial Filtering

Basics: Spatial filtering is another category of spatial domain image processing. It is also called neighborhood processing, or spatial convolution. Neighborhood processing consists of performing an operation that involves only the pixels in a predefined neighborhood about defined center point(x,y). The result of the operation is the response of the process at that point and this process is repeated for every point in the image. The process of moving the center point creates new neighborhoods, one for each pixel in the input image. This process is usually called spatial filtering.

Linear Spatial Filtering: The linear operations consist of multiplying each pixel in the neighborhood by a corresponding coefficient and summing the results to obtain the response at each point (x,y). The coefficients are arranged as a matrix, called a filter, mask, kernel, template, or window. The process of linear spatial filtering consists simply of moving the center of the filter mask w from point to point in an image f. At each point (x,y), the response of the filter at that point is the sum of products of the filter coefficients and the corresponding neighborhood pixels in the area spanned by the filter mask.

The most used linear filters for image enhancement are laplacian and unsharp masking filters. The Laplacian of an image f(x,y) is defined as

$$\nabla^2 f(x,y) = \frac{\partial^2 f(x,y)}{\partial x^2} + \frac{\partial^2 f(x,y)}{\partial y^2} \tag{2.8}$$

Commonly used digital approximations of the second derivatives are

$$\frac{\partial^2 f}{\partial x^2} = f(x+1,y) + f(x-1,y) - 2f(x,y) \tag{2.9}$$

and

$$\frac{\partial^2 f}{\partial y^2} = f(x,y+1) + f(x,y-1) - 2f(x,y) \tag{2.10}$$

As a result,

$$\nabla^2 f = [f(x+1,y) + f(x-1,y) + f(x,y+1) + f(x,y-1)] - 4f(x,y) \tag{2.11}$$

The expression can be implemented at all points (x,y) in an image by convolving the image with some spatial masks. Enhancement using Laplacian is based on the equation

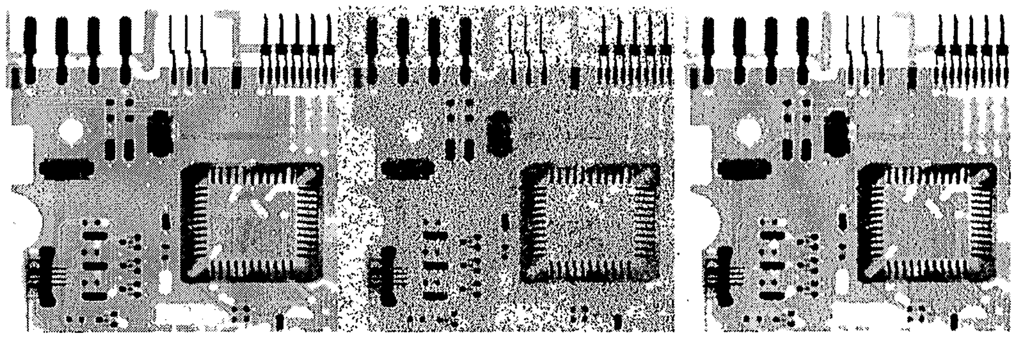
$$g(x,y) = f(x,y) + c[\nabla^2 f(x,y)] \tag{2.12}$$

where f(x,y) is the input image, g(x,y) is enhanced image, and c is 1 if the center cofficient of the mask is positive, or -1 if it is negative[1]. Because the laplacian is a derivative operator that sharpens the image. An image enhanced by using Laplacian filter is shown in Figure 3.

(a) (b)

Figure 3. Enhancement example by laplacian filter (a) Original image (b) Image enhanced by laplacian filter.

Nonlinear Spatial Filtering: Nonlinear spatial filters are based on nonlinear operations involving the pixels of a neighborhood. They are order-statistics filters(also called rank filters). The response of nonlinear filters is based on ordering the pixels contained in an image neighborhood and then replacing the value of the center pixel in the neighborhood with the value determined by the ranking result. Some of the nonlinear filters are; median, max, min filters. The best known order-statistics filter in digital image processing is the median filter, which takes pixel in the middle of the sorted neighborhood pixels as the output pixel. An example of median filter is shown in Figure 4.



(a) (b) (c)

Figure 4. Nonlinear spatial filtering example (a) Original image (b) Image corrupted with salt-and-pepper noise (c) Median filter applied to the noisy image.

2.3.2 Image Enhancement In the Frequency Domain

The Fourier transform gets its name from famous French mathematician Jean Baptiste Joseph Fourier. Fourier found out that any function that periodically repeats itself can be expressed as sum of sine and/or cosine of different frequencies each mutiplied by a different coefficient. It does not matter how complicated the function is, as long as it is periodic and satisfies some mild mathematical conditions it can be represented by a such sum. Even functions that are not periodic (but whose area under curve is finite) can be expressed as the integral of sines and/or cosines multiplied by a weighing function. The formulation in this case is Fourier Transform. Both Fourier series and fourier transform share the important characteristic that a function expressed in either of them can be reconstructed completely by an inverse process, with no loss of information. This allows us to work in the frequency domain and return to the original domain of the function without loss of any information.

2.3.2.1 The One-Dimensional Fourier Transform and its Inverse

The Fourier transform, F(u), of a single variable, continuous function, f(x) is defined by the equation

$$F(u) = \int_{-\infty}^{\infty} f(x) e^{-j(2\pi ux)} dx \qquad (2.13)$$

where $j = \sqrt{-1}$. Conversely, given F(u), we can obtain f(x) by means of the inverse Fourier transform,

$$f(x) = \int_{-\infty}^{\infty} F(u) e^{j2\pi ux} du. \qquad (2.14)$$

These two equations comprise the Fourier transform pair. These equations can easily be extended to two variables, u and v:

$$F(u,v) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x,y) e^{-j2\pi(ux+vy)} dxdy. \qquad (2.15)$$

and similarly for the inverse transform,

$$f(x,y) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} F(u,v) e^{j2\pi(ux+vy)} dudv. \qquad (2.16)$$

