International Journal of Computer (IJC)
ISSN 2307-4523 (Print & Online)

http://ijcjournal.org/

Filtering Approaches in Medical Image Processing: A Tutorial

Muhammad Fateh Khan Sial*

Assistant Professor, Department of Electrical Engineering, The University of Lahore, Defense Road, Lahore, Pakistan, 54700

Email: fateh.khan@ee.uol.edu.pk

Abstract

This paper presents popular filtering approaches adopted in medical image processing. It is aimed to serve as a beginner's guide in Medical Image processing to undergraduate and graduate students of Electrical engineering and Computer science. A general overview of various steps involved in medical image acquisition and analysis is presented. Various statistical distributions representing practical noise problems in images are indicated and corresponding filtering techniques like statistics based filters, frequency domain filters, optimal and adaptive filters have been briefly discussed.

Keywords: image acquisition; image analysis; statistical based filters; noise; optimal filters; adaptive filters.

1. Introduction

Human body is composed of multiple systems like central nervous system, cardio vascular system, muscle-skeletal system, respiratory system, reproductory system and digestive system etc. Each system comprises of several sub-systems [1,2]. For instance, the cardiac system is responsible for oxygenation of blood by passing it through pulmonary system along-with carrying blood throughout the body for transportation of important nutrients. The functionality of visual system is to focus visual info on the retina, conversion of this information into neural signals, encoding and transmission of this information to visual cortex, which interprets the image information [1]. Majority of human physiological systems generate physical signals. These signals can be biochemical (like hormones, neurotransmitters), electrical (like current, voltage) and physical (like temperature, pressure) in nature. State of a system can be assessed by observing and analyzing its corresponding signals. Human internal systems and organs are placed in multiple layers inside human body and observing them requires use of invasive procedures or penetrating radiations.

----

* Corresponding author.

There are several imaging technologies that provide imaging of human internal organs which can be observed, analyzed and stored in computers for the purpose of diagnosis of internal diseases and disorders. Most popular technologies for acquiring images of human biomedical systems include Magnetic Resonance Imaging (MRI), Ultrasonography, Nuclear Medicine Imaging, Tomography, X-ray Imaging, Mammography, Electron Microscopy, Light Microscopy, Trans-illumination and Thermal Imaging [1,9]. The images acquired using these technologies are in electronic form which can be processed and analyzed using Computer-aided Diagnoses. Typical steps in this process include image data acquisition from patient using imaging systems comprising of sensors, transducers, Analog-to Digital Converters and storage systems. Afterwards, the data is processed by filtering and image enhancement. Object detection, features and region extraction schemes are deployed. Images data is analyzed by extraction of features, regions, objects including pattern recognition, classification. Computer aided diagnostic decision is provided to Medical Specialist for ultimate diagnosis and treatment of the patient [4,5].

Computer aided diagnostic system can be divided into various steps [1,2]. The very first step is information collection by measuring an internal process, system or organ. Secondly, investigation for occurrence of a particular disease is carried out. Diagnosis is performed on detection and confirmation of an abnormality or malfunction. Regular information about state of internal system is acquired by regular monitoring. Afterwards, therapy and control are adopted to manage changes in system state to ensure results. Measurements and analysis are performed to evaluate the effects of treatment.

Image acquisition procedures can be divided into invasive, non-invasive, active and passive. Invasive procedures are those which require placing of devices on body, injecting materials and radiation penetration inside the body. Non-invasive procedures require no visible invasion to the body. Active procedures require the patient to perform some activity to stimulate the system of interest to obtain a specific response. These can cause slight discomfort to significant damage to the patient. Passive procedures require no activity to be performed by the patient.

2. Biomedical Image Analysis

It is the responsibility of the medical practitioner to perform the risk-benefit analysis and take the best decision in the interest of the patient [1,2]. It is expected that the computer based analysis of biomedical images will assist the medical practitioner to make a more accurate diagnostic decision. The following discussion enlists different image processing and analysis techniques for multiple biomedical applications [1,2,3,6,9].

2.1 Image Quality and information content

There are many factors that affect the quality and information content of an image acquired by biomedical instrumentation mentioned above. Some of the techniques for biomedical image analysis are discussed below [7],

- Digitization: Computer based processing of digital images requires them to be in digital format which is a two step process; sampling and quantization which cause loss of information and quality in the image. Sampling is the process of converting an analog signal into discrete components separated by uniform intervals. All the mathematical concepts applied to sampling of one-dimensional signals can be extended to two-dimensional signals or images. Quantization is the process of denoting the values of a sampled signal or image using a finite set of fixed values. Each sample value can be represented by a specific number of bits, n. Only 2^n levels are allowed to represent all sampled values. If n = 4 bits are used to represent a pixel value, there can exist 16 values or levels [0, 15] to represent each pixel in an image. If the number of bits/sample is increased, the corresponding quantization levels will also increase, resulting in better image quality.

