International Journal of Emerging Technology in Computer Science & Electronics (IJETCSE)
ISSN: 0976-1353 Volume 20 Issue 3 – MARCH 2016.

PROGRESSIVE IMAGE DENOISING USING DETERMINISTIC ANNEALING AND ROBUST NOISE ESTIMATION

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***Abstract*--- The study of image processing in recent years is found to be extended in many ways,but still the image denoising is in active research process.Though there are other denoising methods that are very good enough to prove that they are numerically impressive and approch theoretical values ,they suffer from visible artifacts.Getting an efficient method to remove noise from theimages,before processing it for further analysis is a great challenge.Noise can degrade any part of the image at the time of producing it or over transmission.The noise removal algorithms are choosen,based on the type of noise present in the image and is further denoised.But, on the other end current methods are becoming more complex,to analyse the image and difficult to implement.In this paper,we say that denoising is a simple physical process,which progressively reduces the noise by deterministic annealing process.The results of our implementation are numerically and visually excellent.**

KeyTerms - image denoising, robustestimation, deterministic annealing, bilateralfiltering ,image smoothing

I. INTRODUCTION

One of the most important problems of image processingisdenoising, the reconstruction of the original imagefrom a noisy image. Noisy images may be produced by noise contamination through an analog process during acquisitionor transport over analog media The common simplifyingassumption is that the image has been contaminated withadditive white Gaussian noise (AWGN). This assumptionincludes that the noise is stationary and uncorrelated amongpixels. Another common assumption is that the variance of thenoise is known. Progress in image denoising has stagnated in recent years.The medal of state-of-the-art is held by block-matching with 3D filtering (BM3D) [2], aging over seven years. Levin and Nadler found that for natural images, BM3D is close to the theoretical limit of denoising [3], but artificial and highlycorrelatedimages still have potential for improvement [3], [4], [5]. However, only a handful of methods numerically improveover BM3D, with modest increase in visual quality. State-of-the-art image denoising methods still produce visible artifacts, especially on sharp edges and in smooth regions of the original image. Such features are common for natural images, like clear sky and human skin, not to speak of synthetic images,where edges and gradients are abundant. Another nuisance is that current methods are complex and thus prohibit thorough analysis. Recently, Knaus and Zwicker demonstrated with dualdomain image denoising (DDID) that simple algorithms can achieve high-quality results [6]. We extend their work and propose progressive image denoising (PID), a method inspired by deterministic annealing and based on robust noise estimation. Deterministic annealing (DA) is a heuristic method that isefficient at solving complex optimization problems where many local extrema exist. Our method produces high-quality results, void of artifacts typical to patch-based methods. It performs not only well for natural images, butalso for synthetic images where artifacts are more apparent.Itis also of practical interest that our algorithm is unusually short, fitting into a column of this paper. Last not least,our formulation using robust estimators and iterative filtering akin to deterministic annealing offers opportunities to explore alternative implementations of the image denoising process.The rest of the paper is organized as follows. We first review anout the energy gradient in images.InSection II we discussed about the system architectureand its definitions. In Section III we explained about our algorithm and its derivation, onimage denoising process using robust noise estimation and deterministicannealing.In Section IV we proposed our method and presented high-quality results compared to other methods.In SectionV , we have concluded that in future the performance can be optimised further by improving window size to follow the growing spatial kernel.

II. SYSTEMARCHITECTURE

In this section, we describe the PID architecture

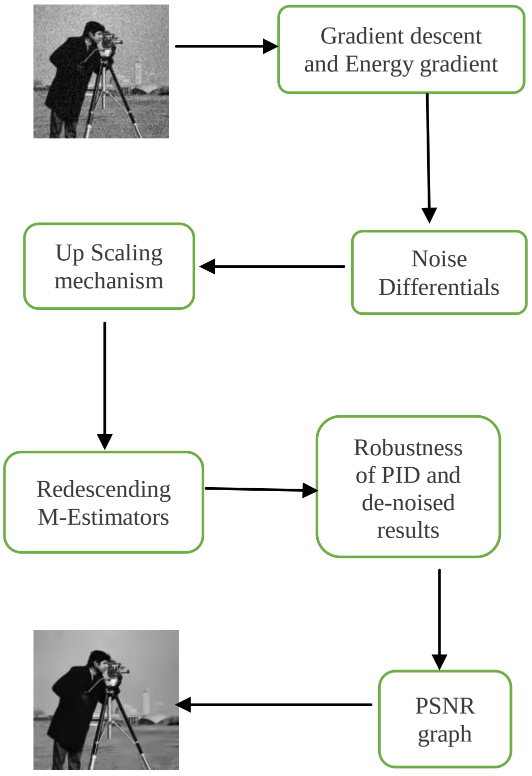
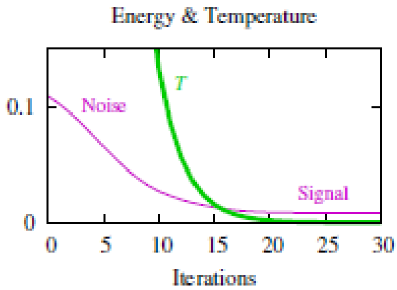