The Fourier transform of a discrete function of one variable, f(x) x=0,1,2,....M-1 is

$$F(u) = \frac{1}{M}\sum_{x=0}^{M-1} f(x) e^{-j2\pi ux/M} \quad for\ u = 0,1,2,....M-1 \qquad (2.17)$$

The inverse discrete Fourier transform(DFT) can be obtained by

$$f(x)=\sum_{u=0}^{M-1}F(u)e^{j2\pi ux/M} \quad for\ x=0,1,2,\ldots\ldots,M-1 \tag{2.18}$$

The concept of the frequency domain follows directly from Euler's Formula

$$e^{j\theta}=\cos\theta+j\sin\theta \tag{2.19}$$

By substituting this expression into Fourier transform we get

$$F(u)=\frac{1}{M}\sum_{x=0}^{M-1}f(x)\left[\cos 2\pi ux/M-j\sin 2\pi ux/M\right] for\ u=0,1,2,\ldots,M-1 \tag{2.20}$$

A useful analogy is to compare the Fourier transform to a glass prism. The prism is a physical device that seperates light into various color components, each depending on its wavelength(or frequency) content. The fourier transform may be viewed as a 'mathematical prism' that seperates a function into also its frequency components. In general the components of the fourier transform are complex quantities. Sometimes it is useful to express F(u) in terms of polar coordinates

$$F(u)=|F(u)|e^{-j\phi(u)} \tag{2.21}$$

where

$$|F(u)|=\left[R^2(u)+I^2(u)\right]^{1/2} \tag{2.22}$$

is called the magnitude or spectrum of the Fourier transform, and

$$\phi(u)=\tan^{-1}\left[\frac{I(u)}{R(u)}\right] \tag{2.23}$$

is called the phase angle or the phase spectrum of the transform. R(u) and I(u) are the real and imaginary parts of F(u). Another quantity used in fourier analysis is the power spectrum defined as the square of the fourier spectrum

$$P(u)=|F(u)|^2=R^2(u)+I^2(u) \tag{2.24}$$

2.3.2.2 The Two-Dimensional Fourier Transform and its Inverse

The discrete Fourier transform of a function(image) f(x,y) of size M x N is given by the equation

$$F(u,v)=\frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}f(x,y)e^{-j2\pi(ux/M+vy/N)} \quad (2.25)$$

for u=0,1,2,.....M-1 and v=0,1,2,.....N-1

The inverse of discrete fourier transform is given by

$$f(x,y)=\sum_{u=0}^{M-1}\sum_{v=0}^{N-1}F(u,v)e^{j2\pi(ux/M+vy/N)} \quad (2.26)$$

for x=0,1,2,....M-1 and y=0,1,2,......N-1

The variables u and v are the transform or frequency variables and x and y are the spatial or image variables.

And the fourier spectrum, phase angle and power spectrum can be defined as

$$|F(u,v)|=\left[R^2(x,y)+I^2(x,y)\right]^{1/2} \quad (2.27)$$

$$\phi(u,v)=\tan^{-1}\left[\frac{I(u,v)}{R(u,v)}\right] \quad (2.28)$$

and

$$P(u,v)=|F(u,v)|^2=R^2(u,v)+I^2(u,v) \quad (2.29)$$

where R(u,v) and I(u,v) are the real and imaginary parts of F(u,v) respectively.

2.3.2.3 Filtering in the Frequency Domain

In digital image processing frequency domain is the space defined by values of Fourier transform of image's samples and its frequency variables. Each term of F(u,v) contains all values of f(x,y), modified by the values of the exponential terms. Generally it is impossible to make direct associations between specific components of an image and its transform. However some general statements can be made about the relationship between the frequency components of the fourier transform and spatial characteristics of an image. The origin of the frequency component corresponds to the average of gray level of an image. The low frequency components correspond to the slowly varying components while high frequencies correspond to faster gray level changes in the image. These changes can be considered as edges of objects or other components characterized by abrupt changes in gray level such as noise.

Low frequencies in the Fourier transform are responsible for the general gray-level appearance of an image over smooth areas, while high frequencies are responsible for detail such as edges and noise. A filter that attenuates high frequencies while 'passing' low frequencies is called a lowpass filter. A filter that has opposite characteristic is called highpass filter. Lowpass filtered images have less sharp detail than the original because the high frequencies have been attenuated. Similarly a hig-passed image have less gray level variations in smooth areas and emphasize transitional gray level detail. Such an image will appear sharper.

Since image enhancement deals with sharpening edges and image details to give a good looking impression of the image while making edges sharper at the same time noise components in the image are also enhanced. Because both edges and noise are represented by high frequency components of image. In order to sharpen the edges while suppressing noise first a smoothing process might be useful. So blurring an image first and then enhancing edges would give better results for image enhancement.

Smoothing in the Frequency Domain: Smoothing in the frequency domain is achieved by attenuating a specific range of high-frequency components in the transform of a given image. It is done by low-pass filtering. The basic model in the frequency domain is given by

$$G(u,v)=H(u,v)\times F(u,v) \tag{2.30}$$

where F(u,v) is the fourier transform of the image to be smoothed. the objective is to select a filter transfer function H(u,v) that yields G(u,v) by attenuating the high-frequency components of F(u,v).

Some of the mostly used low-pass frequency domain filters are; ideal low-pass filter (ILPF), Butterworth low-pass filter(BLPF), and Gaussian low-pass filter. An ideal low-pass filter has the transfer function,

$$H(u,v)=\begin{cases}1 & if \;\; D(u,v)\le D_0 \\ 0 & if \;\; D(u,v)>D_0\end{cases} \tag{2.31}$$

where D_0 is a non-negative number and D(u,v) is the distance from point (u,v) to the center of the filter. The locus of points for which D(u,v) = D_0 is a circle. The ideal filter "cuts off" all components of F outside the circle and leaves all components on, or inside, the circle. A Butterworth low-pass filter of order n, with a cutoff frequency at a distance D_0 from the origin has the transfer function,

$$H(u,v)=\frac{1}{1+\left[D(u,v)/D_0\right]^{2n}} \tag{2.32}$$

Unlike the ILPF, the BLPF transfer function does not have a sharp discontinuity at D_0 The transfer function of a Gaussian lowpass filter (GLPF) is given

$$H(u,v)=e^{-D^2(u,v)/2\sigma^2} \tag{2.33}$$

where σ is the standard deviation.