- Matrix representation: Images are generally denoted as a 2D function *f(x, y)*. Hence a digital image can be interpreted as a matrix or array. An *M x N* matrix has *M* rows and *N* columns and its size is given as rows x columns.
- Dynamic range: it is defined as the difference between the maximum and minimum values in an image.
- Contrast: It is the difference between region of interest in an image and its background.
- Histogram: it provides information about the spread of grey levels over the complete dynamic range of an image for all its pixels values. It provides quantitative information on the probability of occurrence of each grey level in an image.
- Entropy: Entropy is a statistical measure used to express histogram of probability density function as a single number. It provides a summarized measure of statistical information content of an image.
- Fourier Transform: It maps an image from space domain to frequency domain to assess the spectral content and energy distribution over the spectrum. Sharp edges, directional elements, image patterns and noise information can be derived from the spectrum. After the frequency domain transformation of an image, it is convenient to apply filters to remove noise, enhance image, extract features/components and pattern recognition. Most real life images have most of the spectral energy concentrated in the low frequency range. Sharp features and fine details correspond to high frequency range [1,2,3,10,7].

These are some of the measures and methods adopted for image quality enhancement. The main purpose is to improve the accuracy in decision making in biomedical diagnosis applications.

2.2 Noise Probability Density Function (PDF)

Any undesired signal, pattern or image can be considered as noise. It can cause performance degradation in the medical diagnoses procedures [4,1]. It is the disturbance from random sources that interfere in the signal of interest. It Is characterized by the probability density function. Various statistical averages are useful in image analysis steps like spectrum analysis, filtering, compression and pattern classification [5].

- Gaussian distribution: It is completely characterized by mean μ and variance σ as follows [4],

$$p_x(x) = \frac{1}{\sqrt{2\pi}\sigma} exp\left[\frac{-(x-\mu)^2}{2\sigma^2}\right] \quad (1)$$

- Poisson distribution: It is mainly dependent on mean μ of the random process. Larger values of mean make it resemble with Gaussian distribution [4],

$$p(x) = exp(-\mu)\frac{\mu^x}{x!} \qquad (2)$$

- Laplacian Distribution: It is completely characterize by its mean and variance [4],

$$p(k) = \frac{1}{\sqrt{2}\,\sigma} exp\left[\frac{-\sqrt{2}|k - \mu|}{\sigma}\right] \qquad (3)$$

- Rayleigh Distribution: It is determined by a and b which are also used to calculate mean and variance, where *u(x)* is a unit step function [4],

$$p(k) = \frac{2}{b}(x-a)exp\left[\frac{-(x-a)^2}{b}\right]u(x-a) \qquad (4)$$

3. Filtering Approaches

Various filtering approaches have been developed to remove noise related artifacts. These include time and frequency domain filters, non-linear and adaptive filters [10,4,5].

3.1 Statistics based filters

Various statistics of pixels in an image frame are computed using moving window filters. The output is stored in a separate matrix or array [1,2,3].

- Mean Filter: Mean of the pixel values in the neighborhood is calculated to get the true pixel value of the image. This filter can readily suppress noise caused by uniform and Gaussian distributions.
- Median Filter: The median of a data set divides it into half. This filter divides the pixel values by median. Half the pixel values are above it and half below. It provides better noise removal as compared to Mean filter.
- Multi-frame Averaging: Several frames of images are acquired and averaged out to remove noise.

3.2 Order Statistic Filter

These filters arrange the pixel values in the neighborhood of the pixel of interest. These values are ranked from minimum to maximum. Order of the filter represents the position of that particular pixel in the list [1].

- Min Filter: The output of this filter is the very first entry in the rank-ordered list. It is helpful in removing scattered bright spots or high-valued impulse noise.
- Max Filter: This filter provides the last entry in the list resulting in the removal of low-valued impulse noise or dark spots in the image.

- Min/Max filter: If the min/max filters are applied in a sequence, these are called Min/max filter. It helps in the removal of salt and pepper noise.
- Median Filter: The filter output is the middle entry in the list.
- α-Trimmed Mean Filter: Rank-order list is trimmed by α in the start and end of the list. Mean of this reduced list is calculated by this filter. Its value lies between the output of the mean and median filter.
- L –filters: All the elements in the rank ordered list are weighted and combined at the output of this filter. Higher order filters can be designed by using appropriate weights.

