CHAPTER 1

INTRODUCTION

1.1 DIGITAL IMAGE PROCESSING

1.1.1 Image Pre-processing

Term “Image pre-processing”, indicates the significant functions on
the images at the lowest stage of generalization which is predominantly
dedicated to the incredible augmentation of the image data, paving the way
for the containment of the unwanted deformations or the improvement of
certain image features vital for the additional processing, without involving
any sort of enhancement in the image data content. Nevertheless, the related
technique invariably exploits the incredible redundancy in the images.
Habitually, the pixels adjacent to a particular object in the real images contain
an identical or analogous brightness value. With the result, if it is possible to
choose a deformed from the image, reinstatement as an average value of the
adjacent pixels may happen when a choice of a deformed from the image is
possible (Miljkovic et al. 2009).

1.1.2 Digital Image Processing

In this context, image processing habitually represents the task of
digital image processing involving both optical and analog image processing.
Digital Image Processing (DIP), in essence, characterizes a multidisciplinary
science which effectively employs the tenets from an assortment of domains
like the optics, computer science, mathematics, surface physics and the visual psychophysics (Basava Prasad et al. 2014).

Certain vital applications of image processing in computer vision encompass remote sensing, feature extraction, face recognition, finger-print identification, optical sorting, argument veracity, microscope imaging, line departure warning mechanism, Non-photorealistic depiction, medical image processing, and morphological imaging. Incidentally, an image essentially embraces various sub-images habitually labeled as the regions or regions-of-interest (Mustafa Hassan et al. 2015). Further, the images generally are home to various clusters of objects each of which serves as the foundation for a particular region or region-of-interest. It is pertinent to note that, in a large majority of cases, image processing invariably requires images to be offered in digitized form. For the purpose of the digitization process, the input image is sampled on a distinct lattice, with every sample or pixel quantized by a predetermined number of bits.

A digital image, for the purpose of illustration is at the outset, transformed into an analog signal which is scanned onto an output. Image processing is very intimately linked to the computer vision and computer graphics. Even within computer graphics, the images are physically organized from the surroundings, physical models of objects and lighting, instead of being obtained by means of imaging tools from natural scenarios. This is a vogue in a large majority of animations. Computer vision, on the other hand, represents regularly evaluated superior quality image processing by which the computer or software is inclined to infer the objective contents of an image or a sequence of images as in the case of the videos or the three Dimension full-body magnetic resonance scans.

Digital image processing is endowed with the amazing skills of permitting the employment of highly complex techniques, and thus presents
both the highly intricate accomplishments at easy and straightforward tasks, and the performance of methods otherwise unachievable by means of analog approaches.

1.2 IMPACT OF NOISE ON IMAGES

Further, the digital image is sensitive to a diversity of noise, which adversely affects the quality of the image. Hence, the underlying objective behind the image denoising is to invest in regaining as much original image details as feasible by eradicating the redundant noise (Gulati et al. 2012). Images are frequently corrupted by noises, which crop up either in the course of the image capture or communication. Hence, noise elimination has surfaced as a significant function in the image processing task.

1.2.1 Causes of Noise Occurred on Images

In fact, noise is triggered by the faults committed during the image acquisition procedure which leads to the failure of pixel values to represent the actual intensities of the real scenario. Further, noise decrease constitutes the task of eliminating noise from a signal. Incidentally, noise is generally measured by the percentage of the pixels which are tainted. The tainted pixels, in turn, are either fixed to the highest value or possess single bits. In this regard, there is a bunch of techniques by which noise can be initiated into an image, in accordance with the manner in which the corresponding image is generated.

In the event of the image being scanned from a photograph produced on film, the film grain crops up as a source of noise. Noise can also be created on account of the mutilation of the film. Alternatively, it may also be originated even by a scanner. If the image is achieved directly in a digital format, the system intended for collecting the data like the Charge-coupled
device (CCD) detector may trigger the noise. Moreover, the electronic diffusion of the image data is one of the highly potential sources for the generation of the noise. In the next section, the various types of noises are addressed.

1.3 TYPES OF NOISES

Generally, the categories of faults which may crop up together with the kind of noise on the image are well known. Therefore, ability to analyze certain type of the standard noises is available for the purpose of removing or scaling down the noise in the color image. In this connection, Image Noise may be broadly categorized into five distinct types as detailed below:

1. Amplifier noise (Gaussian noise),
2. Salt-and-pepper noise (Impulse noise),
3. Shot noise, Quantization noise (uniform noise),
4. Film grain, Non-isotropic noise,
5. Speckle noise (Multiplicative noise) and the Periodic noise.

i) Amplifier Noise (Gaussian noise)

The typical model of the amplifier noise is the additive, Gaussian is dependent on each and every pixel and the signal intensity, triggered predominantly by the Johnson–Nyquist noise (thermal noise), together with the one emanating from the reset noise of the capacitors ("kTC noise"). It represents an idealized version of white noise, which is induced by the arbitrary oscillations in the signal. In the color cameras in which a higher amplification is employed in the blue color channel when compared with the green or red channel, it is only natural that added noise makes its appearance in the blue channel. The amplifier noise, in fact, reflects a vital segment of the
noise of an image sensor, and hence involves the steady noise level in the dark areas of the image. Every pixel in the image in the Gaussian noise is duly altered from its original value habitually by a trivial quantity. A histogram, on the other hand, depicts a plan of the volume of deformation of a pixel value against the frequency of its occurrence and effectively exhibits a normal distribution of noise (Buades et al. 2005). Despite a host of the parallel distributions being feasible, the Gaussian (normal) distribution is generally acknowledged as an excellent model, thanks to the central limit theorem which substantiates that the sum of diverse noises exhibits a tendency to inch closely towards a Gaussian distribution.

ii) Salt-and-Pepper Noise (Impulse Noise)

This brand of noise is also known as the impulse noise or spike noise or random noise or independent noise. In this version of the noise indicating the sparse light and dark disturbances, the pixels in the image appear to be extremely divergent in the color or intensity feature, quite different from the adjoining pixels. The Salt and pepper deprivation is generally triggered by the quick and abrupt annoyances in the image signal. Normally, this kind of noise adversely affects only a trivial number of the image pixels.