Fig. 1. Architecture of Progressive Image Denoising

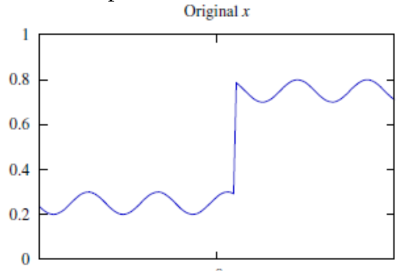
A. System Description

Fig. 1 shows the design of the PID. As indicated in Fig. 1, the construction of denoised image will undergo the following steps

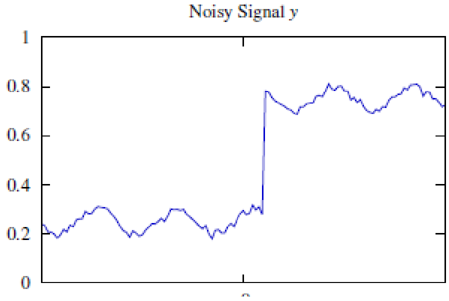
1) Gradient Descent and Energy gradient :
Image gradients are used to extract information from the images.These information are obtained from the original image.Each pixel measures the change in intensity of that same point in the original image, in a given direction.The full range of direction,the x and y directions are calculated.Robust feature and texture matching is also done in image gradient.Illumination change or camera properties can cause two images of the same scene to have drastically different pixel values.This makes matching algorithms to fail to match very similar or identical features.An image gradient is adirectional change in the intensity or color in an image. In graphics software for digital image editing, the term gradientis defined as a gradual blend of color that can be considered as an even gradation from low to high values, as used from white to black in the images to the right.The gradient of the image is one of the fundamental building blocks in image processing.



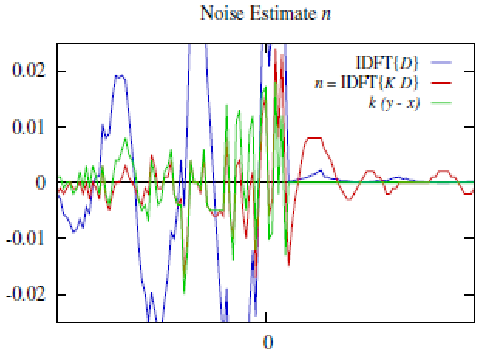
2) Noise Differentials :Image noise is defined as any odd variation in brightness or color information in images,and is usually in form of electronic noise. This type of noise is produced at the time of capturing or image transmission.Noise means,the pixelsthat show different intensity values rather than true pixel values.



Noise in images can be classified as Impulse noise or Salt-and-pepper noise, Amplifier noise or Gaussian noise, Shot noise, Quantization noise or uniform noise, Film grain,on-isotropic noise,Multiplicativenoise or Speckle noise and Periodic noise.Theuse bilateral filterof best suited filter to remove noise from the image.



A bilateralfilter performs non-continuous, edge-preserving and noise-extracting and smoothing effect filter for images. Each intensity pixel value is replaced by weighted average of intensity values from nearby pixels. Crucially, the weights depend not only on Euclidean distance of pixels, but also on the radiometric differences.



The bilateral filter is defined as

$$I^{\text{filtered}}(x) = \frac{1}{W_p} \sum_{x_i \in \Omega} I(x_i) f_r(\|I(x_i) - I(x)\|) g_s(\|x_i - x\|),$$

where the normalization term

$$W_p = \sum_{x_i \in \Omega} f_r(\|I(x_i) - I(x)\|) g_s(\|x_i - x\|)$$

3) Up-Scaling Mechanism :Upscaling is defined as the automatic conversion of a low resolution image or video to high definition resolution. This process can fix resolution issues.In computer graphics,image scaling is the process of reproportion a digital image. Scaling is a non-trivial process that achieves a balance in efficiency, smoothness and sharpness. Incase of bitmap graphics, as the size of an image is reduced or enlarged, the pixelsthat consist information about the image makes it increasingly visible, making the image appear "soft" if pixels are averaged, or having rough values. With vector graphics the losing of quality may be in processing power for re-rendering the image, which may be noticeable as slow re-rendering with still graphics, or slower frame rate and frame skipping in computer animation.

