CHAPTER 4

PREPROCESSING ALGORITHM

The first step of AESDDM (Phase I of the research work) is preprocessing, which consists of tasks that enhance the visual quality of the input mango fruit image, so as to improve the performance of the subsequent steps of defect detection. This step is considered as important as almost all images acquired through digital cameras have noise added to it. The main goal of Phase I is to remove unwanted pixels (noise) from the input mango fruit image, while retaining important details.

As mentioned in earlier chapters, fruit images are often degraded by the presence of impulse noise. In general, the task of removing/suppressing noise from an image is considered as a challenging area as it is irreversible and removal of significant details result in decreasing the overall performance of the ADDS. Raman and Himanshu (2010) have further stressed this fact by reporting that the usage of correct denoising algorithms is very important before analysis, recognition and fault detection.

During image acquisition, inhomogeneities occur due to variance in relative position of the light source, camera position and the fruit position. These inhomogeneities make some part of the image appear darker and many have uneven contrast. Moreover, the presence of impulse noise (appearing as bright dots or dust particles) also degrades and distorts the images. Impulse noise can be fixed-valued (salt and pepper) or random-valued noise. Both of these can be mistakenly identified as defect pattern and therefore it is imperative that it is removed.

Presence of noise degrades spatial and contrast resolution and obscures the underlying structure of an image. Further, it has a negative impact on fruit imaging where the presence of noise shows a reduction of surface detectability of approximately a factor of eight (Bamber and Daft, 1986). This radical reduction in contrast resolution prevents automatic defect detection algorithms to perform efficiently and gives the image a grainy appearance. Hence, denoising is considered as a critical pre-processing step by many ADDS of agricultural products.

An effective noise reduction method for this type of noise involves the usage of any one of the several types of available noise reduction techniques. They include median filter (Hsieh *et al.*, 2013), Vector Median Filter (VMF) (Jubair and Dey, 2012), Switching Median Filter (SMF) (Mukhopadhyay and Mandal, 2014), anisotropic diffusion filter (Barbu, 2014) and wavelet-based filters (Liu, 2015). All of these methods have been enhanced and optimized for noise removal by several researchers (Yue *et al.*, 2015; Zeng *et al.*, 2015).

Among the various proposed methods, the median filter is one of the most commonly used non-linear filters. This method has the advantages of being successful in removing impulse noise, being simple and computationally inexpensive. However, the median filter has two main disadvantages as listed below.

(i) Signal weakening (image edges are blurred)

(ii) Affects non-corrupted (noise free) image pixels

From the review of literature (Chapter 2), it can be understood that eventhough several solutions have been proposed to solve this problem, the issue is still not yet completely resolved. Among the various solutions, the usage of a switching median filter is more popular (Judith and Kumarasabapathy, 2011). This research work enhances the conventional SMF by including adaptive fuzzy and PSO techniques to remove impulse noise from mango fruit images. The chapter begins with a formal discussion on the fundamentals of noise, followed by a brief discussion on traditional switching median filter and the proposed noise removal algorithm.

4.1. IMPULSE NOISE

Any digital image is degraded by the presence of two undesirable effects, namely, blur and noise. Blur is generally inherent to image acquisition systems (Shannon and Weaver, 1998) and degrade edge content and makes the transition from one color to the other very smooth. Image noise, on the other hand, is the random variation of brightness or color information in images produced by the capturing devices like camera. The presence of noise in mango fruit images is considered as an undesirable characteristic that may affect the performance of subsequent steps of AESDDM like segmentation and feature extraction. This necessitates the need for an efficient restoration or denoising algorithm that can remove or suppress these unwanted pixels while preserving important features.

The mango image, after acquisition using digital camera, consists of either gray-scale values or colour values, encoded in the form of a matrix. This matrix is either 2-dimensional (gray scale) or 3-dimensional (color images). Each element of the matrix is of the form (i, v(i)), where i is the pixel (Picture element) and v(i) is either a single real value indicating its grayness level or a triplet of values indicating its color details usually in the form of red, green and blue color components. The v(i) values are the result of light intensity measurement, usually made by a Charged Coupled Device (CCD) matrix coupled with a light focusing system. Each captor of the CCD is roughly a square in which the number of incoming photons is being counted for a fixed period corresponding to the obturation time.

