A THESIS REPORT

ON

“FUSION OF FEATURES TO ENHANCE QUALITY OF IMAGE”

Submitted in partial fulfillment of the requirement for the award of the degree

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Submitted by

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DECLARATION

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CERTIFICATE

This is to certify that the thesis ***"**Fusion of features to enhance the quality of image "* is authentic work of **Mr. Sonoo kumar** under my guidance and supervision in the partial fulfillment for the Degree of **Master of Technology Degree in Signal Processing & Digital Design** to Department of Electronics and communication Engineering, Delhi Technological University, Delhi, India. To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University/Institute for the award of any other degree.

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ABSTRACT

The current research work is aimed towards improving the image quality. To begin with such capabilities it is necessary to go back in the past and identify the work of previous author that has given us the same result and provided the kind of concept required for image denoising. The understanding of images is not important but for the current research work that needs to be used for examples used in this report. As the work is considered few filters are used that will be of more imperatives because they keep the understanding of the more advanced filters. As the work is more important and relevant the important results will be based on new filters. In such the same will be done for basic filters their names include, mean, median and Gaussian filters. These filters have a better part of leading and learning on the same context as that of the advanced filters. Since these filters are very basic and needs less time for implementation they remain very popular. But on the other side their implementation is easier doesn't make them good for actually filtering. The same results will be understanding the same related for the same and thus the results will be compared and understanding of the same. This way the same will be implementation is also called the way of relation and consideration. Volterra is a not a new term but with significant improvement of time will lead to change in the improvement in the same will be made. The volterra equations are kind of recursive equations will be imperatives. This way the same will be applicable for the equations and thus the same will be used for the results and called upon and mark upon the improvement in image quality. The results will be totally based upon the quality of the images so achieved.

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CHAPTER 1

1.1 INTRODUCTION

image deblurring plays an important role in digital image processing. there are many methods for removing blur from images. there are two types of image deblurring model

- linear model
- non linear model

generally linear models are used because of its benefits of high speed, but this has limitations that it doesn't preserve edges. nonlinear model can preserve edges in much better way than linear model.

many methods are available based on assumption about an image that lead to blurring. this report will explain these assumption and explain a new method for deblurring.

is noise a help or a hindrance? despite intriguing phenomena such as stochastic resonance, noise is largely viewed a necessary evil for applied science. filter-ing images of contours, the problem studied here, is especially susceptible to noise because spatial di erentiation is often involved iniiobtaining initial mea-surements (fig. 1, top). large noise levels, however, can actually simplify the ltering problem analytically, making di cult problems (asymptotically) man-ageable [22]. for example, here we derive nonlinear contour enhancement lters that operate in a neighborhood of an in nite noise limit. process model of individual curves, we have developed a prior for images of these curves, which we call the curve indicator random eld (cirf), and we have obtained the complete cirf statistics. the main contributions of this report are three new linear and nonlinear volterra lters for computing the posterior mean of the cirf for noisy contour images.

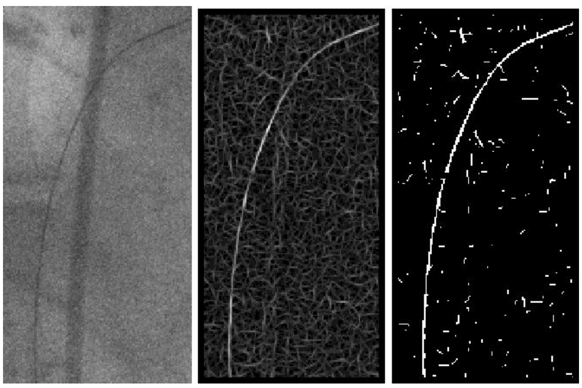
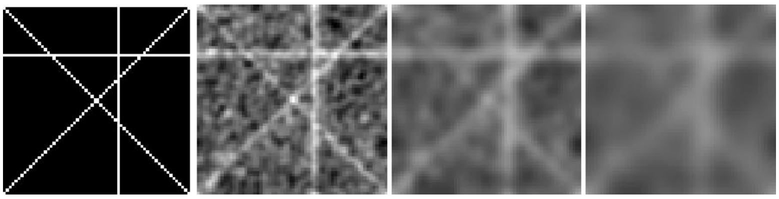


fig-1 local image thresholding responses



b:

fig. 1. (a) (left) a guide wire imaged uoroscopically during surgery. finding the wire in noise is important [11] because surgery can take hours, all the while exposing the patient to radiation. nonlinear lters for overcoming noise without merging or attenuating contours.

1.2 LITERATURE SURVEY

This section reviews the background research work carried out for noise removal, image segmentation, denoising static and dynamic color images and edge extraction. The proposed approach based on Volterra series is motivated by the work done on noise filtering and image segmentation in the literature. This process has been extensively studied for nonlinear image processing which includes image restoration, segmentation andanalysis.

