International Journal of Scientific Engineering and Technology (ISSN : 2277-1581)
www.ijset.com, Volume No.1, Issue No.2 pg:148-152 01 April 2012

Image Enhancement Based on Abstraction and Neural Network

Trapti Sahu, Shabahat Hasan
R.K.D.F.I.S.T. Bhopal (M.P.) India
trapti.jec@gmail.com

Abstract: this paper presents a hybrid technique for image enhancement with ability of de-noising it integrates two different processing aspects into one. The proposed algorithm uses the image abstraction technique for detecting the information density in different parts of image then accordingly operates the smoothing filter and after filtering the information's of edges are recombined with the filtered image. The proposed technique also utilizes the Neural Network for filtering noise generated edge patterns. Hence the approach not only enhances the image but also avoids the enhancement of noise. The simulation of algorithm shows that it improves the perception; remove noise while maintaining the structure information intact it is also found that the proposed technique is quite fast.

Keywords: image enhancement, Neural Network, empirical analysis.

1. Introduction

There are many definitions available for the term image enhancement one of them is "Image enhancement is basically improving the interpretability or perception of information in images for human viewers and providing `better' input for other automated image processing techniques" [1][2]. On other words the objective of image enhancement is to modify its features according to the requirements of processing space. While considering the above mentioned things it is clear that enhancement techniques are very relevant to the field where the processed image to be used, because of this several techniques are available for enhancement of image depending upon the use (like human perceptions, medical imagery or very complex radar systems). Another problem with enhancement techniques is that most of the method required a properly de-noised image otherwise the noise generated artifacts could also get enhanced hence de-noising is often a necessary and the first step to be taken before the images data is analyzed. It is necessary to apply an efficient de-noising technique to compensate for such data corruption. Because of the characteristics of noise Image de-noising still remains a challenge for

Asst. Prof. Shabahat Hasan
R.K.D.F.I.S.T Bhopal (M.P.) India

Researchers because of nature of noise. This paper describes methodologies for noise reduction (or de-noising) giving an idea to soft computing algorithm to find the reliable estimate of the noise pattern in given degraded image.
As discussed above the noise modeling in images is greatly varies depending upon capturing instruments, data transmission media, image quantization and discrete sources of radiation. It is difficult to design a single mathematical model for all types of noise instead a soft computing based black box model could be a much better solution for noise model. This paper also considers information based processing depth for each part of image which not only reduces the processing time but also protects the information loss.

2. Related Work

Image enhancement has remained a fundamental problem in the field of image processing. There exist many techniques that can enhance a digital image without spoiling it. The enhancement methods can broadly be divided in to the following two categories:

1. Spatial Domain Methods
2. Transform Domain Methods

Spatial domain techniques, directly deal with the image pixels. The pixel values are manipulated to achieve desired enhancement, on the other hand in frequency domain methods, the image is first transferred in to other domains (like frequency) and all the enhancement operations are performed on that domain of the image and then the Inverse transform is performed to get the resultant image. These enhancement operations are performed in order to modify the image brightness, contrast or the distribution of the grey levels. As a consequence the pixel value (intensities) of the output image will be modified according to the transformation function applied on the input values [1]. Some methods of both domains are discussed below

2.1 Grey scale manipulation (Spatial Domain)

The simplest form of operation is when the operator T only acts on a pixel neighborhoods in the input image, that is only depends on the value of F at (x,y). This is a grey scale transformation or mapping. The simplest case is thresholding where the intensity profile is replaced by a step function, active at a chosen threshold value. In this case any pixel with a grey level below the threshold in the input image gets mapped to 0 in the output image. Other pixels are mapped to 255.

2.2 Histogram Equalization (Spatial Domain)

This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values.
The method is useful in images with backgrounds and foregrounds that are both bright or both dark. In particular, the method can lead to better views of bone structure in x-ray images, and to better detail in photographs that are over or under-exposed. A key advantage of the method is that it is a fairly straightforward technique and an invertible operator. So in theory, if the histogram equalization function is known, then the original histogram can be recovered. The calculation is not computationally intensive. A disadvantage of the method is that it is indiscriminate. It may increase the contrast of background noise, while decreasing the usable signal.