When the light source is constant, the number of photons received by each pixel fluctuates around its average in accordance with the central limit theorem. In other terms, fluctuations of order for n incoming photons can be expected. In addition, each captor, if not adequately cooled, receives heat spurious photons. The resulting perturbation is usually called “obscurity noise”. This can be roughly written as

$$ov(i) = v(i) + n(i) \tag{4.1}$$

where ov(i) is the observed value, v(i) is the gray or color values and n(i) is the noise introduced. The amount of noise (n(i)) introduced is signal dependent, that is, n(i) is large when v(i) is large. The main goal of noise removal algorithms is to reduce n(i) while preserving details in v(i). These algorithms first estimates a noise model and then use this model to filter noise in the mango fruit image. The second step, filtering, must be carefully designed so that the resultant enhanced image is as close to the noise free image. The process is shown in Figure 4.1.

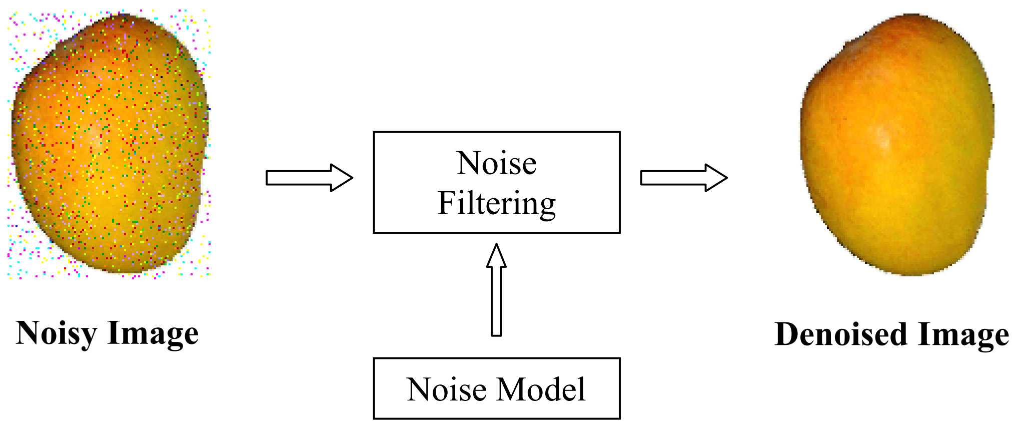


Figure 4.1 : General Noise Removal Process

As mentioned in Chapter 3 (Methodology), a mango fruit image is degraded by the presence of the most commonly occurring impulse noise, namely, Salt & Pepper. Impulse noise, also called as impulsive or spike noise (Gonzalez and Woods, 2007), is caused by faults in camera sensors and memory card, or due to transmission in a noisy channel (Shapiro and Stockman, 2001; Boncelet, 2005). For images corrupted by Salt & Pepper noise, the noisy pixels can take only the maximum and the minimum values in the dynamic range.

The mango fruit image degraded by Salt & Pepper noise will have dark pixels in bright regions and bright pixels in dark regions. Both are considered to be more serious than all the others, as they cause difficulties during defect detection. Figure 4.2 shows the effect of Salt & Pepper noise on the selected four types of mango fruit images.

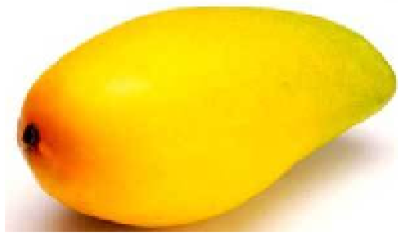
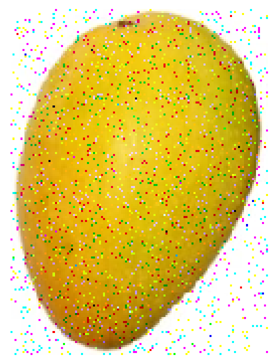
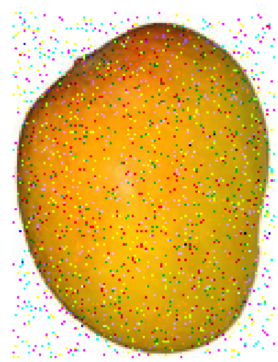
Type of Mango Fruit	**Noise-Free Image**	**Degraded Image**
Alphonso		
Banganapalli		
Neelam		
Sendura		