On scrutiny, the image is observed to contain dark and white dots, thus inviting the fond name “salt and pepper noise”. The characteristic sources for this type of noise encompass the speckles of dust in the interior of the camera and the inflamed or defective part such as the Charge-coupled device (CCD) elements. An image tainted by the salt-and-pepper noise invariably contains dark pixels in bright regions. The converse is also true. It is generally stimulated by the dead pixels, analog-to digital converter flaws and the bit faults in the communication.
iii) **Shot Noise**

The overriding noise in the lighter segments of an image from an image sensor is characteristically the one triggered by the statistical quantum fluctuations, such as the fluctuations in the number of photons sensed at a particular exposure stage. The corresponding noise is popularly known as the photon shot noise, which invariably possesses a root mean square value in direct proportion to the square root of the image intensity, and the noises at various pixels are not dependent on one another. This version of the noise exhibits a tendency to toe the line of a Poisson distribution, which does not differ considerably from the Gaussian. Over and above the photon shot noise, it is also possible to have supplementary shot noise from the dark leakage current in the image sensor, which is given the name the "dark shot noise" or the "dark-current shot noise" (Farooque et al. 2013).

iv) **Quantization Noise (Uniform Noise)**

This kind of noise is generally triggered by quantizing the pixels of a sensed image to a host of discrete levels. It possesses a roughly uniform distribution, and is normally, signal-dependent. However, it emerges as signal independent when noise sources are abundant resulting in the dithering or in cases where the dithering is unambiguously initiated (Lakhwinder Kaur et al. 2013).

**Film Grain**

The grain of photographic film normally characterizes a signal-dependent noise, associated with shot noise. In other words, if the film grains are evenly dispersed (equal number per area), and if each grain possesses an identical and independent probability of transforming into a dark silver grain after the absorption of the photons, the number of the corresponding dark grains in a specified area tends to be arbitrary with a binomial distribution.
However, in the case of areas with inferior probability, the corresponding distribution tends to be very close to the classic Poisson distribution of the shot noise. Still, an easy and plain Gaussian distribution is habitually preferred and employed as an appropriate and precise model.

Non-Isotropic Noise

It also happens that certain types of noise sources surface with an amazing orientation in the images. For instance, the image sensors are at times subjected to row or column noise. Scratches in the film represent an instance of the non-isotropic noise. Despite the difficulty involved in the elimination of the entire image noise cutting back the image noise to a limited extent is still possible. In this regard, corrective filters offer a ray of hope as a potential tool which extends a helping hand in considerably cutting down the image noise.

v) Speckle Noise (Multiplicative Noise)

While Gaussian noise can be shaped by the arbitrary values supplemented to an image, speckle noise can be fashioned by the arbitrary values multiplied by the pixel values, and thus it is also known by the name “multiplicative noise”. This version of the noise has emerged as a zooming challenge in the case of certain radar applications (Kaur et al. 2012).

Periodic Noise

When the image signal is subjected to an intermittent hassle instead of an arbitrary disturbance, the image obtained is tainted by the periodic noise, with the impact of having bars over the image. When the images are communicated through the channels, they become tainted with impulse noise on account of the noise-contaminated channels. The corresponding impulse
noise is home to a large number of positive and negative spikes. The positive spikes, in turn, possessing values far greater than the background emerge as the bright spots, while the negative spikes containing values lesser than the background appear as the darker spots. However, the two kinds of spots for the positive and negative spikes are visible to the human beings. Moreover, the Gaussian type of noise is also found to adversely affect the image (Vandana Devi et al. 2015).

1.4 NEED OF IMAGE DENOISING

Hence, it is highly essential to initiate the denoising as the primary step before assessing the image data. Thus the paramount need of the hour is to launch an efficient denoising method to recompense for the relative data contamination (Motwani et al. 2004). However, continuation of the image causing to heart burns to the intriguing investigators is rather disheartening, especially in view of the fact that the noise elimination brings in artifacts, and results in the blurring of the images (Alka Vishwa et al. 2013).

1.4.1 Evolution of Image Denoising

Over the years, Image Denoising has continued to be a pressing issue in the realm of image processing. In this regard, the wavelets turned out a spectacular performance in the image denoising thanks to the glittering qualities like sparsity and multi-resolution configuration. As the Wavelet Transform was offered a red carpet welcome due to its sterling performances in the past twenty years, there was a flood of innovative techniques devoted to the purpose of denoising in the wavelet domain. The cynosure of enthusiasm was shifted from the sphere of the Spatial and Fourier to the realm of the Wavelet transform.