2.3 Image Smoothing (Spatial Domain)

The aim of image smoothing is to diminish the effects of camera noise, spurious pixel values, missing pixel values etc. in this method pixel intensity is replaced with the median of pixel intensities within a window centered at that pixel. If a part of the window falls outside the image, intensities within the portion of the window inside the image is used. Circular windows are used to make smoothing independent of the image orientation.

2.4 Image Sharpening (Spatial Domain)

The main aim in image sharpening is to highlight fine detail in the image, or to enhance detail that has been blurred (perhaps due to noise or other effects, such as motion). With image sharpening, we want to enhance the high-frequency components; this implies a spatial filter shape that has a high positive component at the centre.

2.5 Filtering (Frequency Domain)

Low pass filtering involves the elimination of the high frequency components in the image. It results in blurring of the image (and thus a reduction in sharp transitions associated with noise). An ideal low pass filter would retain all the low frequency components, and eliminate all the high frequency components. However, ideal filters suffer from two problems: blurring and ringing. These problems are caused by the shape of the associated spatial domain filter, which has a large number of undulations. Smoother transitions in the frequency domain filter, such as the Butterworth filter, achieve much better results.

There are too many methods are available and it is difficult to mention all of them also we are only utilizing the spatial domain methods hence no need to further discussion.

3. Edge Detection Techniques

Edge detection is a fundamental tool in image processing and computer vision, particularly in the areas of feature detection and feature extraction, which aim at identifying points in a digital image at which the image brightness changes sharply or, more formally, has discontinuities. The same problem of finding discontinuities in 1D signal is known as step detection.

3.1 Sobel Operator

The Sobel operator is used in image processing, particularly within edge detection algorithms. Technically, it is a discrete differentiation operator, computing an approximation of the gradient of the image intensity function. At each point in the image, the result of the Sobel operator is either the corresponding gradient vector or the norm of this vector. The Sobel operator is based on convolving the image with a small, separable, and integer valued filter in horizontal and vertical direction and is therefore relatively inexpensive in terms of computations. On the other hand, the gradient approximation which it produces is relatively crude, in particular for high frequency variations in the image.

Mathematically, the operator uses two 3×3 kernels which are convolved with the original image to calculate approximations of the derivatives - one for horizontal changes, and one for vertical. If we define A as the source image, and G_x and G_y are two images which at each point contain the horizontal and vertical derivative approximations, the computations are as follows:

$$\mathbf{G}_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} * \mathbf{A} \quad \text{and} \quad \mathbf{G}_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix} * \mathbf{A}$$

Where * here denotes the 2-dimensional convolution operation.
The x-coordinate is here defined as increasing in the "right"-direction, and the y-coordinate is defined as increasing in the

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"down"-direction. At each point in the image, the resulting gradient approximations can be combined to give the gradient magnitude, using:

$$\mathbf{G} = \sqrt{\mathbf{G}_x{}^2 + \mathbf{G}_y{}^2}$$

Using this information, we can also calculate the gradient's direction:

$$\mathbf{\Theta} = \operatorname{atan2}(\mathbf{G}_y, \mathbf{G}_x)$$

Where, for example, θ is 0 for a vertical edge which is darker on the right side.

3.2 Roberts Operator

The Roberts' Cross operator is used in image processing and computer vision for edge detection. It was one of the first edge detectors and was initially proposed by Lawrence Roberts in 1963. As a differential operator, the idea behind the Robert's Cross operator is to approximate the gradient of an image through discrete differentiation which is achieved by computing the sum of the squares of the differences between diagonally adjacent pixels.