Sharpening in the Frequency Domain: Image sharpening in the frequency domain can be achieved by highpass filtering process, which attenuates the low-frequency components without disturbing high-frequency information in the Fourier Transform.

Since this process is the opposite of the low-pass filtering the high pass filters can be obtained by using the relation

$$H_{hp}(u,v)=1-H_{lp}(u,v) \tag{2.34}$$

where $H_{lp}(u,v)$ is the transfer function of the corresponding lowpass filter. Basic highpass filters are ideal, butterworth, and gaussian highpass filters.

A 2D ideal highpass filter is defined as

$$H(u,v)=\begin{cases}0 \text{ if } D(u,v)\le D_0\\ 1 \text{ otherwise}\end{cases} \tag{2.35}$$

where D_0 is a specified nonnegative quantity, and $D(u,v)$ is the distance from point (u,v) to the center of the frequency rectangle.

Transfer function of a Butterworth highpass filter (BHPF) of order n with cutoff frequency D_0 from the origin is defined as

$$H(u,v)=\frac{1}{1+\left[D_0/D(u,v)\right]^{2n}} \tag{2.36}$$

Gaussian highpass filter (GHPF) in two dimensions is given by

$$1-e^{D^2(u,v)/2D_0^2} \tag{2.37}$$

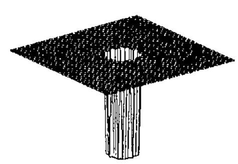


Figure 5. Transfer function of an ideal highpass filter

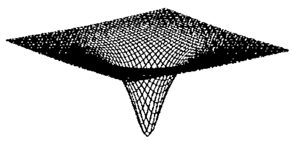


Figure 6. Transfer function of a butterworth highpass filter

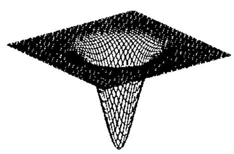
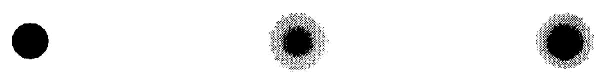


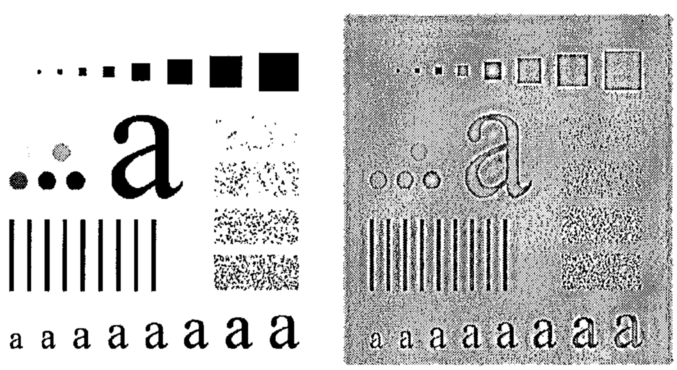
Figure 7. Transfer function of a gaussian highpass filter



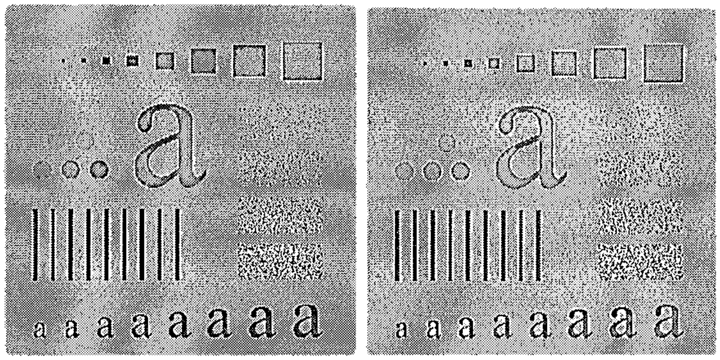
(a) (b) (c)

Figure 8. Images of transfer functions (a) Ideal highpass filter (b) Butterworth highpass filter (c) Gaussian highpass filter

An example of applying highpass filters to an image is shown in figure 9.



(a) (b)



(c) (d)

Figure 9. Application of highpass filters to an image (a) Original image (b) Ideal highpass filtered image (c) Butterworth higpass filtered image (d) Gaussian highpass filtered image.

2.4 Resolution Enhancement

In [31] it is shown that the incoherent transfer function of an optical system is the autocorrelation function of its pupil function. This implies that the transfer function is band-limited, that is it goes to zero for all frequencies above some cutoff frequency. This cutoff frequency corresponds to the diffraction limit of resolution. Energy at frequencies beyond the diffraction limit is lost. Restoration techniques that seek to recover the information beyond the diffraction limit are referred to as superresolution techniques. Basically it is a method of obtaining a high resolution image from observed multiple low resolution images[1]. This approach is called super resolution image reconstruction or simply resolution enhancement in literature[32]-[62] and has attracted many researchers.

One of the techniques of resolution enhancement in image processing is described in [63]. The algorithm that is the basis for this thesis approaches resolution enhancement problem by using a nonlinear extrapolation method in frequency domain. This enhancement method uses shape invariant properties of edges across scale that utilizes the Laplacian transform and Laplacian pyramid representation[64]. The multiresolution representation consists of set of filtered copies of the image, obtained by iteratively filtering with a generating kernel. The multiresolution pyramid represetation utilizes scale-space theory[65]-[67]. The pyramid representation is used in many application areas. In [64] it is used as a compression method. S. Ranganath [68] used multiresolution representation for filter design and implementation. In [69], [70] it is used as an enlargement method of digital images. H. Greenspan and M.C. Lee [71] combined image enhancement and pyramid coding scheme. The basic idea behind Laplacian pyramid representation is to get high resolution components of an image from its low resolution components.