Right from the publication of the Donoho’s Wavelet based thresholding technique in the glorious year of 1995; there has been a deluge in
the publication of various investigations devoted to the denoising task. Admitting the fact that Donoho’s theory could not be described as ‘revolutionary’ in the literal sense of the term, the advantages that accompanied his techniques were so important that they virtually eliminated the need for the tracking or correlation of the wavelet maxima and minima across the diverse scales as envisaged by Mallat (Thorat et al. 2014). With the result, there emerged a zooming enthusiasm in the wavelet based denoising approaches right from the time when Donoho’s brought in a simple technique to successfully address a thorny issue. The disinterested investigators vied with one another in flagging off innovative methods to estimate the constraints for the thresholding of the wavelet coefficients. The Data adaptive thresholds were kick-started so as to usher in an optimum value of threshold. Subsequent investigations established the fact that amazing augmentation in the perceptual quality could be achieved by the translation invariant techniques dependent on the thresholding of an Un-decimated Wavelet Transform. The corresponding thresholding approaches were initiated on the non-orthogonal wavelet coefficients with the objective of considerably cutting down the artifacts. The Multi-wavelets were also elegantly employed to usher in identical outcomes.

Further, the Probabilistic models employing the statistical properties of the wavelet coefficient forged ahead and excelled the parallel thresholding approaches by gaining an unbeatable edge over the peer techniques. Of late, a renewed enthusiasm and an enhanced endeavor have been witnessed, with the untiring investigators investing their sweat and blood and focusing on the Bayesian denoising in the Wavelet domain. The Hidden Markov Models and Gaussian Scale Mixtures have also emerged as star
performers inviting extensive public appeal and acclaim. Literature is literally flooded with various publications related to the popular topics in this regard, with the research blooming in full swing.

Many researches have been carried out on the Tree Structures ordering the wavelet coefficients in accordance with their magnitude, scale and spatial location. Further, the Data adaptive transforming like the Independent Component Analysis (ICA) has been deeply investigated for sparse shrinkage. The horizon of exploration is widened with a special focus on employment of diverse innovative statistical tools to fine-tune the statistical qualities of the wavelet coefficients and their neighbors. Upcoming experimenters, it is hoped making strenuous efforts in the direction of denoising approaches (Megha Soni et al. 2014).

1.5 TYPES OF IMAGE DENOISING APPROACHES

At present, there are two fundamental approaches to image denoising viz., the spatial filtering techniques and the transform domain filtering methods.

1.5.1 Spatial Filtering

One of the time-tested techniques to take away noise from image data is the deft deployment of the spatial filters, which can be broadly categorized in two distinct groups, viz., the non-linear and linear filters.
Figure 1.1 Hierarchical Diagram of Denoising Techniques

i) Linear Filters

A Linear filter serves the purpose of eliminating certain specified categories of noise. The Averaging or Gaussian filters emerge as the ideal candidates for the purpose. Unfortunately, these filters are plagued by a volley of deficiencies in as much as they exhibit a tendency to distort the sharp edges
and cause destruction to the lines and the parallel excellent image details. Further, they turn out a very substandard accomplishment in the presence of signal-dependent noise, for example, and the Gaussian mask consists of elements decided by a Gaussian function. This convolution phenomenon brings the value of each pixel into an intimate accord with the values of its neighbors.

As a rule, a smoothing filter invariably sets each pixel to the average value, or a weighted average, of itself and its immediate neighbors and the Gaussian filter is merely one probable set of weights. Smoothing filters have a tendency of distorting an image, in view of the fact that the pixel intensity values which are considerably greater or lesser than the immediate neighborhood would "smear" across the area. On account of the related distortion, linear filters are not generally employed for the purpose of noise decrease, despite being habitually utilized as the foundation for the nonlinear noise reduction filters.

ii) Adaptive Filter

The wiener function is highly relevant to a Wiener filter which represents one of the categories of a linear filter and is applied on an image adaptively, fashioning itself to the local image variation. When the variation is huge, the wiener is able to ensure only modest smoothing. On the other hand, in the case of small variations, the wiener comes out with flying colors having accomplished impressive smoothing. It is established that this technique scores an edge over the linear filtering by ushering in superior outcomes.

Further, the adaptive filter is found to be highly discriminating via-a-via an analogous linear filter, in conserving the edges and other high-frequency segments of an image. Moreover, there is no need for any design
functions. Wiener2 function is able to successfully tackle all the primary estimations employing the filter for an input image. Wiener2, on the other hand, takes an elongated evaluation period in relation to the time spent by the linear filtering.

The performance of the Wiener is seen to be excellent when the noise is constant-power ("white") additive noise, like the Gaussian noise. An alternate technique for eradicating the noise is by means of developing the image under a smoothing partial differential equation identical to the heat equation which is known as the anisotropic diffusion (Kaur et al. 2012).

iii) Non-Linear Filters

During the last few years, a slew of nonlinear median type filters like the weighted median, rank conditioned rank selection, and the relaxed median have been elegantly flagged off, with the intention of overwhelming the deficiencies (Chaabouni et al. 2012).

Median Filter

A median filter represents an excellent example of a non-linear filter. When correctly configured and constructed, it goes a long way in appropriately conserving the image detail. The following steps have to be carried out for purpose of performing a median filter.

- Each and every pixel in the image has to be taken into account.

- Subsequently, orchestrate the adjacent pixels into order based upon their intensities.

- Substitute the original value of the pixel with the median value from the list.
A median filter represents a rank-selection (RS) filter constituting a predominantly ruthless member of the family of rank-conditioned rank-selection (RCRS) filters. A highly milder member of the corresponding family, for instance, is one which chooses the closest of the adjacent values when a pixel's value is exterior in its vicinity, and leaves it unaffected otherwise, is at times favored, particularly in the photographic applications.