1.2.1 Removal of Gaussian and Mixed Gaussian-impulse Noise

In the early development of image processing, linear filters were the primary tools for image enhancement and restoration. They have poor performance in the presence of non additive noise and in situations where system nonlinearities or Gaussian statistics areencountered . The Volterra series have been recognized as a powerful mathematical tool leading to another class of nonlinear filters called polynomial filters .The problem of eliminating noise from an image without causing degradation of image details has been considered frequently in recent literature. Efficient implementation structures of quadratic filters using systolic arrays, distributed arithmetic, and linear convolutions with multipliers are introduced by Hsing et al. The implementations are based on matrix decompositions and consist of a set of parallel 1-D FIR filters in cascade with a set of sequential square-in add-out type of operations. the best compromise among the various conflicting figures of merit.Ian J. Morrison and Peter J.W. Rayner [44] developed a new technique for signal estimation using Volterra series. Since the linear filter is known to be optimal for Gaussian noise, they applied general nonlinear filters based on Volterra series. Nonlinear Wiener filters based on Volterra series provide a means of improving signal estimation accuracy when the corrupting noise is non-Gaussian. The filter coefficients are obtained by solving a matrix equation. The matrices contain higher order autocorrelation terms of the observable signal and cross correlation terms between the observable signal and the noise. It is found that, the nonlinear filter degenerates to the optimum linear filter for the Gaussian noise, but in the case of non-Gaussian noise, the nonlinear filter reduces the effect of corrupting noise to give better estimate of the signal. Significant improvements in performance over the linear filter are achieved at the expense of an increase in complexity of implementation. Speckle is a chaotic phenomenon which results from coherent energy imaging as applicability of various existing nonlinear filtering methods as well as a new speckle model based quadratic Volterra filter, to solve the problem of smoothing speckle noise in digital images while preserving important edge information. The quadratic Volterra filter consists of a linear part and is mainly responsible for noise smoothening. This filtering strategy allows for consideration of the local correlation of speckle noise. To reduce the number of parameters in the Volterra filter, a tensor product basis approximation is introduced by Robert D. Nowarts et al. [76]. This approximation could be implemented more efficiently than the original Volterra filter. The advantage of this technique is that, it reduces the implementation complexity and the design method does not require prior knowledge of the filter or input. Such approximations are also useful in reducing the complexity of Volterra filter for identification and modeling problems. Useful bounds are obtained on the approximation error.

1.2.2 Noise Removal in Color Images

The main objective of noise filtering in color images is to process the image such that the result is more acceptable when compared to the original image for a specific application[73]. Noise introduces error and undesirable side effects at different stages of image processing. Nonlinear techniques [28] are able to suppress Gaussian noise, preserve important signal elements such as edges and fine details, and eliminate degradations occurring during signal formation or transmission through nonlinear channels. Noise filtering in color images has always been a topic of intensive research. A variety of approaches have been suggested for removal of noise in color images. Different criteria such as impulsive noise suppression, edge and other detail preservation have been used to characterize the performance of color imaging. B. Smolka et al. [89] proposed an adaptive soft switching filter based on the vector median and similarity function for impulse noise suppression. The design concept is based on the nonparametric estimation of the density probability function of pixel in a sliding filtering window. Silva and Ponomaryov [86] also proposed nonlinear filtering techniques based on directional processing to suppress impulsive noise and to preserve fine image details.

image processing by using the vector approach and rank M-type K-nearest neighbor algorithm.

Bogdan Smolka [9] proposed a new class of filter for impulsive noise removal in color images. The basic idea behind the new image filtering technique is the maximization of similarities between pixels in a predefined filtering window. Impulse noise removal utilizing second-order difference analysis has been proposed by Dung Dang and Wenbin

Luo [27]. They developed a new detection and filtering algorithm that consists of (i) a two stage detection scheme that employs second order difference between pixels to determine the integrity of the image pixels and (ii) a noise filtering process that estimates the original value of each noisy pixel utilizing the information gathered from (i).

The color and texture are of considerable importance for image segmentation and analysis and they have been discussed intensively in literature. Texture is one of the basic

1.2.3 Noise Removal in Dynamic Image Sequences

Noise filtering is one of the most important operations used in image and video processing.The importance of noise filtering in dynamic images is constantly growing because of the increasing use of television and video systems in consumer, commercial, medical and communication applications. Other applications that have benefited by the use of digital video include multimedia services, autonomous navigation, motion analysis, object tracking, surveillance and medical imaging. To reduce noise in video sequences, several noise reduction methods based on averaging technique have been proposed, such as motion compensated spatio-temporal averaging [10], adaptive weighted averaging [66] [85], adaptive weighted averaging with unknown noise variance [80] and the probabilistic filter [4] for temporal noise. Though these algorithms remove Gaussian noise, they are less effective for removing salt and pepper and mixed Gaussian-impulse noise.Some noise filters namely Concatenated Median

Filter (CMF) [5] and Center Weighted Median (CWM) filter [42] remove salt and pepper noise well, but are less suited to eliminate Gaussian noise. Bruni and Vitulano [11] proposed movie noise reduction based on a suitable combination of Wiener filter and Wavelet Transform (WT). Earlier works involved linear motion compensated spatio-temporal filters by minimizing Mean Squared Error (MSE), assuming the noise to be additive white Gaussian [32].

Unfortunately in the presence of non-Gaussian noise, application of linear filters causes blurring which degrades edge details and textures. Better results can be obtained using nonlinear methods such as Order Statistics Filters [48] [96] [46].