CHAPTER 3

DESIGN AND IMPLEMENTATION

3.1 Introduction

This chapter deals with the procedures that are used in enhancing the digital images by a nonlinear method in the frequency domain. Since the quality of images mostly depends on visual perception, the tecnique is about enhancing the perceptual sharpness of an image as described in [63]. The enhancement algorithm increases the frequency content of the image by using shape-invariant properties of edges across scale. Edges are an important property of images since they correspond to object boundaries or to changes in surface orientation or material properties. The sharpening of edges enhances the visual appearance of the image. An edge can be characterized by a local peak in the first derivative of the image brightness function or by a zero in the second derivative, the so-called zero-crossing [66]. An ideal edge (a step function) is scale invariant in that no matter how much one increases the resolution, the edge appears the same(a step function). This property provides a way for identifying edges and and a method for enhancing the edges.

Since noise in an image appears as high frequency component, the enhancement procedure also enhances noise components. So first the image is gotten rid of noise components then enhancement procedure is applied. In this work after noise removal the new high spatial frequencies are created by incrementing frequency content of the image via using shape-invariant properties of edges across scale. The augmentation procedure is based on a multiresolution image representation [64] and can be described using scale-space formalism. The enhancement procedure includes extrapolation across scale using a nonlinearity that generates phase coherent higher harmonics.

3.2 Noise Considerations

Since median filters have been used extensively as multichannel image filters [7] in this thesis noise removal filter is considered as vector median filter which is very effective in impulsive noise. In multichannel, and especially color image processing, it is accepted that the vector approach is more appropriate compared to traditional approaches. This is because of the inherent correlation that exists between the image channels [22]. In vector approach, each pixel value is considered as an m-dimensional vector(m is the number of image channels, in the case of color images, m=3), whose characteristics, i.e. magnitude and direction, are examined.

3.2.1 Vector Median filtering

In the environments corrupted by impulse noise, bit errors and outliers, the most popular non-linear filters are based on order-statistic theory where a well-known median filter has a great popularity. With a sample ordering, atypical image samples are moved to borders of the order set and the median value is noise-free sample with the highest probability in comparison with other samples present in the input set . Vector filtering algorithm is used in multichannel or color images in order to preserve the inherent correlation between color components.

3.2.2 The Vector Median filtering algorithm

Let $y(x):Z^l \rightarrow Z^m$ represent a multichannel image, where l is an image dimension and m characterizes a number of color channels. In the case of standard color images, parameters l and m are equal to 2, and 3 respectively. Let W={$x_i \in Z^l$; i=1,2,...,N) represent a filter window of a finite size N, where $x_1, x_2, \ldots, x_N$ is a set of noisy samples. The central sample $x_{(N+1)/2}$ determines the position of window. Let us consider that each input vector x_i is associated with the distance measure.

$$L_i = \sum_{j=1}^{N} \left\| x_i - x_j \right\|_\gamma \qquad \text{for } i=1,2,\ldots,N \tag{3.1}$$

where γ represents the selected norm,e.g. for absolute distance (γ=1), for Euclidean distance(γ=2), etc. The distance between two m-channel samples $x_i=(x_{i1},x_{i2},\ldots,x_{im})$ and $x_j=(x_{j1},x_{j2},\ldots,x_{im})$ given by the expression $\left\| x_i - x_j \right\|_\gamma$ is generalized as

$$\left\| x_i - x_j \right\|_\gamma = \left(\sum_{k=1}^{m} \left| x_{ik} - x_{jk} \right|^\gamma \right)^{1/\gamma} \tag{3.2}$$

where γ characterizes the used norm, m is the dimension of vectors and x_{ik} is the kth element of x_i .

If distance measures $L_1, L_2, \ldots, L_N$ serve as an ordering criterion, i.e.

$$L_{(1)} \leq L_{(2)} \leq \ldots L_{(r)} \leq \ldots L_{(N)} \tag{3.3}$$

it means that the same ordering is implied to the input set $x_1, x_2, \ldots, x_N$ which results in the ordered input sequence

$$x^{(1)} \leq x^{(2)} \leq \ldots x^{(r)} \leq \ldots x^{(N)} \tag{3.4}$$

The sample associated with $x^{(1)} \in W$ associated with the minimum distance vector is the output of the VMF introduced by P. E. Trahanias and A. N. Venetsanopoulos [21]. An example of applying vector median filter to a color image that is affected by impulse noise is shown in figure 10.

(a) (b) (c)

Figure 10. Experimental results of vector median filtering (a) original lena color image (b) noisy lena image (c) vector median filtered noisy lena image.

3.3 Enhancement By Nonlinear Extrapolation

After the image being removed from noise, the enhancement procedure by nonlinear extrapolation in frequency domain is applied to enhance the perceptual sharpness of an image. Extrapolation means extending a signal outside a known interval. Extrapolation in the spatial coordinates could improve the spectral resolution of an image, whereas frequency domain extrapolation could improve the spatial resolution [70]. The frequency content of the image is augmented by using shape-invariant properties of edges across scale. The enhancement procedure is based on a multiresolution image representation [64]. And this procedure can be described by using scale-space formalism [66].

3.3.1 Image representation across scale

In frequency domain an image can be represented by its frequency components as long as there is no aliasing and overlapping.

Original image=Low-resolution components+ High-resolution components

with low and high resolution components taken from the same image. An edge of finite resolution can be created by starting with a low-resolution image (e.g using Gaussian) and then adding bandpass components. To create an edge twice the resolution requires the creation of a bandpass at the next level referred to as $L_{\_1}$. The point here is that a high-resolution image can be obtained from a lower resolution one by adding a bandpass component, such as the Laplacian. And also a high resolution of an ideal edge can be predicted from a low-resolution one.

Image enhancement mostly deals with enhancement of edges of an image. The edge representations across different image resolutions or frequency components are evaluated. Because they correspond to object boundaries or to changes in surface orientation edges are important characteristics of images. The concept of an edge is found frequently in discussions dealing with regions and boundaries. Edge points can be thought as pixel locations of abrupt gray-level change. The boundary of a finite region forms a closed path and is thus a global concept. Edges are formed from pixels with derivative values that exceed a preset threshold. An edge can be characterized by a local peak in the first derivative of the image brightness function, or by a zero in the second derivative, the so called zero-crossing [ZC]. An ideal edge (a step function) is scale invariant in that no matter how much one increases the resolution, the edge appears the same (i.e., remains a step function) [70]. This property provides a means for identifying edges and a method for enhancing real edges.