In order to perform edge detection with the Roberts operator we first convolve the original image, with the following two kernels:

$$\begin{bmatrix} +1 & 0 \\ 0 & -1 \end{bmatrix} \quad \text{and} \quad \begin{bmatrix} 0 & +1 \\ -1 & 0 \end{bmatrix}.$$

Let I(x, y) be a point in the original image and $G_x(x, y)$ be a point in an image formed by convolving with the first kernel and $G_y(x, y)$ be a point in an image formed by convolving with the second kernel. The gradient can then be defined as:

$$\nabla I(x,y) = G(x,y) = \sqrt{G_x^2 + G_y^2}.$$

The direction of the gradient can also be defined as follows:

$$\Theta(x,y) = \arctan\left(\frac{G_y(x,y)}{G_x(x,y)}\right).$$

P_{11}	P_{12}	P_{13}	P_{14}
P_{21}	P_{22}	P_{23}	P_{24}
P_{31}	P_{32}	P_{33}	P_{34}
P_{41}	P_{42}	P_{43}	P_{44}

E_{11}	E_{12}	E_{13}	E_{14}
E_{21}	E_{22}	E_{23}	E_{24}
E_{31}	E_{32}	E_{33}	E_{34}
E_{41}	E_{42}	E_{43}	E_{44}

4. Neural Network

The term neural network was traditionally used to refer to a network or circuit of biological neurons [5]. The modern usage of the term often refers to artificial neural networks, which are composed of artificial neurons or nodes. Thus the term has two distinct usages:

1. Biological neural networks are made up of real biological neurons that are connected or functionally related in a nervous system. In the field of neuroscience, they are often identified as groups of neurons that perform a specific physiological function in laboratory analysis.
2. Artificial neural networks are composed of interconnecting artificial neurons (programming constructs that mimic the properties of biological neurons). Artificial neural networks may either be used to gain an understanding of biological neural networks, or for solving artificial intelligence problems without necessarily creating a model of a real biological system. The real, biological nervous system is highly complex: artificial neural network algorithms attempt to abstract this complexity and focus on what may hypothetically matter most from an information processing point of view. Good performance (e.g. as measured by good predictive ability, low generalization error), or performance mimicking animal or human error patterns, can then be used as one source of evidence towards supporting the hypothesis that the abstraction really captured something important from the point of view of information processing in the brain. Another incentive for these abstractions is to reduce the amount of computation required to simulate artificial neural networks, so as to allow one to experiment with larger networks and train them on larger data sets.

5. Proposed Algorithm

The proposed algorithm works on detection and enhancing the important information of an image while suppressing the noise generated false information contents this method has advantage that it does not dissolve the impulsive noise but eliminate it.

The proposed algorithm can be divided into two parts described in following steps.

Part 1: Training of Neural Network

Step1. Generate the initial noisy patterns of selected size (like 16X16, 4X4 etc.) by Gaussian distribution of different mean (from 0 to 0.8) and variance (0 to 0.8).

Step2. Generate the edge image from above generated image by using 'Sobel' operator and 'Roberts' operator.

Step3. Divide the original image into non-overlapping blocks of selected size (like 3X3, 5X5, 7X7 etc.).

Figure 1: Example image left with Pixel values P_{xy} and their corresponding Edge values E_{xy} in right Matrix.

Step4. Now train the neural network using image pixels of selected block as training vectors (by converting that block into row vector) and corresponding edge value (0 or 1) as label. For example if in fig1 we take a block of 3X3 and placed it on upper left corner then corresponding edge value will be E_{22}.

Part 2: Generating Enhanced Image

Step1. Generate the smoothed image by filtering the given image using median filter.
Step2. Find out the edges using 'Sobel' and 'Roberts' operator.
Step3. Now from the edge image find out the points of edges and extract the pixels around that pixel location from given image according to windows size. Example let the E_{12} be the edge then extracts the pixels from upper left corner by 3X3 windows size here windows size is considered 3X3.
Step4. Now pass this vector to previously trained neural network.
Step5. If the neural network predicts an edge then remove the edge information from edge image else keep it intact.
Step6. Apply the median filter to all blocks of image except the blocks which contains the edges.

