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# Review Of Different Filters For Low Quality Fingerprint Images

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***Abstract***— **Noise or unexplained variations in data, can affect most images to some extent. Image analysis is a complex process and can be simplified if this noise can be removed or filtered out. Image filters may be used to emphasize edges, that is, boundaries between objects or parts of objects in images. Filters, used for removing noise, provide an aid to visual interpretation of images, and can also be used as a precursor to further digital processing, such as segmentation. This paper has a review of various types of Linear and Non Liner filters, that are used for various applications in particular its use in Segmentation of low quality fingerprint image. Then based on advantages and disadvantages of above filters, the researcher have preferred Gabor filter over other filters. The researcher 'Vishal' is of the opinion that the advantages and performance efficiency of Gabor filters can be improved by mathematical tricks for overcoming the drawback of its complexity.**

***Keywords:*** **Image processing, fingerprint image segmentation, pixel features, coherence, Filters, Gabor Filters, Gaussian Filters.**

## INTRODUCTION

Any fingerprint feature extraction and matching algorithm cannot ensure high performance unless the quality of input fingerprint image is good. Objectively measuring the quality of fingerprint image is not possible, hence the quality roughly corresponds to the clarity of the ridge structure in the fingerprint image [17,8]. Where as a 'good' quality fingerprint image has high contrast and well defined ridges and valleys, a 'poor' quality fingerprint is marked by low contrast and ill-defined boundaries between the ridges. The prime reasons for degrading the quality of a fingerprint image are:

1. Presence of creases, bruises or wounds may cause ridge discontinuities.

2. Excessively dry fingers lead to fragmented and low contrast ridges.

3. Sweat on fingerprints leads to smudge marks and connects parallel ridges.

Since most of the algorithms are designed to perform on well defined ridge structures, the quality of fingerprint encountered during verification varies over a wide range. Hence to enhance the quality of Fingerprint images various filtering techniques are used depending upon the type of filter being used.

## 2. TYPES OF FILTERS

Pixel values are changed by filters, taking into account the values of neighboring pixels too. Filters may be applied after transformation of pixel values or may either be applied directly to recorded images. Filters can be broadly classified as:

- Linear Filters.
- Non Linear Filters.

### Linear Filters

The output values of linear filters are linear combinations of the pixels in the original image and hence the name Linear Filter. Linear methods are much simpler in mathematical analysis than non linear filters, hence are far better and better understood. For example, if a linear filter is applied to the output from another linear filter, then the resulting filter is a linear filter [9,6]. Also, the result would be the same if the order in which the two filters were applied was reversed. Two complementary ways in which Linear Filters can be studied are:

- Spatial Domain.
- Frequency Domain.

### Linear Filters in Spatial Domain

**1)** Simple moving average filter is an example of Linear Filters in Spatial Domain.

**Advantage**: Simple and Fast.

**Disadvantage**: It has two major drawbacks**.**

**1**. It is circularly symmetric (i.e. not isotropic), but smoothes further along diagonals than along rows and columns.
**2**. Discontinuities in the smoothed image are seen because weights have an abrupt cut-off rather than decaying gradually to zero.

**2)** Gaussian Filter is another example of linear filter. Gaussian Filters are separable and, at least to a lattice approximation, circularly symmetric.

**Advantage**: There is no discontinuity in the smoothed image.

Weights in the Gaussian filters hare specified by the probability density function of a bivariate Gaussian, or Normal, distribution with variance σ sq.

Hence the Gaussian filters are preferred over average moving filters.

The frequency response of Gaussian filter is about the zero frequency and also radially symmetric. It is the weighted sum of up to four

Gaussian envelopes [19]. The number of Gaussians summed to give the filter is controlled by the field labeled *Number of filters to combine*. For each Gaussian there is a central frequency, a width specified in terms of the Gaussian's sigma, and the amplitude at the central frequency. The common choice for the amplitudes of the Gaussians ensures that the frequency response at zero frequency is one .Hence a filter is generated that does not change the mean of the data.

### Gabor Filter

A Gabor filter is a good choice for selecting the components of an image that contribute to a limited range of frequencies. If the components selected in the dialog are "both" or "positive only", the range has a contribution from frequencies about

cf * (cos(a), sin(a))

Where:

**cf** represents the central frequency magnitude specified in the dialog

**a** represents the central frequency angle.

the range has contribution from frequencies about

-cf * (cos(a), sin(a))

This is obtained if the components selected in the dialog are "both" or "negative only",

.

A Gaussian envelope is used to limit both components. The envelope has its one of the axes oriented along the radial direction from the zero frequency to the central frequency. The envelope's width along the axes is given in terms of the sigma for the Gaussian.