3.3.2 Pyramidal Representation of the Image

Pyramid representations of digital signals are either Gaussian pyramid presentations as a sequence of low-frequency components or Laplacian pyramid presentations as a sequence of high frequency components. The Gaussian pyramid is a sequence of Gaussian components $G_0, G_1 ..., G_N$ obtained by providing a procesing scheme that consists of Gaussian filter (W) processing and downsampling (DS) once, twice, …, N times on the original digital image. Hence, the Gaussian component G_{n+1} is given by

$$G_{n+1}^0 = W * G_n \tag{3.5}$$

$$G_{n+1} = DS(G_{n+1}^0) \tag{3.6}$$

where the asterisk indicates the convolution operation. The high frequency components lost in this process are $L_0, L_1, ..., L_N$ and their sequence is called a Laplacian pyramid. The Laplacian component L_n can be computed from

$$L_n = G_n - EXPAND(G_{n+1}) \tag{3.7.a}$$

$$EXPAND(G_{n+1}) = 4 \times (W * G_{n+1}^0) \tag{3.7.b}$$

where G_{n+1}^0 is the image obtained by inserting 0 into G_{n+1} (upsampling) and the size is identical to G_n. Here the two dimensional Gaussian filter (W) is a seperable filter and the coefficient sequence of its one dimensional Gaussian filter is 1/16, ¼, 3/8, ¼, 1/16. The higher-resolution image G_{-1} obtained from original image G_0 is given by

$$G_{-1} = L_{-1} + EXPAND(G_0) \tag{3.8}$$

Since L_{-1} is unknown, it is necessary to estimate L_{-1} somehow. Based on Laplacian pyramid representation, the procedure for resolution enhancement of digital images is reduced to the problem of estimation of unknown higher-resolution Laplacian component L_{-1}. Figures 11 and 12 are examples of gaussian and laplacian pyramidal representations of lena image, respectively.

(a) (b) (c)

Figure 11. Application of gaussian pyramid to Lena image (a) Level 1 (b) Level 2 (c) Level 3

(a) (b) (c)

Figure 12. Application of Laplacian pyramid to Lena image (a) Level 1 (b) Level 2 (c) Level 3

Since, convolution in spatial domain is the same as multiplication in the frequency domain the pyramid representation in the frequency domain is as follows

$$G_{n+1}^{0} = W \times G_n \tag{3.9.a}$$

$$L_n = G_n - G_{n+1}^{0} \tag{3.9.b}$$

$$\begin{aligned} &G_{n+1} = Subsampled\, G_{n+1}^{0} \\ &n = 0 \ldots (N-1) \end{aligned} \tag{3.9.c}$$

where G_n is termed the *n*th-level Gaussian image and *Ln* is termed the *n*th-level Laplacian image. Generally, the weighting function, *W*, is Gaussian in shape and normalized to have the sum of its coefficients equal to 1. The values used for the LPF, which is a 5-sample separable filter, are (1/16, 1/4, 3/8, 1/4,1/16). Figure 13 presents an example of a Laplacian pyramid representation.

Here the Gaussian pyramid consists of lowpass filtered(LPF) versions of input image, with each stage of the pyramid achieved by Gaussian filtering of the previous stage and corresponding subsampling of the filtered output. The Laplacian pyramid consists of bandpass filtered (BPF) versions of the input image, with each stage of the pyramid constructed by subtraction of two corresponding adjacent levels of the Gaussian pyramid.

(a)

(i) (ii) (iii)

(b)

Figure 13. Gaussian components of Lena image (a)Original (b) (i)G_1 (ii)G_2 (iii) G_3.

(i) (ii) (iii)

Figure 14. Laplacian components of Lena image (i) L_0 (ii) L_1 (iii) L_2.

(a)

(i) (ii) (iii)

(b)

Figure 15. Gaussian components of peppers image (a)Original (b) (i)G_1 (ii)G_2 (iii) G_3.

(i) (ii) (iii)

(c)

Figure 16. Laplacian components of peppers image (i) L_0 (ii) L_1 (iii) L_2.

3.3.3 The Enhancement Procedure

The Laplacian pyramid consists of the edge maps of the input image at different resolutions. Here the concentration is on the edge representation of the image across different image resolutions. The Laplacian pyramid preserves the shape and phase of the edge maps across scale. The application of Laplacian transform to an ideal edge results in a self-similar transient structure as in figure 18 [71]. An edge of finite resolution would produce a decrease in amplitude of these transients with increasing spatial frequency, with the magnitude of the edge going to zero at frequencies above the Nyquist limit. An edge of finite resolution can be created by starting with a low-resolution Gaussian image and then adding on all the bandpass transient structures. To create an edge with twice the resolution requires the creation of a self-similar transient at the next level, hereby referred to as L_{-1}.

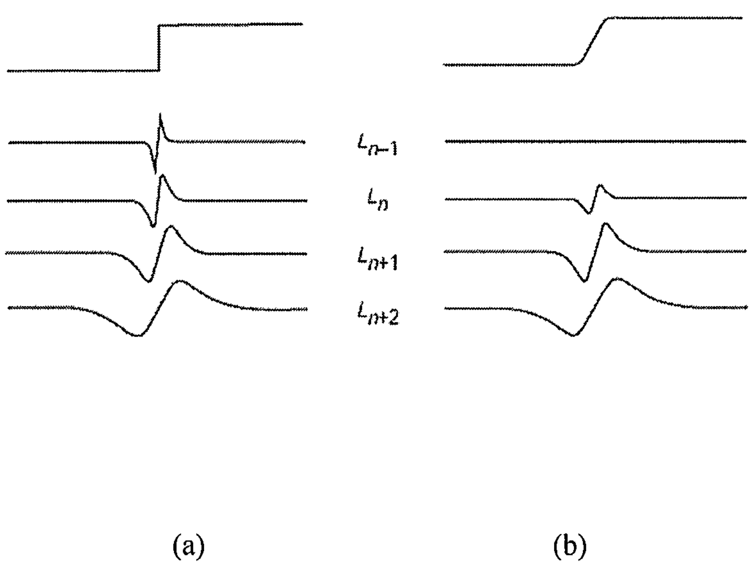


Figure 17. Laplacian transform on an edge (a) an ideal edge (b) an edge of finite resolution.