The Median and the parallel RCRS filters exhibit excellence in eliminating the salt and pepper noise from an image, with comparatively trivial distortion of the edges, and thus endearing them eligible for the effective employment in the domain of the computer vision applications. The Median filtering is analogous to the employment of an averaging filter, in as much as each output pixel is fixed to an average of the pixel values in the vicinity of the related input pixel. Nevertheless, with the median filtering, the value of an output pixel is decided by the median of the adjoining pixels, instead of the mean. The median is found to be less susceptible to extreme values known as the outliers via-a-via the mean. Hence the Median filtering is competent to efficiently eradicate the outliers without causing any change in the sharpness of the image (Farooque et al. 2013).

**Fuzzy Filter**

The Fuzzy filters are competent to furnish amazing outcomes in the image-processing functions which successfully tackle certain deficiencies of the classical filters. The Fuzzy filter is well-geared to address the issue of ambiguous and tentative data. At times, it is necessary to restore a deeply noise tainted image containing a number of reservations where the fuzzy set theory appears with a helping hand.

Each pixel in the image is characterized by a membership function and diverse categories of the fuzzy rules which take into account the neighborhood data or the parallel data for eradicating the noise with indistinct
edges but the fuzzy filters effectively carry out both the edge conservation and the smoothing. Image and fuzzy set may be shaped in an identical manner.

1.5.2 Transform Domain Filtering

The transform domain filtering techniques can be categorized in phase with the selection of the basic functions, which, in turn, may again be subdivided into two distinct types viz., the adaptive and non-adaptive data. The Non-adaptive transforms have emerged as widely acknowledged methods, These are detailed below (Thorat et al. 2014).

a) Non-adaptive transforms

Spatial-Frequency Filtering

Spatial-frequency filtering generally constitutes the employment of low pass filters by means of the Fast Fourier Transform (FFT). Elimination of the noise in the frequency smoothing techniques is carried out by designing a frequency domain filter and adapting a cut-off frequency when the noise segments are de-correlated from the functional signal in the frequency domain. These techniques are found to incur a lot of time and also heavily depend on the cut-off frequency and the filter function conduct. In addition, they are likely to generate the artificial frequencies in the processed image.

Wavelet domain

Filtering functions in the wavelet domain are generally categorized into two distinctive techniques viz., the linear and nonlinear approaches.

Linear Filters

The Linear filters like the Wiener filter in the wavelet domain bring in optimal outcomes when the signal corruption is shaped as a Gaussian
procedure and the precision standard is represented by the mean square error (MSE). Nevertheless, devising a filter based on this theory habitually ends up in a filtered image which is highly distressing visually vis-à-vis the original noisy signal, though the filtering function effectively cuts down the MSE. In a wavelet-domain spatially adaptive FIR Wiener filtering for image denoising is launched where wiener filtering is carried out only within each scale and intra-scale filtering is not permitted (Patil et al. 2013).

**Non-Linear Threshold Filtering**

The most researched realm in denoising employing the Wavelet Transform is the non-linear coefficient thresholding based techniques. The process effectively employs the sparsity quality of the wavelet transform and the efficacy of the Wavelet Transform for mapping the white noise in the signal domain to the white noise in the transform domain. Thus, while signal energy emerges as highly focused into fewer coefficients in the transform domain, noise energy does not toe the line.

It is this significant postulation which facilitates the severance of the signal from noise. The process where the small coefficients are eradicated without affecting the others is known as the Hard Thresholding. However, the captioned technique produces bogus blips, otherwise called the artifacts, in the images on account of the failed endeavors in regard to the elimination of comparatively huge noise coefficients. It is with the intention of overwhelming the deficiencies of the hard thresholding that the wavelet transform employing soft thresholding has been given the green signal.

In this approach, the coefficients greater than the threshold are minimized by the absolute value of the threshold itself. Identical to the soft thresholding, the parallel methods of applying the thresholds include the semi-soft thresholding and Garrote thresholding. A large majority of the
wavelet shrinkage literature is dependent on the techniques for selecting the optimal threshold which is either adaptive or non-adaptive to the image.

**a. Non-Adaptive thresholds**

The VISU Shrink represents a non-adaptive universal threshold, which invariably depends only on a number of data points. It possesses the asymptotic equivalence indicating superlative execution with regard to the MSE when the number of pixels tends to infinity. The VISU Shrink is competent to achieve overly smoothed images in view of the fact that its threshold choice tends to be unduly huge on account of its reliance on a number of pixels in the image.

**b. Adaptive Thresholds**

The SURE Shrink elegantly employs a deft blend of the universal threshold and the SURE (Stein’s Unbiased Risk Estimator) threshold and ushers in a superlative performance vis-à-vis that of the VISU Shrink. The Bayes’ Shrink is able to make a significant reduction in the Bayes’ Risk Estimator function assuming the Generalized Gaussian prior and thereby bringing in the data adaptive threshold. The Bayes’ Shrink scores a clear edge over the SURE Shrink in a large majority of the instances.

The Cross Validation substitutes the wavelet coefficient with the weighted average of neighborhood coefficients to reduce the generalized cross validation (GCV) function furnishing the optimum threshold for every coefficient. The hypothesis that it is possible to discriminate the noise from the signal exclusively dependent on the coefficient magnitudes is infringed when noise levels are superior to the signal magnitudes. In the backdrop of such an elevated noise scenarios, the spatial design of the neighboring wavelet coefficients is capable of casting a vital part in the noise-signal
categorizations. The signals invariably exhibit a tendency to generate significant features such as the straight lines and curves, as against the noisy coefficients which habitually spread out arbitrarily.

**Non-orthogonal Wavelet Transforms**

The Un-decimated Wavelet Transform (UDWT) is also one of the methods which have been extensively employed for disintegrating the signal to furnish a visually superior solution. As the UDWT tends to be shift invariant, it is capable of keeping at bay the visual artifacts like the pseudo-Gibbs phenomenon. Despite the presence of incredible enhancement in the outcomes, the employment of the UDWT considerably scales up the cost of computations, thereby making it unviable. The standard hard/soft thresholding has been expanded to the Shift Invariant Discrete Wavelet Transform.