4. Frequency Domain Filters

Generally the images have most of their energy concentrated in the lower frequency range whereas noise has uniform spectrum across the whole signal bandwidth.

The signal to noise ratio of these images can be improved by filtering out the higher frequency components [4,5]. To apply filtering operation the 2D image has to be converted into frequency domain and inverse transformed after the desired filtering operation is performed [1,2,3,10].

4.1 Ideal Low Pass filter

This filter sets all the components in the Fourier transform of an image to zero after a particular cutoff frequency D_o. The transfer function of the filter *H(u,v)* is given below,

$$H(u,v) = \begin{cases} 1 \ if \ D(u,v) \le D_o \\ 0 \ \ otherwise \end{cases} \tag{5}$$

Where *D(u,v)* is the distance of the pixel at *(u,v)* from the origin *(0,0)* where the spectrum is located.

$$D(u,v) = \sqrt{u^2 + v^2} \tag{6}$$

4.2 Butterworth LP Filter

This is a low pass filter whose response is the passband is maximally flat. The transfer function of the 2D BW lowpass fitler is follows,

$$H(u,v) = \frac{1}{1 + (\sqrt{2} - 1)\left[\frac{D(u,v)}{D_o}\right]^{2n}} \tag{7}$$

Where *n* is filer order, *D(u,v)* is the distance from the origin, D_o is the cutoff frequency.

5. Optimal Filtering

5.1 Wiener Filter

This filter is aimed at minimizing the mean squared error between the output and input image [7,9]. The filter output is therefore termed as least mean square (LMS) estimate.

$$\tilde{F}(k,l) = \left|\frac{S(k,l)_f}{S(k,l)_f + S(k,l)_n}\right| G(k,l) \tag{8}$$

The filter output depends on the power spectral density of original signal $S_f(k,l)$ and noise $S_n(k,l)$. Gain $G(k, l)$ of the filter Is dependent upon Signal to Noise ratio. As the value of the signal increases, gain improves as well. Maximum value of the gain is unity when Power Spectral Density of noise is zero. Suppression of noise results in blurring of sharp edges and features in an image.

6. Adaptive Filters

6.1 The local LMMSE Filter

The original image and its corrupted versions are correlated using statistical parameters which are not known in advance [6,7]. The mathematical representation of the degradation model $g(m,n)$ comprises of the original image data $f(m,n)$ and the noise process $\eta(m,n)$.

$$\boldsymbol{g(m,n) = f(m,n) + \eta(m,n)} \tag{9}$$

However the statistical estimation can be done locally in the spatial neighborhood of the pixel of interest. . This type of estimate is called local LMMSE estimate, also known as Wiener Filter. It is calculated using pixel-by-pixel operation as follows.

$$\boldsymbol{\tilde{f}\,(m,n) = \mu(m,n) + \left|\frac{\sigma^2\,(m,n) - \sigma_\eta{}^2(m,n)}{\sigma^2\,(m,n)}\right| [g(m,n) - \mu(m,n)]} \tag{10}$$

The working principal of this approach is that an estimate $f(m,n)$ is calculated for an actual image f(m, n) by applying a linear operator to $g(m,n)$. σ^2 is the local signal variance.

$$\boldsymbol{\varepsilon^2(m,n) = \overline{[\tilde{f}\,(m,n) - f(m,n)]^2}} \tag{11}$$

Local mean squared error is calculated by subtracting the original from estimate, squaring it up and calculating the statistical averaging.

6.2 Refined LLMMSE Filter

If the local signal variance is high, it infers that processing window is overlapping an edge [6]. Its direction is calculated by applying a gradient operator, where the edge can have eight possible directions. Keeping in view the direction of the edge, the processing window is divided into two uniform portions. The statistics calculated for the portion/sub-area containing the pixel of interest are used for further processing. This filtering approach reduces noise in the neighborhood of edges without blurring.

6.3 Adaptive 2D LMS Filter

It is a fixed window Wiener filter in which the coefficients are tuned adaptively with the image characteristics. Filter coefficients for a particular pixel are calculated by minimizing the mean square error between the desired pixel value and the estimated pixel value by deploying the method of steepest descent.

6.4 Adaptive Rectangular Window (ARW) LMS Filter

This filter is designed on the assumption that if we determine the size of a neighborhood, in which the sample values have the same statistical parameters, the relevant statistics can be calculated using aposteriori parameters.