1.2.4 Color Image Segmentation

Image segmentation is an important step for many image processing and computer vision applications. The interest is motivated by applications over a wide spectrum of topics. For example, analyzing different regions of an aerial photo helps to better understand the vegetation cover. Scene segmentation is helpful to retrieve images from large image databases for content-based image retrieval [79] [88]. Most of the segmentation methods require image features that characterize the regions to be segmented. In particular, texture and color have been independently and extensively used [72] [21]. The color information is a multi-dimensional vector and hence the segmentation techniques for gray imagescannot be directly applied. The existing color image segmentation techniques can be broadly classified into eight approaches based on edge detection, region growing, clustering, neural network, fuzzy, tree/graph based approaches, probabilistic or Bayesian approaches and histogram thresholding. An edge detector helps in finding the boundary of an object. These methods exploit the fact that the pixel intensity values change rapidly at the boundary of two regions. Ahuja et al. [3] described how pixel neighborhood elements can be used for image segmentation. Prager proposed a set of algorithms to perform segmentation of natural scenes through boundary analysis [71]. The goal of the algorithm is to locate the boundaries of an object correctly in a scene. First, preprocessing of the images is done to clean up the raw data by smoothening and noise removal. Second, the edge representation is generated. Perkins [70] acknowledged that edge based segmentation has not been very successful because of small gaps that allow merging of dissimilar regions. In order to avoid these problems, the paper proposes an expansion-contraction technique in which edge regions are expanded to close gaps and then contracted after the separate regions have been labeled. Chan et al. [15] developed a new adaptive thresholding heuristic algorithm for image segmentation using variation theory.

1.3 REMARKS

From the above discussions, it is evident that, linear filters are most suitable for impulse noise cancellation only and they cause blur during filtering. Also, linear filters do not remove Gaussian and mixed Gaussian-impulse noise effectively. For this reason, nonlinear filters based on Volterra series are considered in this work. It is distinguished from the other methods [39] [47] by employing FIR widowing algorithm to calculate filter coefficients.

This thesis presents a method for segmenting color images for Volterra filtered images. The Volterra filter enhances the uniform zones by preserving edges. Hence segmentation of filtered images gives more features compared with other conventional segmentation methods. Here, segmentation is done in HSI space using K-means clustering technique [87]. HSI color representation is compatible with the vision psychology of

human eyes [91]. Both the hue and intensity components of HSI are utilized. The cyclic property of the hue component is also taken into consideration.

The application encompass the problem of noise removal using Volterra filter in color images and proposes an efficient technique capable of removing the Gaussian and mixed Gaussian-impulse noise while preserving important image features. The Gray

Level Co-occurrence Matrix is used to evaluate the various textural parameters. For texture classification and analysis, the importance of Volterra filter is discussed.

The proposed filter based on Volterra series [58] [57] is also considered for denoising of dynamic image sequences. Here, the proposed method does not consider the motion

1.4 MOTIVATION AND OBJECTIVES OF THE WORK

In this thesis, the ideas presented in the literature survey are extended and a second orderVolterra filter using FIR Hamming window technique is designed. Here, a new class of Volterra series based filters for image enhancement and restoration is proposed. The approximation proposed in this work is different from those reported in the literature survey. A class of second order Volterra filters which acts as both lowpass as well asHighpass filter is proposed to optimize effectively the trade-off between noise removal and edge preservation. Both the Gaussian and mixed Gaussian-impulse noise is considered and

the robustness of the designed filter is tested.The designed filter has two kernels namely linear and nonlinear kernels. Thecalculated coefficients are arranged in the form of block-lexicographic matrix form.Symmetry conditions are imposed to reduce the number of coefficients. This new formulation technique reduces the number of nonlinear coefficients significantly andhence, the computational complexity. The implementation of this form of nonlinear filter requires only addition and multiplication operations. Finally, the filter performance is evaluated using the statistical parameters such as signal to noise ratio, mean square error,mean absolute error and edge detection error ratio.Further, the features of Volterra filter are used for color image segmentation. The performance of the proposed method is evaluated using parameters such as cluster validity factor and squared error function for different images. The applications of the proposed method include Gaussian and mixed noise removal in color images and dynamic image sequences and restoration of satellite images.

CHAPTER 2

2.1 volterra series

let' s take a system where x(t) is input and y(t) is output and f is effect of system

$$y(t)=fx(t)$$

let system is time invarient and continious,

$$y(t) = h_1 x(t) = \int_\tau h_{(1)}(\tau)x(t-\tau)d\tau$$

here h(t) is linear kernel of system i.e impulse response of system. volterra series is extention of nonlinear system in form of many linear system of different order using different order kernels.

$$y(t) = \text{‘}h_{(0)} + \int_{r} {}_{(1)}(\tau_1)x(t-\tau_1)d\tau_1 :$$

$$+ \int_{r^2} h_{(2)}(\tau_1,\tau_2)x(t-\tau_1)x(t-\tau_2)\ d\tau_1 d\tau_2 :$$

$$+\int_{r^3} h_{(3)}(\tau_1,\tau_2,\tau_3)x(t-\tau_1)x(t-\tau_2)x(t-\tau_3)d\tau_1 d\tau_2 d\tau_2 :$$

$$+\dots$$

or, more generally, the system described by a **volterra series**

$$y(t)= h_0x(t)+ h_1x(t)+h_2x(t)+\dots+h_nx(t)+$$

in which $h_0 x(t) = h^{(0)}$ is a constant and for $n = 1, 2,..$

$$h_nx(t)=\int_{r^n} h_{(n)}(\tau_1,\dots\tau_n)x(t-\tau_1)\dots x(t-\tau_n)d\tau_1\dots d\tau_n$$

is the nth- order **volterra operator**. the integral kernels h *is the* ***volterra kernels*** of the system .