6. Simulation Results

For better analysis of proposed algorithm it is simulated in MATLAB with different images and results are presented here

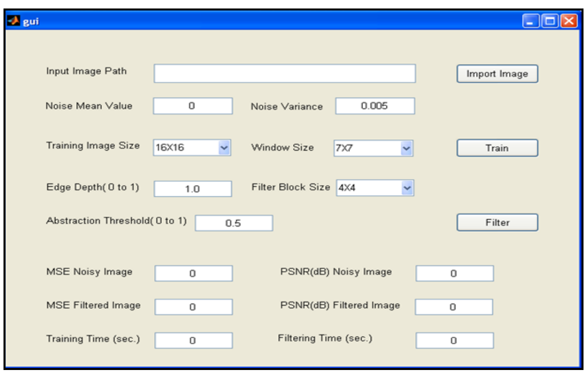

Figure 2: shows the user interface of the designed software.

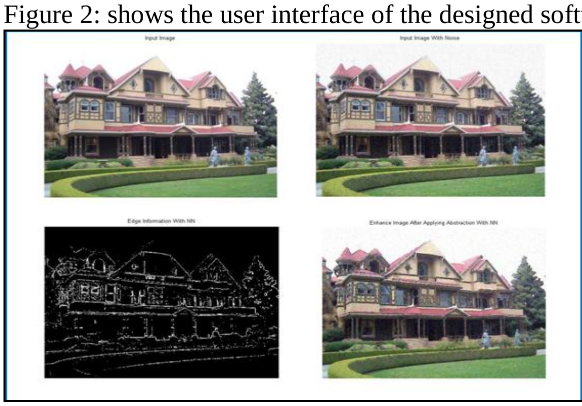

Figure 3: Results for image 1.

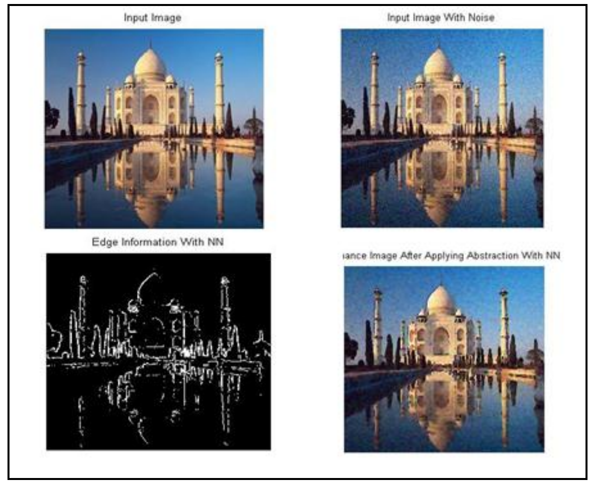

Figure 4: Results for image 2.

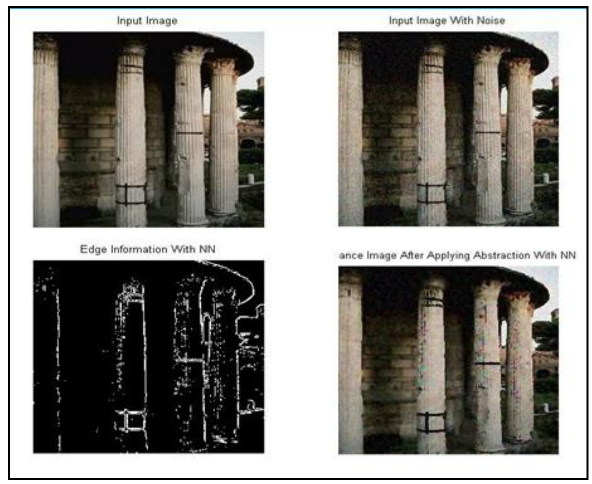

Figure 5: Results for image 3.