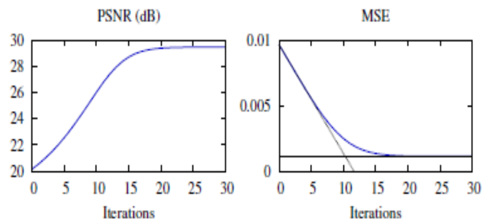
4) Redescending M-Estimator :They are Ψ-type M-estimators which have ψ functions that are non-decreasing near the origin, but decreasing toward origin (0,0)far from the origin. ψ functions can be chosen to redescend smoothly to zero, so that they usually satisfy the function ψ(x) = 0 for all x with |x| > r, where r is considered as minimum rejection point.These properties of the ψ function, makes estimators are very efficient by completely rejecting gross outliers andwhereas other observation point rejection techniques,do not suffer from a masking effect.

Redescending M-estimators have high breakdown points (close to 0.5), and their Ψ function can be chosen to decrease smoothly to 0. This means that moderately large outliers are not ignored completely, and greatly improves the efficiency of the redescending M-estimator.Theredescending M-estimators in Frequency Domain are based on modifying the spectral transform of an image using fouriertransform.This process involves transforming the image to its frequency representation and Perform image processing. And then,Computes an inverse transform back to the spatialdomain.

High frequenciesmay change the pixel values rapidly across the image.whereas,Strong low frequency components correspond to large scale features in the image.Moreover,redescending M-estimators in Spatial Domain (Image Enhancement) involves manipulating or changing an image representing an object in space to enhance the image for a given application.This process is based on direct manipulation of pixels in an image filtering basics, smoothing filters, sharpening filters, unsharp masking and laplacian.

5) Deterministic Annealing :Deterministic annealing is an optimization technique that pursuits to find a global minimum of a cost function. The technique was designed to explore a large portion of data using cost surface randomness,bysttill performing optimization using local information. The procedure starts with changing the cost function to introduce a notion of randomness, allowing a large area to be explored. On every iteration the amount of randomness is unnatural, and a local optimization of performed. Gradually, the amount of imposed randomness is lowered so that when the algorithm terminates it optimizes and yields original cost function, and the solution is obtained to the original problem.

6) PSNR Graph :From the above process weanalyze the robustness of PID with respect to parameter change and we modifythe parameters by a perturbation value $0.6 \leq \beta \leq 1{:}4$. Weplot the PSNR values as functions of iteration number N orperturbation value β.The number of iterationsN needs to be large enough to get good denoising results.



Thegradient descent step factor has the biggest influence on thePSNR.when the iteration N values are decreased ,the noise will be under estimated and simultaneously the image will contain residual noise.similarly when large values of N is chosen the noise in the image is over estimated and the information in the image will be lost.The PSNR increases fast in the beginning, andslows down as the noise becomes smaller. TheMSE shows a strong linear decrease in the beginning andasymptotically approaching the squared bias as the variancedisappears. The plots look similar for any image we denoised.

III. BASIC DEFINITIONS

A. Definitions

Our method based on DDID,where we allow iterations to take place arbitrary fine time steps and by not requiring a distinction between noisy and guide images.DDID produces best resultswhen compared to BM3D.The deterministic annealing is well suited for this noise reduction although DA and SA are heuristic methods suited for complex optimization problems.this optimization solution is suitable for large state space problem with many local minima.stochastic state transitions prevent the algorithm from getting stuck in local minima by allowing energy to increase with some probability.A slow descent of temperature is described by annealing schedule, and gradually the state is frozen at the optimum.The cooling process is accelerated by parameterizing the energy with temperature and the momentary energy is gradually reduced.In our work DA,is used for deriving a gradient of descent. Compared to DDID, PID uses more iterations. Fast Fourier Transform (FFT) is performed on every pixel per iteration,thatcannot be optimized across neighbors,since other pixels are potentially very different bilateral masks. Our focus in this work is to emphasize on the quality and simplicity of the denoising process. We can foresee some performance improvements in the near future.ourmethos is straight forward to parallelize.in our denoising framework we preserve signal as an outlier and noise as the inlier estimation and discarding it.