**Wavelet Coefficient Model**

This technique is concerned with the utmost utilization of the multi-resolution qualities of the Wavelet Transform. Further, it locates the intimate relationship of the signal at diverse resolutions by observing the signal across numerous resolutions. Though this technique is capable of achieving superlative outcomes, it is found to be highly intricate computationally and cost-prohibitive too. The designing of the wavelet coefficients may precede either in the deterministic or statistical method.

**a. Deterministic**

The Deterministic method of modeling includes the generation of the tree structure of the wavelet coefficients with every level in the tree characterizing each scale of renovation and nodes signifying the wavelet coefficients. The optimal tree approximation illustrates a hierarchical analysis
of wavelet disintegration. The Wavelet coefficients of singularities possess huge wavelet coefficients which persist along the branches of the tree. Thus if a wavelet coefficient has a robust presence at a specified node, happening to be a signal, its presence has to be highly manifested at its parent nodes. If it happens to be a noisy coefficient, like e.g., the bogus blip, such type of reliable presence will not be available.

b. Statistical Modeling

This type of method provides its attention on certain enthusing and attractive qualities of the Wavelet Transform like the multi-scale correlation between the wavelet coefficients, local correlation between the neighborhood coefficients and so on. The underlying objective behind the technique is the perfection of the precise modeling of image data by employing the Wavelet Transform. There are two methods which employ the statistical qualities of the wavelet coefficients based on a probabilistic model, which is detailed below.

i. Marginal Probabilistic Model

A host of investigators have come out successful in flagging off innovative homogeneous local probability models for the images in the wavelet domain. Particularly, the marginal distributions of wavelet coefficients are extremely kurtotic, and possess a striking peak at zero and grave tails. The Gaussian mixture model (GMM) and the generalized Gaussian distribution (GGD) are extensively employed sharpening the wavelet coefficients distribution. Despite the GGD being competent to generate amazingly accurate outcomes, the GMM glistens with the quality of ease of use.


**ii. Joint Probabilistic Model**

Hidden Markov Models (HMM) models have emerged as proficient techniques in capturing the inter-scale dependencies, as against the Random Markov Field models which have proved their mettle in capturing the intra-scale correlations. However, the intricacy of the local structures is not effectively defined by the Random Markov Gaussian densities whereas the Hidden Markov Models are well-equipped with the skills needed for capturing the higher order statistics. The correlation between the coefficients at identical scale but residing in an intimate vicinity are fashioned by the Hidden Markov Chain Model whereas the correlation between the coefficients across the chain is designed by the Hidden Markov Trees. When the correlation is captured by the HMM, the Expectation Maximization is effectively employed for evaluation of the requisite constraints from which the denoised signal is evaluated from the noisy observation by means of the well-acclaimed MAP estimator (Motwani et al. 2004).

**1.5.3 Data-Adaptive Transforms**

The character of the adaptive filters fluctuates on the basis of the attributes of the image in the interior of the filter region. Of late, a groundbreaking technique known as the Independent Component Analysis (ICA) has emerged as the cynosure among the inquisitive investigators. The striking feature of the ICA lies in its supposition of the signal to be Non-Gaussian which goes a long way in denoising the images with the Non-Gaussian and the Gaussian distribution. The dismal deficiencies of ICA based technique vis-à-vis the wavelet based approaches are reflected in the cost of evaluation, in view of the fact they employ a sliding window and hence needs sample of noise free data or at least two image frames of the identical scenario. In some applications, it might be difficult to obtain noise free training data (Motwani et al. 2004).
1.6 IMAGE RESTORATION

The Image restoration represents the procedure wherein the tainted image is subjected to denoising methods with the intention of regaining the original image. It is entrusted with the elegant duty of fine-tuning the looks of an image by way of the execution of a restoration task in which a mathematical model is deftly deployed so as to get rid of the image degradation (Firas Ali 2007), which may be triggered on account of the numerous features such as the corresponding object-camera motion, distortion originated by the erroneous focus of the camera and the related atmospheric turmoil (Chug et al. 2015).

The image restoration approach invests its attention on performing certain types of inverse processes with the intent to attain the accurate image. A lion’s share of the image restoration methods normally tends to regain the image either linearly or non-linearly by cutting back certain events of the degradation (Shabnam Sultana et al. 2013).

1.6.1 Image Restoration Phases


Figure 1.2 Stages of Image Restoration
In this regard, the stream of the Image Restoration procedure flows through two phases such as the degradation and restoration phases (Tiwari et al. 2014), which are detailed as follows and also depicted in Figure 1.2.

1. Degradation

2. Restoration

i) Degradation

Deformation habitually crops up in the recorded images, on account of the deficiencies present in the imaging technique and gets aggravated by the arbitrary noise implied in the imaging. The Degradation process functions on the input image f(x, y) to diminish a degraded image g(x, y). With g(x, y) certain data relating to the degradation function H and the data on the noise term are supplemented as the ultimate objective of the image restoration process is to effectively attain an estimate f′(x, y) of the original image f(x, y) (Maurya et al. 2014).

Incidentally, the digital image restoration can be represented as a procedure wherein an earnest attempt is made to achieve an approximation to f(x, y). The blurred image is characterized by means of the equation shown below:

**Blur Type**

In this regard, the general categories of the blur effects cropping up in the digital camera may be broadly categorized in to four distinct types as detailed hereunder.

a) Average Blur

The Average blur represents one of the several devices effectively employed to get rid of noise and specks in an image and has to be utilized
when the entire image is tainted with the noise. This kind of blurring may be dispersed both horizontally and vertically and may be represented as circular averaging by radius.