2.2 estimation of volterra series

expansion coefficients of components of volterra kernel $h_{(n)i_1\dots i_n}$ as coefficients are found by minimizing the mse using finite dataset consisting n input-output pairs $(\mathbf{x}_j, y_j)$

$$\frac{1}{n}\sum_{j=1}^{n}(f(\mathbf{x}_j)-y_j)^2.$$

this problem of minimization is solved by applying the numerical calculations for least squares problems such as pseudo inverses or singular value decomposition, without the need of estimating crosscorrelations.

2.3 techniques to calculate coefficient kernel

there are five techniques which are following

1. cross correlation techniques
2. advance in correlation techniques
3. exact orthogonalalgorithm
4. linear regression
5. kernel techniques

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chapter 3

ESTIMATING NOISY CIRFS

3.1 the likelihood

represents how our ideal contour image u relates to the measurements characterizing the corruptions in local edge and line operator responses. focus on noise contamination in the measurements because (1)

edge/line detection requires di erentiation, which ampli es noise and (2) the local signal-to-noise ratio (snr) drops for xed sensor noise, when the local con-trast (i.e., signal) is low. for concreteness and simplicity, our measurement model is m = u + n , where n is white gaussian noise n with zero-mean and variance $_n^2$, and the likelihood is by a change in variables in m, other observation models with i.i.d. noise can be included, including those estimated from histograms of edge/line operator responses both on and o the actual contours [6, 2].

3.2 the posterior

using bayes' rule, the posterior distribution p (dujm) is proportional to p(mju) times p (du); where du is an in nitessimal region around realization u. the cirf prior is written p (du) := fu 2 dug because a density for u exists only in a generalized sense[2]. expanding the norm in the likelihood (1), the posterior therefore becomes where the subscript := $_n^2$ (the inverse- noise variance) indicates conditioning on the measurements m, and the normalizing constant is although we do not have an explicit expression for the prior p (du) (and so neither for the posterior), in 4 we shall nd that we can indirectly use the prior through its cumulants in order to obtain volterra filters.

3.3 bayes estimation

filtering here means the estimation of the (unknown) cirf u given a noisy re-alization m. in bayes decision theory, estimation is formalized by specifying the posterior and a loss function loss(u; u) that penaltizes estimate u when the true unknown is u ; the bayes estimate is then u**e** := arg min$_{\mathbf{u}}$ _ [loss(u; u)jm]. maxi-mum a posteriori (map) estimation corresponds to the 0/1 loss function, which penalizes all errors equally;

this loss is zero only when the estimate is perfect (at all sites i), and 1 otherwise. despite the popularity of the map estimator, we believe an additive loss function such as the squared error jju ujj^2 is more appropriate for high-noise filtering because it penalizes small errors at a few sites much less than large errors at many sites, unlike the 0/1 loss function (map). therefore we de ne our ltering task to be the computation of the minimum mean squared error (mmse) estimate where again denotes the conditioning on m.by a standard argument [5], the mmse estimate u**e** is equal to the posterior mean _ u of the cirf u .since the posterior mean is generally di cult to compute, we seek simpli-cations. a typical approach would be to approximate the cirf prior with a gaussian, giving rise to mmse linear filtering [2]. we avoid this method, how-ever, because it ignores all the cirf cumulants beyond the mean and covariance. instead, we focus on an aspect of our problem that we have not yet considered: extremely noisy conditions. in this way we can simplify our ltering problem tremendously, while exploiting the higher-order statistical structure of the cirf.

CHAPTER 4

4.1 VOLTERRA FILTERING AT LARGE NOISE LEVELS

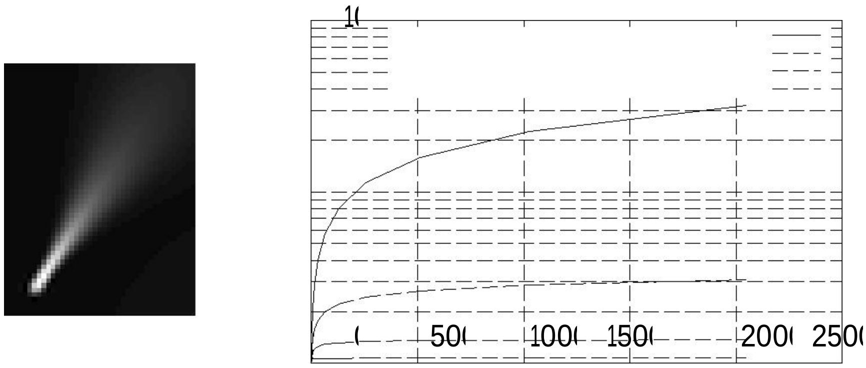
volterra lters constitute one class of nonlinear lters that subsumes linear l-ters . by de nition, the output of a k-th order volterra lter is a k-th degree polynomial[3] function of the input signal. analogous to the connection between mmse linear lters and second-order statistics, mmse volterra lters are related to higher-order statistics. in particular, a mmse k-th order volterra lter gen-erally requires up to the (2k)-th order moments of the input and unknown [1, 20]. unfortunately, the computational complexity of simply applying the gen-eral k-th order volterra is o(n^{k+1}), where n = jij ; solving for the mmse lter coe cients is much more costly in general.