Gabor filter have a wide area of application and its responses are used as general purpose features in many tasks involving computer vision, such as in, face detection and recognition, iris recognition and also in texture segmentation. Gabor filters are also used in feature construction [15,16]. In a typical feature construction, the Gabor filters are utilized via multi-resolution structure, consisting of filters tuned to several different frequencies and orientations. The multi-resolution structure relates the Gabor features to wavelets, but the main difference, non-orthogonality, also is connected to the main weakness of the Gabor features: computational heaviness [4]. Gabor filters are widely used but have a disadvantage of Computational Complexity. The computational complexity prevents their use in many real-time or near real-time tasks, such as in object tracking. Fortunately, many arithmetic tricks exist which can be employed to significantly improve the computational complexity with negligible loss in accuracy.

### Gabor filter in 1-D

The 1-D description is included since most of the results can be conveniently generalized to 2-D filters.
The normalized Gabor filter in the time domain is

$$\psi(t) = \frac{|f_0|}{\gamma\sqrt{\pi}} e^{-\left(\frac{|f_0|}{\gamma}\right)^2 t^2} e^{j2\pi f_0 t}$$

Where:

**f0** is the filter frequency
**γ** is the filter bandwidth.

The filter bandwidth can be also considered as filter sharpness: the sharper a filter is, the narrower is the bandwidth. The Gabor filter is a complex sinusoidal wave of particular frequency modulated by a Gaussian envelope which defines the time duration. The effective time duration is inversely proportional to the effective bandwidth via the uncertainty relation.
In Fourier domain, the Gabor Filter is represented by the following equation :

$$\Psi(u) = e^{-\left(\frac{\gamma\pi}{f_0}\right)^2 (u-f_0)^2}$$

Where
u denotes frequency

### Gabor filter in 2-d

2-d Gabor filter is a product of an elliptical Gaussian in any rotation and a complex exponential representing a sinusoidal plane wave [19]. The Filter's sharpness is controlled on major and minor axis by γ and η. The response of the filter can be normalized to have a compact closed form

$$\begin{aligned} \psi(x, y; f_0, \theta) &= \frac{f_0^2}{\pi\gamma\eta} e^{-\left(\frac{f_0^2}{\gamma^2} x'^2 + \frac{f_0^2}{\eta^2} y'^2\right)} e^{j2\pi f_0 x'} \\ x' &= x\cos\theta + y\sin\theta \\ y' &= -x\sin\theta + y\cos\theta \end{aligned}$$

Where
f0 represents the central frequency of the filter.

θ represents the rotation angle of both the Gaussian major axis and the plane wave.

γ represents the sharpness along the major axis.

η represents the sharpness along the minor axis (perpendicular to the wave).

The Gaussian aspect ratio is given by λ = η/γ. In frequency domain, the normalized Gabor filter is given by

$$\begin{aligned} \Psi(u, v; f_0, \theta) &= e^{-\pi^2\left(\frac{(u'-f_0)^2}{\alpha^2} + \frac{v'^2}{\beta^2}\right)} \\ u' &= u\cos\theta + v\sin\theta \\ v' &= -u\sin\theta + v\cos\theta. \end{aligned}$$

Linear filters in the frequency domain

Instead of representing an image as an *n*n* array of pixel values, we can alternatively represent it as the sum of many sine waves of different frequencies, amplitudes and directions. This is referred to as the frequency domain or Fourier representation

1) **The Laplacian -of-Gaussian** filters are an example of linear filters in frequency domain. These are band-pass filters because they remove both low and high frequencies from an image.

**Advantage:** Operate as edge detectors, whilst managing to smooth out some of the noise.

Outputs Compared

1) If we apply a 5 * 5 moving average filter to the cashmere fibers image [19], the output will be as shown in fig 1.a

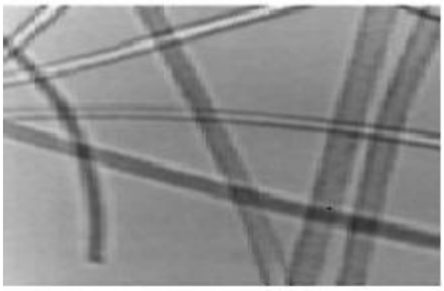

Fig 1.a : Output of a 5 * 5 moving average filter applied to the cashmere fibres image.

The noise in the image is reduced but the blurring of the edges is an important issue.