\textit{b) Motion Blur}

There are several kinds of the motion blur which can be distinguished. They crop up on account of the corresponding motion between the recording device and the background. This motion may take the shape of a translation, a rotation, an abrupt transformation of scale, or certain permutations of the three types of motions. The impact of the Motion Blur effect represents a filter which entails the image appearing to move by supplementing the blur in a particular direction. It is possible to regulate the relative motion by means of the angle or direction such as in the range of (0 to 360 degrees) or (–90 to +90) and/or by distance or intensity in pixels within the range of (0 to 999), depending on the software deployed for the purpose.

\textit{c) Gaussian Blur}

A Gaussian blur generally originated by the blurring of an image by the Gaussian function and is an extensively used effect in the graphics software, classically to cut down the image noise and diminish the detail. It also elegantly functions as a pre-processing stage in the computer vision technique with the intent to fine-tune the image structures at various scales. Further, the Gaussian Blur effect represents a filter which integrates a precise number of pixels incrementally, forming a bell-shaped curve. The blurring is actively concentrated at the centre and feathers at the edges. This is essentially applied on an image when a significant regulation over the Blur effect is needed.
**d) Out-of-focus Blur**

Let us take the case of a camera which images a 3-D scene onto a 2-D imaging plane. Here, certain segments of the scene are highly focused, at the expense of the residual segments, where the focusing is hazard. When the aperture of the camera is circular, the image of any point source constitutes a small disk, called the circle of confusion (COC). The degree of defocus (diameter of the COC) is dependent on the focal length and the aperture number of the lens, and the distance between camera and object. A highly precise model in addition to defining the diameter of the COC, also describes the intensity of allocation inside the COC (Singh et al. 2013).

**Drawbacks of Degradation:**

The telling instances of the diverse kinds of the degradation encompass the blurring initiated by the motion of atmospheric annoyances, geometric deformation brought in by the defective lenses, superimposed hindrance models emanating from the mechanical systems, noise emitted by the electronic sources, as exemplified in the acquisition of the images with a CCD camera, light levels and sensor temperature and they have an incredible sway on the quantity of noise in the consequential image (Firas Ali 2007).

Hence, with an eye on overwhelming the degradation challenges in the image, numerous visibility restoration techniques are performed on the image in order to usher in a superlative quality of the image. Thus the image restoration approaches proficiently perform the duty of metamorphosing the tainted image into a shape which is more or less analogous to that of the original image. In this connection, image enhancement refers to the procedure in which the degraded image is maneuvered to enable fine tuning of the visual manifestation of the image. It effectively enhances the distinction of the image and is a subjective process. However, the image restoration emerges as
a highly objective procedure in relation to the process of the image enhancement (Chug et al. 2015).

### 1.6.2 Restoration

#### i) Classification of image restoration techniques

The image restoration approaches invariably resort to the inversion of certain degrading procedures. They can be generally categorized into two kinds based on the awareness of the degradation such as the deterministic and stochastic methods. The former type viz. the deterministic technique of image restoration is effectively employed, when there is previous awareness regarding the degradation. When such a prior knowledge is conspicuous by its absence, the stochastic approach of image restoration appears as the ideal candidate for employment. In fact, the restoration process leads to the surfacing of the artefacts near the edges, as it is very difficult for the linear techniques to regain the misplaced/lost frequency segments thus paving the way for the incidence of the Gibbs effect (Maurya et al. 2014).

#### ii) Categories of Image Restoration Techniques

The fundamental motive of the Image Restoration is dedication for restoration of the original image from a tainted image which is vague on account of a degradation function, generally known as the Point Spread Function (PSF). The Image Restoration methods are generally classified into two distinct types in accordance with the awareness regarding the PSF:

1) **Blind Image Restoration:** This type of approach permits rebuilding of the original images from tainted images even without the necessity to have any prior knowledge regarding the PSF. In this regard, the Blind Image Deconvolution (BID) represents an outstanding technique owing allegiance to this approach.
2) **Non-Blind Restoration:** This kind of method lends a helping hand for the restoration of original images from tainted images when there is proper comprehension regarding the manner in which image has been degraded, indicating a prior knowledge of the PSF. The telling examples of this kind of techniques include the De-convolution employing the Lucy Richardson Algorithm (DLR), De-convolution utilizing the Weiner Filter (DWF), De-convolution employing the Regularized Filter (DRF) (Kaur et al. 2012).

3) **Point spread function (PSF):** The PSF is a measure of the extent to which an optical system is capable of blurring or spreading a point of light. In fact, it represents the inverse Fourier transform of the optical transform function (OTF) in the frequency domain. The OTF, in essence, deftly defines the feedback of a linear, position-invariant mechanism to an impulse and elegantly represents the Fourier transfer of the point (PSF) (Maurya et al. 2014).

iii) **Blind Image De-convolution Method**

The distinctive procedure which segregates the two signals convolved is popularly known as the de-convolution problem. In cases, where the signals are unidentified, it is included under the umbrella of the blind technique. The segregation of the signals by means of the blind de-convolution methods starts with certain distinctive qualities of both the signals which are to be subjected to the process of de-convolution. For the purpose of getting the solution, certain signal qualities have to be recognized and preserved as vague as possible. In fact, the blind de-convolution is doing its elegant rounds by being extensively employed in the diverse domains of the seismic, speech, signal processing and the image processing.