here we derive linear, quadratic and cubic volterra lters for approximating the posterior mean of the cirf corrupted by large amounts of white gaussian noise. our approach is based on the following observation: in such noisy condi-tions, the inverse noise variance will be small. this suggests that we consider the in nite noise limit where approaches zero; in particular, we perform a taylor series expansion of the posterior mean _ u around = 0. we then ex-ploit simplifying aspects of the cirf, especially the self-avoiding nature of the direction process, to obtain volterra lters that run in in o(n log n) time.

since the cumulants of w are not directly known, we computed them in terms of mccullagh's so-called generalized cumulants (an algebraic structure that eases computations of polynomials of moments and cumulants) of u [15]. we then di erentiated with respect to m_i to get the rst few terms in the taylor expansion of _ u_i as a function of the generalized cumulants of u .

besides spatial homogeneity, two properties of the cirf played a significant role in simplifying our calculations. first, the contour density is small (0 1) in a large number of images, as contours constitute a small fraction of the total image (which is why pen ink does not run out quickly). in the con-tinuum, an extreme form of this claim certainly holds: the bounding contours in an image of smooth surfaces in an occlusion relationship constitute a set of measure zero (with respect to the standard area measure in the plane). this low density is even more appropriate for the cirf based on the direction process, where the curves live in a three-dimensional space. the low density of the cirf was crucial for simplifying mccullagh's formula for expressing generalized cu-mulants in terms of a sum of products of (ordinary) cumulants: we neglect all terms which are a product of two or more cirf cumulants (having magnitude o(^{2}) by prop. 1). thus the low density of the cirf allowed us to express the posterior mean as a weighted o( )-sum of cumulants of u , each of the form the second cirf property that simpli ed our derivation is the approximate self-avoidingness of the direction process. if our markov processes were perfectly straight, they would never return to their starting points, even if in nitely long. we observe in fig. 3 that the direction process rarely returns to its starting position. many permutations in cumulants of the cirf (prop. 1) could therefore be neglected.

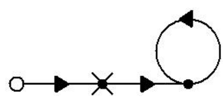
to support the error-prone task of explicitly summing over the permutations in the cirf cumulants in the o( )-sum for the posterior mean, we constructed a diagram corresponding to each permutation (fig. 4). nodes indicate sites, arrows indicate ordering in the permutation, and multiplicative constants such as are r" (g is understood for arrows away from r, g is understood for arrows toward r, and \x" represents an input m at a node). using the diagram we see that the reverse permutation (i; r) gives rise to g m (evaluated at r). in fig. 4b, permuis diag(m)gm using the reversed diagram. in fig. 4c, permutation (r; i; j; k) of term $_{i;j;k}$ cum$_{r;i;j;k}$ m$_{i\,jk}$ has a loop, which represents contour intersection (at node j = k) and arises from the kronecker delta $_{jk}$, which in turn comes from the quadratic term in w . terms that have larger loops can require taking componentwise products of operators such as g g , and are neglected due to the self-avoidingness of the direction process. see [2] for details.these diagrams are loosely analogous to feynman diagrams, which support perturbation calculations in statistical physics and quantum eld theory. inde-pendently of this work, ruderman [22, pp. 29{33] used feynman diagrams to calculate the posterior mean of an underlying signal observed in gaussian white noise, where the perturbation is in terms of the non-gaussian underlying sig-nal. in contrast, the perturbation used here is due to the gaussian noise; the underlying non-gaussian signal (the cirf) is modeled exactly.



average length

fig. 3. (left) the green's operator of the direction process (see 2);

brightness indi-cates average time spent at a site, given that process started near lower left, traveling diagonally to the upper right (parameters: = 1= 24 with 44 directions ; = 100 throughout this report). (right) the self-avoidingness of the direction process: a com-parison of average number of returns to starting location for various markov processes (chains) , plotted as a function of total contour length. the average ii number of returns is at least one because the rst visit is included. unlike random walks on the line, in the plane, or even in space, the average number of returns of the direction process (\plane with orientation") does **not** increase with contour length; the direction process is therefore (approximately) self-avoiding. spatial stepsize (x, etc.) is one, except = 2 = (number of directions); also, throughout this report unless speci ed explicitly.



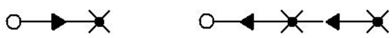


fig. 4. diagrams dramatically simplfied the cumulant permutation computations in the lengthy derivation of the volterra cirf lters. see text.

using this diagram-based technique , we obtained linear, quadratic, and cubic volterra lters which asymptotically approximate the posterior mean of the cirf. let a b denote the vector which is the componentwise product of vectors a and

b, i.e., (a b)$_i$ = a$_i$ b$_i$.

result 1 (high-noise mmse volterra cirf filters). suppose that the curve indicator random eld u (for approximately self-avoiding markov processes) is corrupted with additive gaussian white noise of variance $_n^2$ =: ^{1} to produce measurement vector m. let := g$_{ii}$, where is the average curve length. then

the minimum mean squared error estimate of u given m has the following ap-proximate asymptotic expansion as $_n$! 1 (! 0):

ar filter:

$^{(1)} = f1 \; 2 \; + \; (gm \;\; + g \; m)g + o(\; ^2 + \; ^2 \;)$ (4

dratic filter:

$^{(2)} = f12 \;\; + 3 \; ^{2\,2} + i \;\; (1 \;\; 2 \;\;)(gm + g \;\; m)$

$g \, diag(m) \, gm + gm \;\;\; g \;\; m + g \;\;\; diag(m) \, g \, m) \;\; g$

$^3 + \; ^2 \;)$ (5

ic filter:

$u\tilde{}^{(3)} = f1 \qquad 2 \quad + 3 \; ^{2\,2} \quad 4 \; ^{3\,3}$

$+ (1 \;\; 2 \;\; + 3 \; ^{2\,2} \,)(gm \;\; i + g \, m)$

$+ \, ^2(1 \;\; 2 \;\;)(g \, diag(m) \, gm + \quad gm \quad g \;\; m + g \;\; diag(m) \, g \, m)$

$+ \, ^3(g \, diag(m) \, g \, diag(m) \;\; i \;\; gm + g \, diag(m) \, gm \, g \, m + gm \, g \;\; i \;\; diag(m) \, g \, m + g \, diag(m) \, g \, diag(m) \, g$

$m) \quad g$

V

$^4 + ^2$): (6

these lters compute quickly: by implementing the operator g in the fourier domain [2], its computational complexity is o(n log n) for the direction process, where n = jij. since multiplying a diagonal matrix with a vector has o(n) complexity , the net complexity for all of these lters is therefore o(n log n) for the direction process. this is far better than for the general k-th order volterra lters, which have o(n^{k+1}) complexity.

CHAPTER 5

Results and Discussion

5.1 Introduction

In this report, an algorithm is presented to remove Salt and Pepper noise from grayscale images. Salt and Pepper noise can corrupt the images where the corrupted pixel takes either maximum or minimum gray level. In this work, we reduce Salt and Pepper noise using Improved Volterra(VOLTERRA FILTER). It is implemented, and the effectiveness on denoising is evaluated by PSNR and MSE.The experimental result will show the comparison and the performance of Existing filter with improved filter to de-noise the noised image. Also the simulation result based on MATLAB will be compared with the result of ISIM and VSIM.

Salt & Pepper Noise in the images is caused by malfunctioning pixels in camera sensors, faulty memory locations in hardware, or transmission in a noisy channel. For images corrupted by salt-and-pepper noise, noisy pixels can take only the maximum or the minimum values. There are many works on the restoration of images corrupted by salt & pepper noise. The volterra filterwas once the most popular nonlinear filter for removing salt & pepper noise because of its good denoising power and computational efficiency.However, when the noise level is over 50%, some details and edges of the original image are smeared by the filter. The image processing is an important process in every life application. Image processing is an electronic domain where in image is divided into small unit called pixel and then various operation is carried out. When an image is formed, factors such as lighting (spectra, source and intensity) and camera characteristics (sensor response, lenses) effect the appearance of the image. So, the prime factor that reduces the quality of the image is Noise. Noise hides the important details of images. There are different types of noises which corrupt the images. These noises are appeared on images in different ways: at the time of acquisition, due to noisy sensors, due to faulty scanner or due to faulty digital camera, due to transmission channel errors, due to corrupted storage media.

In image processing, the impulse noise reduction from images plays a very vital role. Impulse noise in images is present due to bit errors in transmission or induced during the signal acquisition stage. There are two types of impulse noise, like Salt and Pepper Noise and random valued noise. Salt and Pepper noise can corrupt the images where the corrupted pixel takes either maximum or minimum gray level. The removal of noise from the image is known as Denoising. Image denoising is one of the most common and important image processing operations in image and video processing applications. The important property of a good image denoising model is that, it should completely remove noise as far as possible as well as preserve edges. Traditionally there are two types of denoising models, i.e. linear filtering and non linear filtering. The main aim of the filtering is to eliminate outliers with maximum signal distortion to the recovered noise free image. Many types of linear filters removes salt and pepper noise but blur the image, the linear approaches were very popular because of its mathematical simplicity. In linear filtering denoising techniques is directly applied to the image pixel without checking the availability of noisy and non noisy pixels. The examples of linear filtering are Mean filter. The disadvantage of this filter is it will affect the quality of non noisy pixel. In the case of non linear filter, this is done by two steps first detection then filtering. First step the position of the noise is detected and in the second step replace the noisy pixel with calculated value. Non linear filtering techniques are implemented widely because of their superior performance in removing salt and pepper noise and also preserving fine details of image. There are many works on the restoration of images corrupted by salt and pepper noise. The volterra filterwas once the most popular non linear filter for removing impulse noise, because of its good denoising power and computational efficiency. Median filters are known for their capability to remove impulse noise as well as preserve the edges.

5.2 TYPES OF FILTER USED

1.MEAN FILTER:- There are two types of filtering schemes namely linear filtering and nonlinear filtering. Mean filter comes under linear filtering scheme. Mean filter is also known as averaging filter. The Mean Filter applies mask over each pixel in the signal. Each of the components of the pixels comes under the mask are being averaged together to form a single pixel that's why the filter is otherwise known as average filter. Edge preserving criteria is poor in mean filter. Mean filter is defined by. Where (x1 ..... xN) is image pixel range. Mean filter is useful for removing grain noise from the photography image. As each pixel gets summed the average of the pixels in its neighborhood is found out, local variations caused by grain noise are reduced considerably by replacing it with average value.

2.MEDIAN FILTER:- Volterra filteris the nonlinear filter. The main idea behind the volterra filteris to find the median value by across the window, replacing each entry in the window with the median value of the pixel.