The enhancement algorithm [63] consists of passing the input image G_0 through a nonlinear filter (to get a higher frequency component L_{-1}) and then adding this image to the input image as shown in figure 18.

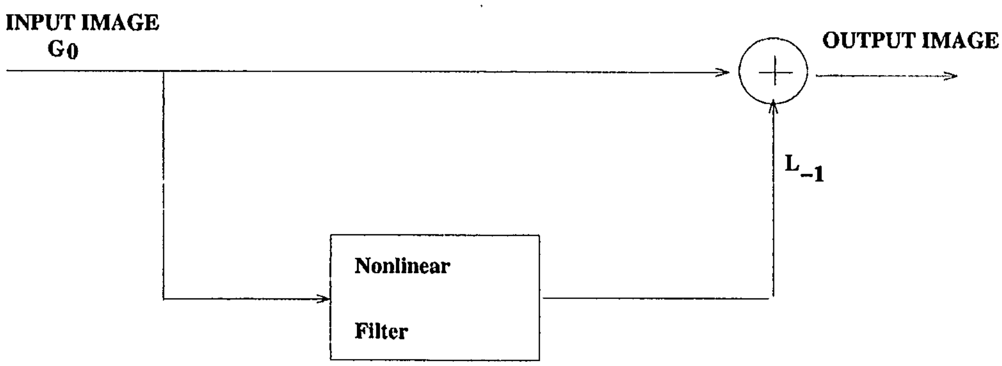


Figure 18. Basic diagram of image enhancement algorithm after noise removal.

In pyramid representation adding the high-frequency component L_0 to the G_1 component can sharpen G_1 to produce the input G_0. An even sharper edge can be produced by predicting a higher-frequency component, L_{-1}, preserving the shape and phase of L_0. The new resolution (L_{-1}) is extrapolated by preserving the Laplacian-filtering waveform shape, together with sharpening by a nonlinear operator. The waveform is the result of bounding(clipping) the L_0 response, multiplying the resultant waveform by a constant and then removing the low-frequencies in order to extract a high-frequency response.

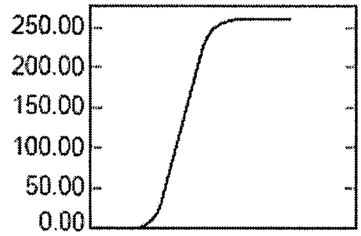
The objective is to form the next higher harmonic of the given signal while maintaining phase. Figure 19 [71] illustrates a one-dimensional high-contrast edge scenario. The given input, G_0, is shown in (a) of the figure, together with its pyramid components, L_0 and G_1, shown in (b) and (c), respectively. From the pyramid reconstruction process, we know that adding the high-frequency component L_0 to the G_1 component can sharpen G_1 to produce the input G_0. Hence a higher-frequency component, L_{-1}, as shown in (d) can be predicted while preserving the shape and phase of L_0, the reconstruction process can be used to produce an even sharper edge, which is closer to the ideal-edge objective, as shown in (e) of Fig. 19. The L_{-1} component cannot be created by a linear operation on the given L_0 component (i.e., the frequency spectrum cannot be augmented using a linear operator). We can, thus, never hope to create a higher-frequency output by a linear enhancement technique. The L_{-1} component can be generated by extrapolating to new resolution by preserving the Laplacian filtering waveform shape, together with sharpening by a nonlinear filter. The waveform as in (f) of Fig. 19 is the result of clipping the L_0 component, multiplying the resultant waveform by a constant, and then removing the low frequencies present (via bandpass filtering) in order to extract a high-frequency response. The enhanced edge output is presented in (g).

$$L_{-1} = HP(sx(BOUND(L_0))) \tag{3.10}$$

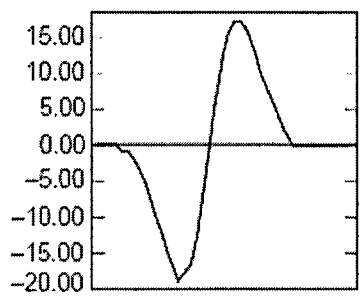
where s is a scaling constant and BOUND(x) is the following function

$$BOUND(x) = \begin{cases} T, & if\ \mathrm{x} > T \\ x, & if\ -T \le x \le T \\ -T, & if\ \mathrm{x} < -T \end{cases} \tag{3.11}$$

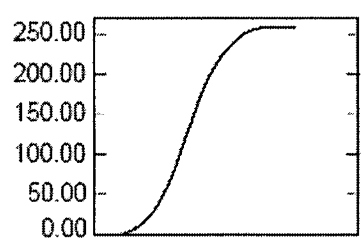
Here $T=(1\text{-}c)x(L_0)_{max}$, with c a clipping constant between 0 and 1.



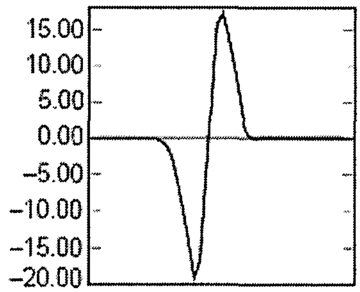
(a) Input image, G_0



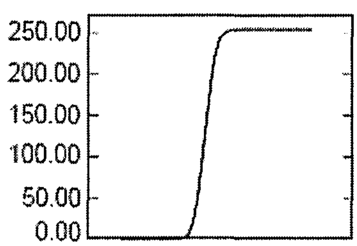
(b) Pyramidal component, L_0



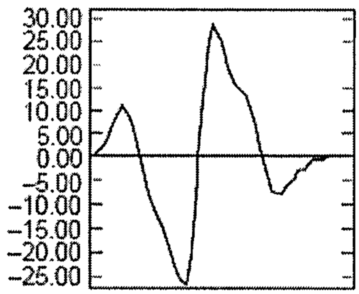
(c) Pyramidal component, G_1



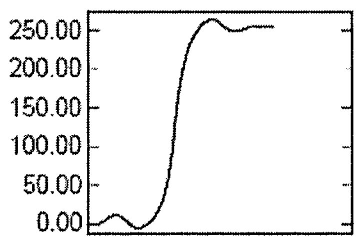
(d) Desired L_{-1}



(e) Desired G_{-1}



(f) Nonlinear component, L_{-1}



(g) Nonlinear edge enhancement

Figure 19. The one dimensional ideal edge scenario.