6.5 Adaptive-neighborhood filter

The fundamental approach in designing this filter is that a pixel of interest is considered as a seed. A region needs to be selected around the seed which contains pixels having same feature or object as the seed. A neighborhood is grown for each image pixel adaptively. It can be variable in size and shape and has to be determined for each pixel. The statistics computed in the adaptive region are expected to match closely with the actual statistics of the local signal and noise values.

6.6 Adaptive Neighborhood Noise Subtraction (ANNS)

An estimate of the additive noise at the pixel (m,n) is calculated from respective adaptive neighborhoods grown in the target corrupted image by using a scale factor which depends on the characteristics of the adaptive neighborhood grown. The value of the scale factor is based on the criteria that the estimated noise variance is equal to the actual noise variance.

7. Scope of Study

There are multiple artifacts that may arise in biomedical images. In this study, several techniques have been presented to model, characterize and removal of these artifacts. It highlights filtering approaches based on simple time averaging over several image frames to filtering over small neighborhoods within an image. It has been shown that various statistical averages can be utilized for the purpose of filtering different types of noise. Popular filtering approaches have been presented for noise removal that fall into various categories like frequency domain, optimal, statistical and adaptive filters.

Studies have been conducted to evaluate the efficacy of various filtering techniques for removal of artifacts and noise [9,10,11]. Analysis of these results show that removal of one artifact could result into introduction of other artifacts. Only adaptive and non linear filters have shown to introduce minimal artifacts during the process of noise removal. This is considered to be the primary limitation or constraint in the analysis of biomedical images.

8. Recommendations

It is highly recommended that images should be preprocessed for the removal of artifacts before any other method for image analysis may be applied. It is possible that theoretical models and assumptions may not fit exactly to a particular problem at hand. Most of the methods used for noise removal and image analysis are considered to be ad-hoc in nature. It implies that these methods have been successfully applied by researchers to solve problems similar in nature. Therefore, it is a common practice to solve the practical imaging problems by applying previously established techniques. Nevertheless, the major challenge remains to be the selection of the most appropriate filtering techniques and the corresponding evaluation of the results. Although several statistical methods are available for measuring the image quality, the most recommended approach for image analysis and assessment remains to be the visual inspection.

9. Conclusion

The paper presents a beginner's perspective into filtering techniques for removal or mitigation of various types of noise from digital images. The filters are classified into space and frequency domain filters. Noise in biomedical images can be modeled as Gaussian, Poisson, Laplacian and Rayleigh distributions. Removal of noise is accomplished using Statistics based filters, higher order statistics based filters, optimal filters like wiener filter and adaptive filters like mean square error based filters. All these filters are designed to target various types of noise problems with minimal sacrifice of signal content of interest, thus improving signal to noise ratio.

References

[1] R. M. Rangayyan. Biomedical Image Analysis. CRC Press, 2005.

[2] R. M. Rangayyan. Introduction to Biomedical Signals. in Biomedical Signal Analysis, 1, Wiley-IEEE Press, 2015.

[3] R. M. Rangayyan. Frequency domain Characterization of Signals and Systems. in Biomedical Signal Analysis:A Case-Study Approach , 1, Wiley-IEEE Press, 2002.

[4] Papoulis. Probability Random Variables and Stochastic Processes. New York: McGraw-Hill 1965.

[5] R. M. Rangayyan. Biomedical Signal Analysis: A Case-Study Approach. New York NY: Wiley 2002.

[6] R. C. Gonzalez, P. Wintz. Digital Image Processing. MA Reading: Addison-Wesley 1987.

[7] S. Haykin. Adaptive Filter Theory. 4th ed. Englewood Cliffs NJ: Prentice Hall PTR 2002.

[8] R. Hunt, 'Digital Image Processing" in Applications of digital signal processing Englewood Cliffs:Prentice Hall 1978.

[9] P. Dhawan, R. M. Rangayyan, R. Gordon, "Image restoration by Wiener deconvolution in limited-view computed tomography" Applied Optics vol. 24 pp. 4013-4020 December 1985.

[10] N. V. Thakor and Y. S. Zhu "Applications of adaptive filtering to ECG analysis: Noise cancellation and arrhythmia detection " IEEE Trans. Biomedical Engineering vol. 38 no. 8 pp. 785-794 1991.

[11] Rangayyan RM, Ciuc M, Faghih F, "Adaptive Neighborhood filtering of images corrupted by signal-dependant noise" Applied Optics, 37(20): 4477-4487,1998.