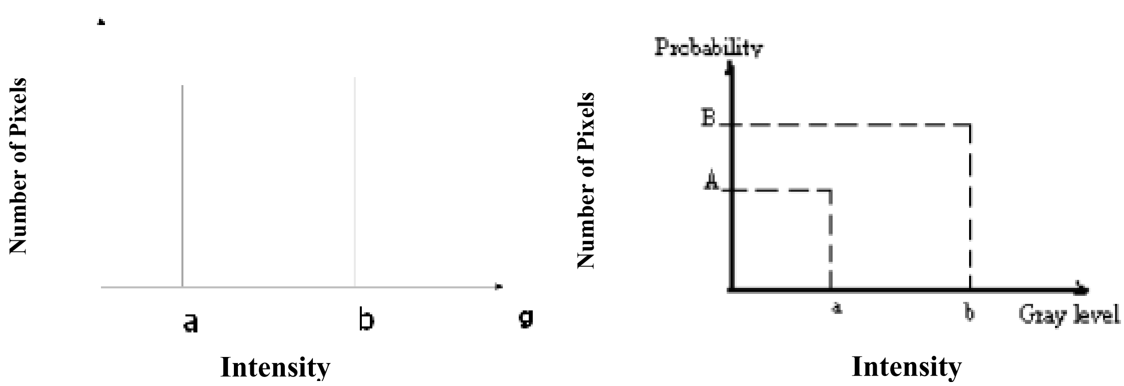
Figure 4.2 : Noise-Free and Noisy Mango Fruit Images

4.1.1. Salt and Pepper Noise Model

Noise can be modeled using either a histogram or a probability density function (pdf) which is superimposed on the probability density function of the original image. The salt & pepper noise can be analytically described using Equation (4.1).

$$NoiseModel_{Salt\&Pepper} = \begin{cases} A & for\ g = a(\text{"Pepper"}) \\ B & for\ g = a(\text{"Salt"}) \end{cases} \qquad (4.1)$$

A histogram and pdf of salt and pepper noise in gray scale image is shown in Figure 4.3a and 4.3b. Here the typical values of ‘a’ and ‘b’ ranges between 0 and 255. x(i,j) is the pixel value in the place (i,j) in the image. Thus N(i,j)=1 indicated the pixel without noise.



(a) Histogram **(b) pdf**

Figure 4.3 : Salt & Pepper Noise Model

In a salt & pepper noise model, there are only two possible values, ‘a’ and ‘b’, whose probability is less than 0.1. Generally, a value above this probability means that image is dominated by degraded pixels.

4.2. SWITCHING MEDIAN FILTER

There are several linear and non-linear methods that are used to remove noise from digital images. Median filter is one of the most popular non-linear algorithms used for removing impulse noise. The reason behind this is its good denoising power and computational efficiency. As mentioned in Chapter 3 (Methodology), in order to handle the issues of median filter, Switching Median Filter (SMF) are used. The conventional SMF classifies the pixels of an image as either corrupted (noisy) or uncorrupted (noise-free). After classification, the median filter is applied on corrupted pixels alone to suppress or remove impulse noise. The SMF outperforms traditional median filters, where no switching operation is performed and each pixel, whether corrupted or uncorrupted, is replaced with the median of its neighbouring window (Bair and Mol, 2011) and hence is frequently used to remove impulse noise in digital images. Figure 4.4 presents the general framework of the conventional SMF.