The result is high-passed in order to leave only the high frequencies of the image. The new output is generated next as the sum of the given input and L_{-1}.

Output image=L_{-1} + Input image

3.3.4 Parameter Estimation

In order to compare enhanced edges with ideal edges blurring (B) and ringing (R) factors are taken into consideration. There is a tradeoff between the perceived ringing side effects and the sharpness of the edges. The clipping parameter, c, has effect on increasing frequency content of the image. The scaling parameter, s, affects the sharpness of edge and thus reduces the blurring effect but increases ringing side-effect. A theoretical evaluation of the parameter estimation is considered. Since final bandpass stage is not critical for achieving good results [63], it is ignored. A special case of a step edge is considered. A 5-tap normalized Gaussian low-pass filter, W, with a Standard deviation of 1.0 is used. Low-pass image G_1 has σ_1=1.345 $(\frac{1}{\sigma_1^2} = \frac{1}{\sigma_0^2} + \frac{1}{\sigma_W^2})$ where σ_0=0.9 for G_0, when this is applied to a unit step edge, U(x), a normalized Gaussian filter produces an error function. Thus,

$$L_0\,U(x)=G_0\,U(x)-G_1\,U(x) \tag{3.12.a}$$

$$L_0\,U(x)=Erf(x/(\sigma_0))-Erf(x/(\sigma_1)) \tag{3.12.b}$$

The maximum of L_0 U(x), L_{0max}, is taken and clipped to get the maxima at T=(1-c)xL_{0max}, where c is the clipping parameter. The maximum, L_{0max}, can be derived by taking the derivative of L_0 U(x) to 0. If we wish to find $x=x_{max}$ for which the derivative of L_0 U(x) is zero, then

$$Erf'(x_{max}/(\sigma_0))-Erf'(x_{max}/(\sigma_1))=0 \tag{3.13}$$

This is equivalent to constraint

$$G(\sigma_0)_{xmax}-G(\sigma_1)_{xmax}=0 \tag{3.14}$$

and then

$$xmax=sqrt(2log(\sigma_1/\sigma_0)/(1/(\sigma_0)^2-1/(\sigma_1)^2)) \tag{3.15}$$

here

$$xmax=sqrt(2log(1.345/0.9)/(1/0.81-1/1.8))=1.085 \tag{3.16}$$

$$L_{0max}=Erf(1.085/0.9)-Erf(1.085/1.345)=0.097 \quad (3.17)$$

The extremes of the ideal signal, L_{-1} are found in a similar way, with σ_{0}, σ_{-1} respectively,

$$xmax=sqrt(2log(0.9/0.45)/(4/0.81-1/0.81))=0.612 \quad (3.18)$$

$$L_{-1max}=Erf(0.612/0.45)-Erf(0.612/0.9)=0.16 \quad (3.19)$$

and thus first constraint is

$$s \times (1-c) \times 0.097=0.16 \quad (3.20)$$

The second measure of the comparison is the slope. The slope of the approximation at the zero-crossing position, s x BOUND($L_0U(x)$), is s times the slope of $L_0U(x)$

$L_0(x=0)=G_0(x=0)-G_1(x=0)$

=(1/(0.9 x sqrt(2 x pi))-1/(1.345 x sqrt(2 x pi))

=0.1467

The slope of the ideal $L_{-1}U(x)$ at the zero crossing position is,

$L_{-1}(x=0)= G_{-1}(x=0)-G_0(x=0)$

=(1/(0.45 x sqrt(2 x pi))-1/(0.9 x sqrt(2 x pi))

=0.44

Thus the second constraint is

$$s \times 0.1467=0.44 \quad (3.21)$$

the scale factor to achieve equal slope is s=3

since,

s x (1-c) x 0.097=0.16 then c=0.45

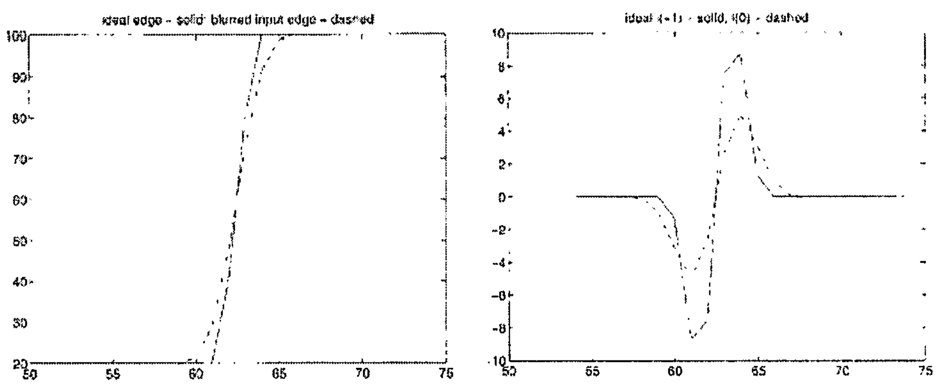
The enhancement parameters are c=0.45 and s=3

CHAPTER 4

RESULTS AND DISCUSSION

In this chapter the results and observations made during the research are documented.