Median value calculation 115, 119, 120, 123, 124, 125, 126, 127, 150. Median value = 124. The pattern of neighbor's pixels is called the "window", when the window contains odd number of values in it than the median is simple: it is just the center value after all the entries in the window are sorted numerically in ascending order. But for an even number of entries, there is more than one center value; in that case the average of the two center pixel values is used. One of the major problems with the volterra filteris that it is relatively expensive and complex computation. For finding the median it is necessary to sort all the values in the neighborhood into numerical order and this filter relatively slow, even it is performed with fast sorting algorithms like quick sort. However the basic algorithm can be enhanced somewhat for the speed purpose.

3.PROGRESSIVE SWITCHING MEDIAN FILTER:- : It is a median-based filter, which works in two stages. In the first stage an impulse detection algorithm is used to generate a sequence of binary flag images. This binary flag image predicts the location of noise in the observed image. In the second stage noise filtering is applied progressively through several iterations. This filter is a very good filter for fixed valued impulse noise but for random values the performance is abysmal. The advantage of using Volterrapreserves the positions of boundaries in an image, making this method useful for visual examination and measurement. The progressive switching median (PSM) filter implements a noise detection algorithm before filtering. But the disadvantage is to removes both the noise and the fine detail since it cannot tell the difference between the two. Both noise detection and filtering procedures are progressively repeated for a number of iterations. As an attempt to improve the PSM filter, an improved proposed.

4.(VOLTERRA FILTER):-

As an attempt to improve the PSM filter, an improved volterra(IPSM) is proposed to enhance progressive volterra filterin term of its noise filtering ability. The proposed algorithm sets a limit on the number of good pixels used in determine median and mean values, and substitute impulse pixel with half of the value of the summation of median and mean value.Experimental results show that the proposed algorithm performs a better noise filtering ability as the images are highly corrupted.

5.GAUSSIAN FILTER:- The Gaussian filtering scheme is based on the peak detection. The peak detection is based on the fact that peaks are to be impulses. The key point is that this filter corrects not only the spectral coefficient of interest, but all the amplitude spectrum coefficients within the filter window.

Some properties of Gaussian filter are:

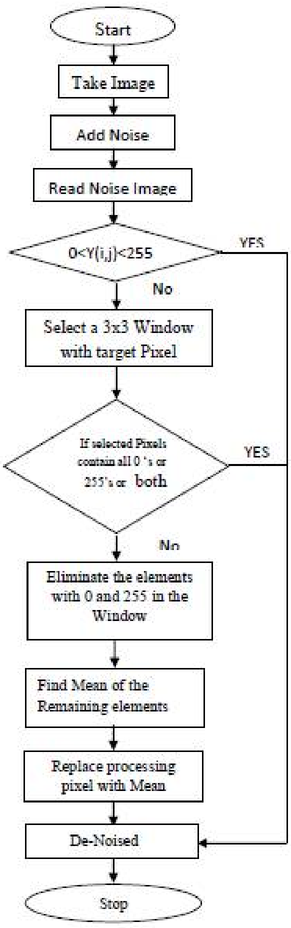
1.The weights give higher significance to pixels near the edge (reduces edge blurring).

2.They are linear low pass filters.

3.Computationally efficient (large filters are implemented using small 1D filters).

4.Rotationally symmetric (perform the same in all directions).

x



Start
Take Image
Add Noise
Read Noise Image
0<Y(i,j)<255
YES
No
Select a 3x3 Window with target Pixel
If selected Pixels contain all 0 's or 255's or both
YES
No
Eliminate the elements with 0 and 255 in the Window
Find Mean of the Remaining elements
Replace processing pixel with Mean
De-Noised
Stop

x

FLOW CHART

METHODOLOGY

ALGORITHM

Step I: Starting from the middle pixel of an image with a 3x3 initial window size. The scanning process will be done through the whole image from middle to the upper left, upper right, lower left and lower right corners of the image.

Step 2: Calculate median from the pixel values of the current window except values of O and 255.

Step 3: This step checks the following conditions: -

(a) If the median is noise-free (i.e. at least one noise-free pixel remains in window) then replace the center pixel with the median and go to Step 5.

(b) If the median is noisy (that means no noise-free pixel is found in window) then increase the window size by one pixel at each of its four sides and perform the Step 2 up to maximum window size.

(c) If the maximum window size (5x5) is reached and still no median is found, then go to next step (Step 4).

Step 4: This step considers the last processed pixel (which was processed just before the current center pixel). As the scanning starts from the middle pixel, it

is more likely of getting last processed pixel within the image boundary. If the last proceed pixel is not 0 or 255 then replace the current center pixel with that processed pixel.

Step 5: Slide the window to the next pixel.

I. OBJECTIVES

Our objectives includes the following:-

Step 1:Select an image on which we want to work for noise filtering.

Step 2:Image represent by pixels, so some pixels are good or some are bad due to some

problem during capturing.Mean filter based on Linear De-noising never check about quality of pixels. It works only in step that is Filtering. So filter based on Median is used in our research work that detects corrupted pixels and then filter.

Step 3: Volterrabased on Non-linear de-noising is

implement on that noisy image and get result.

Step 4: This Filter has a disadvantage that it removes both the noise and the fine

detail pixel since it cannot tell the difference between the two. It can tell only median level pixel.

Step 5: The pixel in fine quality is useful for us, so to overcome this problem we propose a new filter.

Step 6: The proposed filter sets a limit of pixel quality and the pixels higher that limit never change but noisy pixels improved by number of iterations.

Step 7: Result of improved filter compared with existing pixels and analysis of comparison provide us a conclusion of our research work.