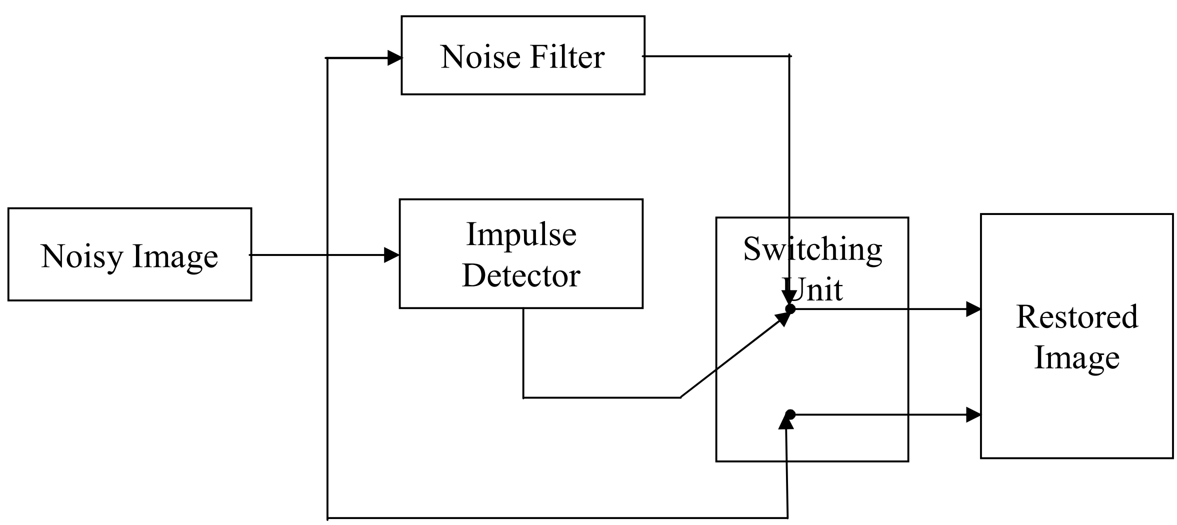


Figure 4.4 : Conventional Switching Median Filter

The output of the conventional SMF is given by Equation (4.2), where x(i, j) is the input pixel, y(i, j) is the denoised (filtered) pixel, f(i, j) is the output of the impulse detector (which is 1 if the pixel is noisy else is 0 if the pixel is noise-free) and med(.) is the median of a window of size n x n whose centre is x(i, j).

$$y(i,j)=\begin{cases} x(i,j) & \text{if } f(i,j)=0 \\ \mathrm{med}(W_{nxn}^{(x)}(i,j)) & \text{if } f(i,j)=1 \end{cases} \tag{4.2}$$

Conventional SMF while being simple and effective in removing impulse noise, have the issue of being non-adaptive to a given, but unknown, noise density, thus increasing the misclassification rate. To solve this issue, an algorithm that can detect impulse noise is first used. Several techniques like fuzzy approaches (Bose *et al.*, 2014), neural network-based approaches (Kaliraj and Baskar, 2010) and boundary-based approaches (Ng and Ma, 2006) have been proposed.

As mentioned earlier, to overcome the issues present in SMF, AFSF was designed and the implementation detail of the algorithm is presented in the following section.

4.3. ADAPTIVE FUZZY SWITCHING FILTER (AFSF)

As median filter cannot differentiate between thin lines (edges) and impulse noise, during noise removal the conventional SMF may accidently remove edges from images as noise. To avoid this, the AFSF was designed to use a set of convolution kernels. Impulse detection can be performed using different kinds of operators including Laplacian and Lulu (Kao, 2001; Dong and Xu. 2007). AFSF uses a set of four one dimensional Laplacian operators (Figure 4.5) during noise detection. Here, a 5 x 5 window around the pixel I is selected and this window is convolved with its noisy counterparts. Thus, by convolving the group of kernels with the input image, NI, four convolutionary results are obtained for each pixel.

4.3.1. Impulse Noise Detection

The impulse noise detection algorithm is based on two important assumptions (Zhang and Karim, 2002). The first assumption is that the noise-free image consists of locally smooth varying regions separated by edges. The second assumption is that the value of a noisy pixel is substantially greater than that of its neighbours.

0	0	0	0	0
0	0	0	0	0
-1	-1	4	-1	-1
0	0	0	0	0
0	0	0	0	0

-1	0	0	0	0
0	-1	0	0	0
0	0	4	0	0
0	0	0	-1	0
0	0	0	0	-1

0	0	-1	0	0
0	0	-1	0	0
0	0	4	0	0
0	0	-1	0	0
0	0	-1	0	0

0	0	0	0	-1
0	0	0	-1	0
0	0	4	0	0
0	-1	0	-1	0
-1	0	0	0	0

Figure 4.5 : Four 5 x 5 Laplacian Kernels (K_p)

The, impulse noise detection step estimates the minimum absolute value (r(i, j)) of these four convolutions, using Equation (4.3).

$$r(i, j) = \min\{ |x(i, j) \otimes K_p; p = 1 .. t| \} \qquad (4.3)$$

The value of r(i, j) is then analyzed to detect impulse noise as given below.

1. When both r(i, j) is large and the four convolutions are large or almost the same, then the centre pixel is impulse noise.
2. When r(i,j) is small and the four convolutions are close to zero, then the centre pixel is noise-free
3. if r(i,j) is small and any one of the convolutions is close to zero and other three are large then the centre pixel is considered as an edge.

With the analysis, it can be understood that when $w(i, j)$ is large, then $x(i, j)$ is corrupted by noise else it is considered as noise-free. Each detected noisy pixel is then replaced by the median value of the window, as explained in the previous section.