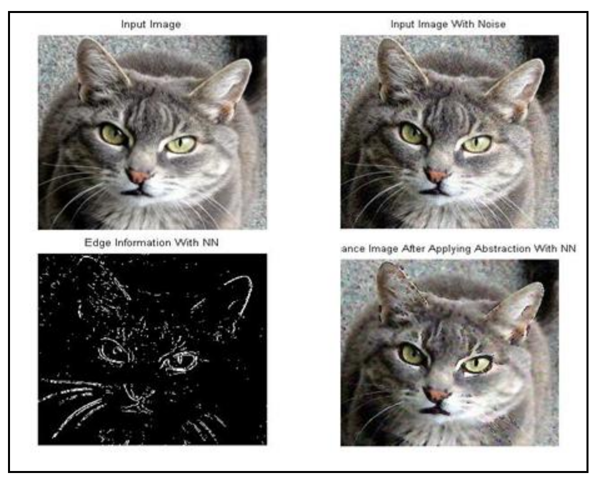

Figure 6: Results for image 4.

The description of each window in figure 3 to 6 is as follows
1. Top left Original Image,
2. Top Right Noisy Image,
3. Bottom Left Abstract,
4. Bottom Right Enhanced Image.

Table 1

Noise Mean	Noise var.	Training Time(s)	Window Size	Edge Depth	Filter Block size	Abstraction threshold
0	0.5	16X16	7X7	1.0	4X4	0.5

Table 2

image	MSE		PSNR		Training Time	Filtering Time
	Noisy	Enhanced	Noisy	Enhanced		
1	287.2	138.9	23.5	26.7	3.99	5.30
2	317.3	148.4	23.1	26.4	3.99	5.29
3	287.5	186.5	23.5	25.4	3.99	5.39
4	309.9	182.6	23.2	25.5	3.99	5.41

Table 1: shows the simulation parameters values for all images, and Table 2: shows the numerical values of simulation results for all images.

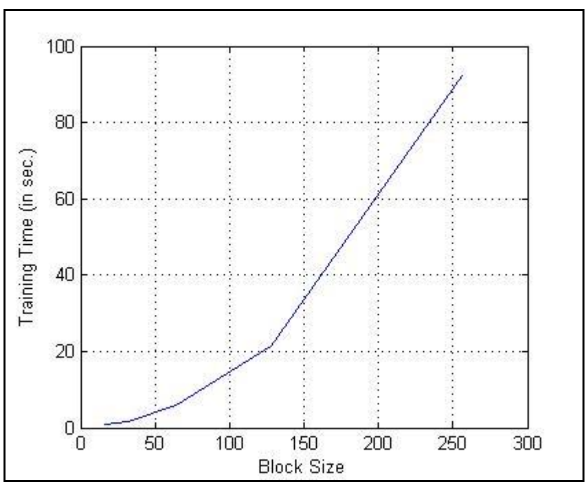

Figure 8: Plot of block size vs. training time

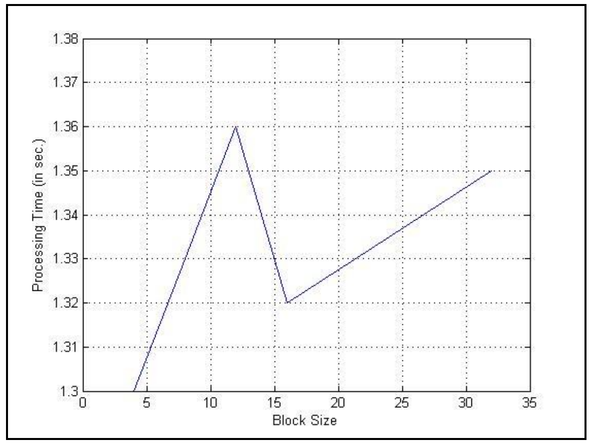

Figure 8: Plot of block size vs. processing time

7. Conclusion

After simulating the algorithm with different images and analyzing results it's clear that proposed algorithm sufficiently reduces the effect of noise patterns in the abstracted image, (the figure 3 and 4 shows the clear difference between the edges abstracted by NN & without NN) also the proposed technique takes almost same time for processing even with different block size although the training time grows exponentially hence in future it is needed to minimize.

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