In view of the quickly varying refractive index of the atmosphere, the ground-based imaging technique was subjected to several types of blurring and this phenomenon emerged as the debut setting for applying the
restoration method. The scenario has experienced a sea change with a red carpet welcome being extended by the multifarious practical applications making a clarion call for the blind de-convolution technique these days. The blind de-convolution of images is at present carried out by means of either of the two methods (Mythili et al. 2011).

1) At the outset, the degradation function, PSF, gets recognition and is followed by the application of any one of the outstanding classical restoration approaches like the inverse filtering, wiener filtering, pseudo inverse filtering, for the purpose of detection of the accurate image. This technique has the sheen of significant simplicity together with incredible reduction in the computation costs. The techniques toeing this kind of approach are termed as the priori blur identification methods.

2) The recognition of the PSF and the accurate image is performed concurrently in the restoration techniques.

iv) Non-blind De-convolution

The non-blind approaches such as the inverse filtering and the wiener filtering represent the direct techniques of the image restoration, though they are adversely affected by certain grave deficiencies. They turn out the sub-standard restoration outcomes with the vague awareness of the blurring. The Inverse filtering approach for the image restoration may be elegantly employed to effectively regain the image if the blur kernel or point spread function is identified; however, the noise magnification paves the way for the inferior de-blurring upshots.

i) De-convolution using Wiener Filter

The Weiner Filtering also constitutes a non blind approach for rebuilding the tainted image when there is proper awareness of the PSF. It is
endowed with the skills of effectively eradicating the additive noise and inverting the blurring concurrently. It is able to carry out the de-convolution by means of the inverse filtering such as the high pass filtering and efficiently eliminate the noise with a compression function like the low pass filtering. It is contrasted with an evaluation of the preferred noise-free image. The input to a wiener filter represents a degraded image tainted by means of the additive noise. The output image is evaluated with the help of a filter.

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\[ a) \quad \text{Inverse filtering} \]

Direct inverse filtering is generally considered as the easiest method devoted to the restoration process. In this technique, an evaluation of the Fourier transform of the image is carried out by dividing the Fourier transform of the degraded image by the Fourier transform of the degradation function. The approach turns ideal in the absence of any additive noise in the degraded image. However, if the noise is added to the tainted image then the outcomes of direct inverse filtering are far from satisfactory. The direct inverse filtering meets with a waterloo and fails miserably when the tainted image contains the additive noise. This is because of the fact that the noise tends to be arbitrary and hence it is not easy to locate the noise spectrum.

\[ \text{ii) De-convolution using Regularized Filtering} \]

Regularized filtering is efficiently employed when the parameters such as the smoothness are performed on the restored image and only scant knowledge is available regarding the additive noise. The blurred and noisy image is regained by a constrained least square restoration technique which deftly deploys a regularized filter. The regularized restoration furnishes the outcomes identical to those of the wiener filtering, though it holds a divergent perspective. In this type of filtering, only minimal previous data is needed for the purpose of carrying out the restoration. The regularization filter is
habitually selected as a discrete Laplacian, which can be regarded as an estimate of a Wiener filter.

iii) De-convolution using Lucy Richardson

The DLR characterizes a non-blind approach of image restoration, which is generally employed to regain a degraded image which is tainted by an identified PSF. It represents an iterative process wherein the pixels of the observed image are expressed by means of the PSF (Mythili et al. 2011).

1.6.3 Image In-Painting

The Image In-painting refers to an innovative method effectively employed to restore the spoiled image and to fill up the regions which are omitted in the original image in a visually conceivable manner. The In-painting, in essence, represents the method of renovating an image in a hidden form, and has persisted to be an art cultivated from times immemorial. The versatile applications of the novel approach encompass the reconstruction of the spoilt photographs and films, elimination of the superimposed text, deletion/substitution of redundant objects, red eye rectification, image coding. The ultimate objective of the In-painting is dedicated to the conversion of the spoiled region in an image (Senthilsevi et al. 2014).

The Image In-painting techniques can be broadly categorized into various kinds as detailed below.

**Texture Synthesis Algorithm**: They effectively sample the texture from the region outside the region required to be in-painted. It is well-established in the case of the textures, replicating the two dimensional patterns with certain arbitrariness (Senthilsevi et al. 2014).
Structure Recreation: They make an earnest endeavor to rebuild the configurations such as the lines and object contours. They are habitually employed in cases where the region to be in-painted is very minute. Further, the vital attention is concentrated on the linear structures which are deemed to be one dimensional pattern like the lines and the object contours (Senthilsevi et al. 2014).

1.7 APPLICATIONS OF IMAGE INPAINTING

- Repairs to the Photographs: With the passage of time, it is only natural that the photographs generally become blemished or dented. It is very easy to get rid of the corrosion with the deft deployment of the In-painting.

- Elimination of the Redundant Objects: By the proper application of the In-painting, it is possible to eliminate the redundant objects and texts from the image.

- Special Effects: The In-painting is elegantly employed for the purpose of generating special effects.

- Video In-painting: If it is enlarged to the domain of the video In-painting, it emerges as an attractive gadget for the purpose of generating special effects etc (Senthilsevi et al. 2014).

1.7.1 Applications of Image Restoration in the field of Image Restoration

- The debutant application of the digital image restoration in the engineering community was in the ever-zooming arena of the astronomical imaging. The extraterrestrial surveillances of the Earth and other planets in the Milky Way were tarnished by the
motion blur on account of the sluggish camera shutter momentum in relation to the cosmic spacecraft motion. The astronomical imaging degradation challenge is habitually originated on account of the Poisson noise, Gaussian noise and the like.