5.3 SIMULATION AND PERFORMANCE ANALYSIS

CASE 1:- WITH MATLAB

This method has been implemented using Matlab as the simulation tool. The proposed filter is tested with Image 'CAMERAMAN.tif' of size 250 x 250. The image is corrupted by Salt and

Pepper noise at various noise densities and performance is measured using the parameters such as Peak-Signal-to-Noise Ratio (PSNR), Mean Square Error (MSE).

The parameters used to define the performance are:

 Peak Signal-to-Noise Ratio (PSNR):

PSNR = 20 log10 (255 ⁄ RMSE)

.....where Root Mean square error (MSE)

 Mean Square Error (MSE) :

MSE = √1 ⁄ MN Σ (Yij-Xij)2 i, j

The simulation results and data are shown below:

In figure 1 a in built cameraman image available in matlab software has been loaded in matlab workspace and the data type of image has been converted to double type due to addition of noise intensities

figure 1- original image

Figure 2 is a demonstration of noise which is introduced in the original image. When salt and pepper noise is added the entire image space is filled with intensity values 0 or 255. This means pepper and salt respectively. The image in figure 2 has been shown with 50% noise meaning that approximately half of the pixels are actually corrupt now.

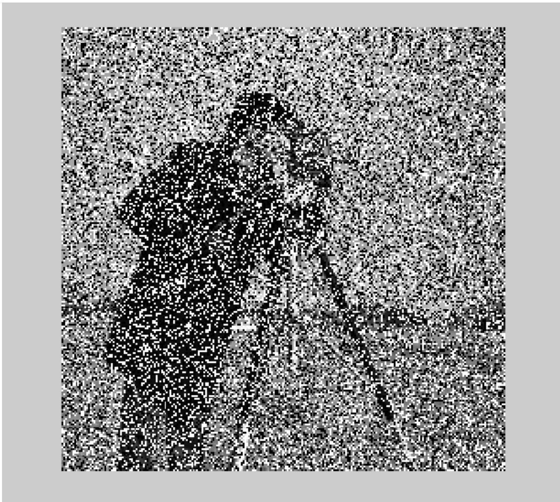


figure 2- image with 50% noise

In figure 3 the result seen is a filtering effect introduced in this image that is available readily namely progressive switching median filtering. Due to this filtering noise has reduced but the quality of image remains unsatisfactorily.

Figure 3- denoised image with psm filter

In figure 4 a highly drastic change can be seen as a lot of change could be seen in the existing image for the purpose of filtering. The improvements made in the complete image is available in the form of 50% noise available. But now when image quality remains suspended in volterraits efficiency is improved by applying a better filter. This better filter is nothing but a two stage filtering of image using psm filter in the first image and low pass Gaussian filter in the second stage**.**

Figure 4- denoised image with improved psm filter

After concluding the results on cameraman image it is necessary that some modification work could be made more presentable by adding another table where image noise is being added with the original image so percentage noise is one point the other point is the performance evaluation of the modification technique using peak signal to noise ratio and mean square error. As per the formulation of formula stated at the beginning both terms are reciprocal to one another. If psnr increases then mse increases.

PERFORMANCE ANALYSIS

1. MEAN SQUARE ERROR
2. PEAK SIGNAL TO NOISE RATIO

NOISE LEVEL	PSM FILTER VALUE	IMPROVED PSM FILTER VALUE
10%	27.7040	28.2234
20%	25.9289	26.3476
30%	23.3906	24.8467
40%	21.0970	22.6880
50%	18.1642	20.2267
60%	13.8232	17.2921
70%	11.5963	11.0782
80%	9.6791	9.1715

Table 1. PSNR and MSE for percentage noise added

In this table a good amount of noise is added in the cameraman image as the table 1 shows noise addition of range 10% to 80%. In this report two parameters psnr and mse are seen. If 10% noise is added psnr for psm filter is 27dB similarly for improved psm is 26 dB. At 50% noise psm shows 18dBs whereas IPSM shows 20dB. Similalr when noise is added to 80% then PSM snr is approximately9.6 dB wheras Improved PSM is approximately 9.17 dB. It is important to notice that Improved psm performs better that PSM and the results are good at this level but at high density of noise both psm and improved psm are at the same level of performance parameters psnr and mse.

Chapter 6

Conclusion and future scope

I. CONCLUSION

It is conclude that noise from an image can be removed using some denoising filters. Median filters are used for this noise reduction. Volterrais one of them which have a drawback that it uses number of iterations many times for each type pixel like good or bad. So it is improved in term of filtering ability. So in this research work we fix a limit of pixel quality. Filtering detect pixels that has lower quality than that fixed value. So numbers of iterations are less as compared to existing progressive switching filtering. Also the waveform of Modelsim and Xilinx are compared on the negative edge clock having clock enable and the results are evaluated. The percentage noise removal and noise effects are same using MATLAB only and with MATLAB and modelsim only.

In this report, we explored some of the denoising techniques for image denoising. Here we analyzed and present a literature review of some of the proposed denoising techniques that will be useful for the users by getting a brief introduction of these techniques so that they can make use of any one of them if needed. Image processing is a widely growing field as many of the nowadays applications are making use of it. Therefore, there is also a need of image denoising techniques due to introduction of noisy elements during image acquisition. Hence, our concern is to provide a collective brief review of some of these techniques in a single report to provide ease to the image users. Further our work is to implement an optimal fuzzy base noise removal technique for removing noise from colored images that will be explained with details in next report.

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