4.1 Simulation Results



(a) (b)

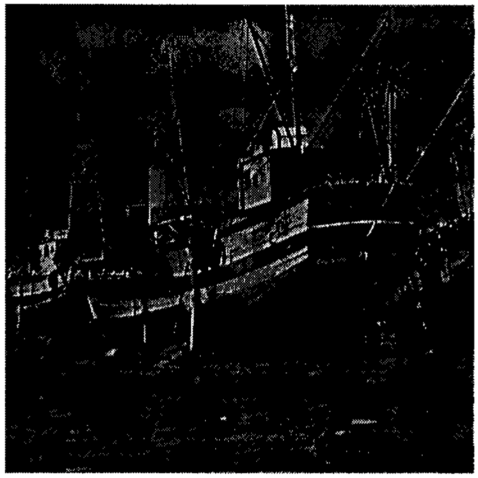
Figure 20. The effect of parameter set to a step edge (a) input curves, ideal step edge(solid) and input blurred edge(dashed) (b) corresponding Laplacians, ideal L_{-1} (solid), and extracted L_0(dashed).

In figure 20 the effect of parameter set in a step edge is demonstrated. The figure presents the ideal edge and the given input edge (a) with corresponding Laplacian curves(b). Figures 21-25 present application of enhancement method to several images and table 1 gives statistical values for original and enhanced images.

(a)

(b)

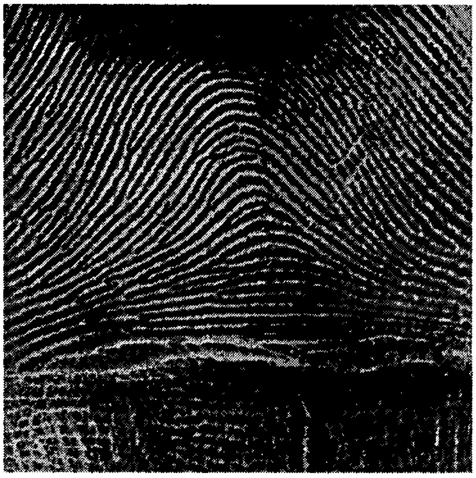
Figure 21. Simulation results for lena image (a) Original image (b) enhanced image.



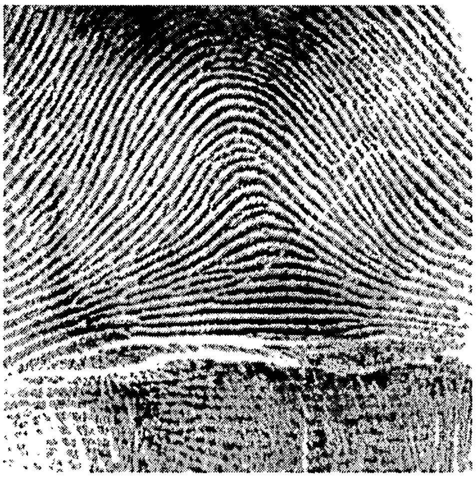
(a)

(b)

Figure 22. Simulation results for boat image (a) Original image (b) enhanced image.



(a)



(b)

Figure 23. Simulation results for fingerprint image (a) original (b) enhanced image.

(a)

(b)

Figure 24. Simulation results for barbara image (a) original (b) enhanced image.

(a)

(b)

Figure 25. Simulation results for flintstones image (a) original (b) enhanced image.

Table 1. Statistical results for experimented images.

images	original image		enhanced image	
	global mean μ	standard deviation σ	global mean μ	standard deviation σ
lena	124.0505	0.0490	62.1856	0.0247
boat	129.7080	0.0355	65.1712	0.0189
fingerprint	141.5236	0.0189	71.0575	0.0161
barbara	117.3928	0.0334	58.8844	0.0205
flinstone	136.4463	0.0166	69.8308	0.0094

The implementation of the algorithm on real images showed that the enhancement scheme produced visually pleasing enhanced versions of existing images. The implementation can be incorporated in real-time applications such as high definition television. The computations were simple and easy to be implemented.

4.2 System Descriptions

The programs are written and run on a Compaq nx9010 laptop computer. (System processor: Intel Pentium III with 512 MB RAM and Windows XP operating system. The programming tool is Matlab verison 6,5.

4.3 Data constraints

The images used in the algoritms are of size 512x512 pixels and PNG (Portable Network Graphics) and TIFF (Tagged Image File Format) formats are selected for images. When the size of the image increases the algorithm slows down due to memory specifications. This constraint can be removed by implementing the algorithm on computer that have better technical specifications.

CHAPTER 5

CONCLUSION

The proposed scheme has been developed as an improvement on resolution enhancement of digital images. A combination of impulsive noise removal and resolution enhancement procedures was implemented. The main goal was to increase the sharpness of images in order to make images overally sharpened and visually agreeable to the user's perception.

Since edges are one of the most effective factors in identifying the sharpness of an image, the enhancement procedure aimed to increase the sharpness of edges and thus to augment the sharpness of the image. A method of enhancing the edges in an image has been developed. The method used frequency domain approach in edge enhancement scheme. To prevent impulsive noise components being enhanced (because noise components are contained in the high frequency components of the image as edges), an impulsive noise removal procedure was applied to the image. An order statistics method which is called vector median filtering has been implemented as a noise removal procedure. Median filtering was better in preserving sharp edges and it was efficient for smoothing of spiky noise. Since it uses median value of a neighborhood, vector median filtering method gave good results in suppressing noise, especially impulse noise, while preserving edges that were subject to resolution enhancement procedure. The multiresolution pyramid representation was used to obtain edge map of images. The method utilized Laplacian transform and Laplacian pyramid representation that depends on scale-space theory. Nonlinear extrapolation across scale was used as the method of obtaining high frequency components of the image. The algorithm achieved the perceptual effect of image enhancement, with both time and storage savings because of the simplicity of computations involved. The ease of implementation enables it to be incorporated in real time applications and other image processing applications such as compression.

The issue of only edges in an image was introduced in this study. Other objects in an image such as lines, dots etc. were not addressed. The other objects in images require additional analysis. The enhancement of lines and other objects in an image may be subject of future work. Also research work is progressing to adapt the algorithm to make it suitable for enhancing images based on the statistical characteristics of the objects to be recognized.

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