- In the amazing arena of medical imaging, the contribution made by the image restoration knows no bounds. The image restoration is extensively employed in the domain of the mammograms, for the filtering of Poisson distributed film-grain noise in the chest X-rays and the digital angiographic images, and also for the purpose of eliminating the additive noise in Magnetic resonance Imaging.

- A vital application of the restoration approach is dedicated for the regaining of very old and degenerated films. The motion picture restoration is habitually related to the digital methods which are effectively employed to eradicate the scratches and dust from the good-old movies and also to add attractive colors to the black and white films. The literature is literally flooded with a multitude of fruitful investigations in the horizon of restoration of image sequences along with a reasoned review of the recent works in this regard.

- The ever-zooming domain of the applications for the digital image restoration is in the realms of the image and video coding. The novel approaches are green-signaled with an eye on scaling up the coding efficiency, and dipping down the bit rates of the coded images. Many fruitful explorations have been carried out to put in place proficient techniques devoted to the
restoration of the coded images as a post-processing exercise to be undertaken soon after decompression.

Further, the Digital image recovery is also effectively employed for the purpose of restoring the tainted X-ray images of aircraft wings to incredibly augment the aeronautical federal control processes. It is intended for the recovery of the motion instigated in the current frame or multiple effects, and is habitually utilized for the restoration of the television images tainted evenly.

1.8 RESEARCH CONTRIBUTIONS

Denoising is a major challenging factor in the field of image processing. Many researchers have utilized filter methods for meeting the challenge. The filter-based methods efficiently remove noise; however, they do not preserve image quality and information. A good noise filter is mandatory to fulfil the following criteria: (1) smothering noise and (2) safeguarding helpful data in the picture. Recently, hybrid filters were developed to remove the impulse noise and restore the images by preserving the information. This method is not suitable for removing the higher level impulse noise and other types of noises. Moreover, the existing filters can remove only single type of noise from the images. So, the application of existing filter methods degrades the denoising performance. To overcome the aforesaid drawbacks, a hybrid filter with Adaptive Genetic Algorithm has been proposed. In this thesis we are motivated to apply the idea of denoising and restoration using the hybrid filter.

Based on aforementioned investigations, in this thesis, an attempt has been made to investigate the denoising and restoration of images using a new filter based method using Adaptive Genetic Algorithm (AGA).
1. To improve the quality of an image by preserving the edge pixels of an image and by removing the random impulse noise using both filtering and non-filtering techniques. Therefore, the research plans to analyse the better restoration in filtering method using Decision Tree Based Impulse Detector (DTBID) process & non-filtering method using Levenberg Marquardt algorithm and artificial neural network.

2. To enhance the sharpness of an image by suppressing Gaussian & Speckle noises using both iterative and non-iterative methods. To compare the quality metrics like PSNR, SSIM and Convergence time, few iterative methods like interpolation, inpainting and denoising are analysed and compared with the non-iterative method called adaptive bilateral filtering.

3. To restore the image from noisy image by shining the pixel values using soft computing technique. To enhance the Signal to Noise Ratio (SNR) and retain the original content of an image a novel technique is proposed.

4. An innovative technique is proposed for improving the denoising ratio called Optimized Gradient Histogram Preservation (OGHP) and Stein’s Unbiased Risk Estimate (SURE) Shrinkage. Therefore, we sketch to analyse the excellence of the milestone method by analysing and contrasting with the modern noise free image restoration technique.

1.9 ORGANISATION OF THE THESIS

Chapter 1 provides the exhaustive background theory required to understand this thesis. In the background theory, the concept of image processing, different types of noises in Digital Image Processing (DIP), denoising and restoration of an image & different algorithm and enhancement
of an image along with edge preservation have been presented. Later, the motivation, objectives of this research and the organization of the thesis have been discussed clearly.

Chapter 2 presents a survey which provides a concise discussion of the earlier denoising and restoration techniques using different image formats, importance of DIP, different noise reduction techniques, comparative study between image processing and other system which uses similar techniques and some recent developments in digital image restoration.

Chapter 3 deals with the restoration of an image by preserving the edge pixels of an image and by removing the random impulse noise using both filtering and non-filtering techniques. Therefore, we plan to analyze the better restoration in filtering method using DTBID process & non-filtering method using Levenberg Marquardt algorithm and artificial neural network.

Chapter 4 presents enhancement of the sharpness of an image which is done by suppressing Gaussian & Speckle noises using both iterative and non-iterative methods. In order to compare the quality metrics like PSNR, SSIM and Convergence time, few iterative methods like interpolation, inpainting and denoising are analyzed and compared with the non-iterative method called Adaptive Bilateral Filtering (ABF).

Chapter 5 addresses the proposed method by shining the pixel values using soft computing technique to restore the image from noisy image. Hybrid filter with AGA is used to enhance the SNR and retain the original content of an image. In this proposal, enhancement of both black and white & color images are concentrated on the selected image chromosomes during restoration.
Chapter 6 discusses the method of considering the improvement of denoising ratio with the help of Optimized Gradient Histogram Preservation (OGHP) and Stein’s Unbiased Risk Estimate (SURE) Shrinkage. Also to prove the efficiency of PSNR & AGA technique is also used at the final stage of restoration.

In Chapter 7, the conclusions of major contributions offered in this thesis are presented. Quality enhancement of a noisy image is done by using a new denoising & restoration techniques. First, image denoising algorithms have been developed in order to improve the sharpness of an image. Second, image restoration is done by shining the pixel values and by concentrating on the selected image chromosomes. Also image restoration has been performed using OGHP and SURE shrinkage techniques. Finally all the quality metrics (like PSNR, SSIM and Convergence time etc.,) are compared with the existing filter methods.