2) Laplacian Filter can be obtained by subtracting the output from the moving average filter from the original image [19], on a pixel-by-pixel basis. (Fig 1.b)

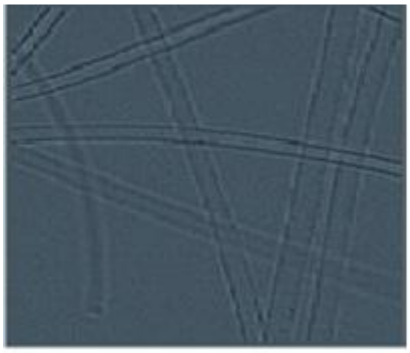

Fig 1.b : Laplacian Filter - the original image minus its smoothed version

3) When output from the Laplacian filter is added to the original image, again on a pixel-by-pixel basis [19], the output is as seen in the Fig 1.c

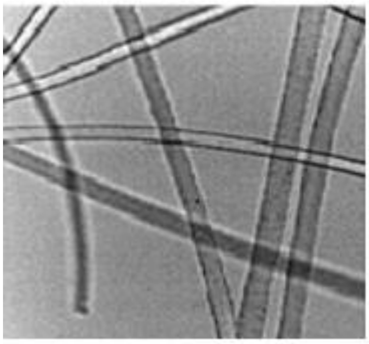

Fig 1.c : Output from the Laplacian filter is added to the original image (pixel by pixel)

### Nonlinear Filters

Non-linear filters are more diverse and difficult to categorize, and are an important area of research [19]. Simultaneously blurring of edges during noise reduction is a major issue in linear filters but this problem is overcome by non linear filters and hence non linear filters are potentially more powerful. The less secure theoretical foundations may be an issue in non linear filters because they can produce features which are entirely spurious. However, with proper care during use, Non linear filters can produce better results.

**Advantage:** The Nonlinear filters are able to simultaneously reduce noise and preserve edges.

**Disadvantage:** They have less secure theoretical foundations and are not easy to compute.

### Types of Non Linear Filters

Nonlinear smoothing filter is an example of non linear filter.
Advantage: It overcomes the important drawback of linear filters of edge blurring during the noise reduction
However, the simplest, most studied and most widely used nonlinear filter is the moving median.

**Histogram-based Filters**

The moving median filter is different than the moving average filter in terms of outputs only. The moving median filter produces as output at a pixel, the median, rather than the mean, of the pixel values in a square window centered on that pixel [19].

**Spatially-adaptive Filters**

Median filters can be improved upon by making use of the spatial distribution of pixel values. Since this information is available it seems sensible to make use of it and not simply form a histogram.

**Nonlinear edge-detection Filters**

Boundaries between objects , or parts of objects, in images are known as edges. A large response is expected from edge filter at a location if pixels in the neighborhood show a systematic pattern of changes in value.
**Advantage**: Better edge filtering without blurring.

## 3. LINEAR VISA-VIS NON LINEAR FILTER

The advantages of Linear Filter are**:**

- The Fast Fourier Transform algorithm helps in efficient computations.
- Further insight into how filters work, such as categorizing them as low-pass, high-pass or band-pass.
- Opportunities to design new filters, such as:
  1) Ideal high -pass filters and low pass filters.
  2) The Wiener filter for image restoration.

The disadvantages of Liner filters are:

- During the noise reduction the edges are blurred inevitably, because both edges and noise are high-frequency components of images.

The advantages of Non Liner filters are**:**

- The Nonlinear filters are able to *simultaneously* reduce noise and preserve edges.

The disadvantages of Non Liner filters are:

- The theoretical foundations of the Non-linear filters are less secure.
- The Non-Linear Filters have complex computations.

## **4.** GABOR FILTERS: PREFERRED OVER OTHER FILTERS

Gabor filters have features that are beneficial in feature extraction for many computer vision tasks [4,12]. Though, Gabor filters are popular but they have a disadvantage of computational complexity which has prevented its use in variety of applications. The advantages and performance efficiency of Gabor filters led researchers to find various mathematical tricks with the help of which this drawback of Gabor filter can be overcome.
Multi-resolution features are of special importance. The computations can be significantly improved by utilizing effective filter envelopes, which reduce the computational complexity in the spatial domain and space complexity in the frequency domain. The utilization of highest required frequency for the purpose of image downscaling remarkably improve both spatial and frequency domain filtering [18,19]. Gabor filters, can be used in variety of ways and can replace filters like Gaussian filters in applications such as Segmentation of low quality fingerprint images.

## 5. CONCLUSIONS

Filtering plays an important role in any image recognition system as the images may be disoriented or of low quality. Hence it is important to choose the appropriate filter.
Filters are classified on the basis of the output they generate. Large number of Linear and Non-linear filters are being used in various applications based on their advantages and disadvantages. Disadvantages of certain filters can be removed by application of some mathematical tricks, which not only removes the disadvantages but also improves the performance of the filters in many ways. Use of Gabor filters instead of filters like Gaussian filters in some applications such as segmentation of low quality fingerprint images might improve the efficiency of the process as Gabor filters have both frequency-selective and orientation- selective properties and have optimal joint resolution in both spatial and frequency domains[20].

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