IV. PROPOSED SCHEME

We presenr PID as simple process by iterating filtering scheme ,where the gradient descent is analysed first,and the information from the images is extracted.Every pixel has a intensity change of values in the original image,due to illumination change or camera movement.All those image gradient are observed and their corresponding energy values are calculated.Progressively,the noise signals are estimated by a signal x hasbeen contaminated with additive white Gaussian noise n and variance σ^2 .The task is to decompose the noise contaminated signal y into its original signal x and noise instance n like

$$y = x + n.$$

But,denoising with gradient descent is calculated by, using the below formula,

$$x_{i+1} = x_i - \nabla\lambda \mathrm{E}(x_i)$$

After computing,the gradient descent we conceptual;y divide noise signals into three classes,namely large and medium amplitude signals and small amplitude noise. Large amplitude signals

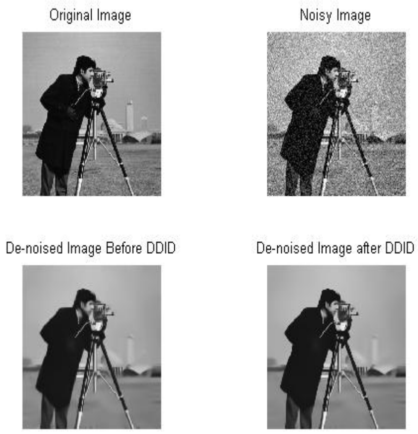
are easily recognized in the spatial domain. When the amplitude of the signal is smaller and therefore more similar to the noise, signal and noise cannot be reliably distinguished in the spatial domain. Hence,signalis auto-correlated and noise is uncorrelated. By using robust estimators we reject large amplitude gradients in the spatial domain and medium amplitude waves in the frequency domain, and finally we estimate the small amplitude noise without bias introduced by the signal.Finally we perform a discrete Fourier transform to obtain the masked signal in the frequency domain $\mathcal{F}_p$, yielding the Fourier coefficients $D_{i,p,f}$ for frequency f as

$$D_{i,p,f} = \sum_{q \in \mathcal{N}_p} d_{i,p,q}\, k_r\left(\frac{|d_{i,p,q}|^2}{T_i}\right) k_s\left(\frac{|q-p|^2}{S_i}\right) e^{-j\frac{2\pi}{2r+1} f\cdot(q-p)}.$$

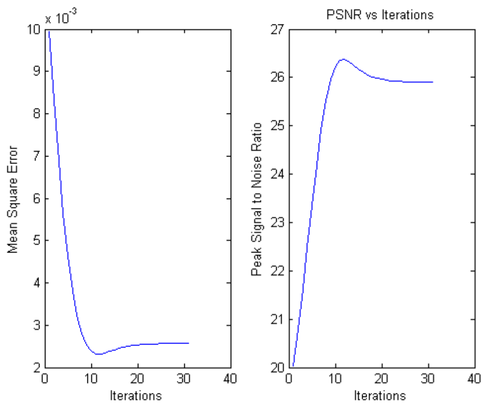
Here,we use imaginary number j $=\sqrt{-1}$ to avoid confusion with time i.Now,for completeness of the process we also give the code of the DDID step.

```
function x = PID(y, sigma2)

    N       = 30;
    r       = 15;
    sigma_s = 7;
    gamma_r = 988.5;
    gamma_s = 2/9;
    alpha   = 1.533;
    lambda  = log(alpha) * 0.567;
    [dx dy] = meshgrid(-r:r);
    r2      = dx.^2 + dy.^2;

    x = y;
    for i=1:N, xp = padarray(x, [r r], 'symmetric');
        parfor p=1:numel(y), [Y X] = ind2sub(size(y), p);

            % Spatial Domain
            d = xp(Y:Y+2*r , X:X+2*r) - x(p);           % Eq. 4
            T = sigma2    * gamma_r * alpha^(-i);       % Eq. 8
            S = sigma_s^2 * gamma_s * alpha^(i/2);      % Eq. 9
            k = exp(- d.^2 / T) .* exp(- r2 / S);       % Eq. 5

            % Fourier Domain
            D = fft2(ifftshift(d .* k));                % Eq. 5
            V = sigma2 * sum(k(:).^2);                  % Eq. 7
            K = exp(- abs(D).^2 / V);                   % Eq. 6
            n = sum(sum(D .* K)) / numel(K);            % Eq. 6

            x(p) = x(p) - lambda * real(n);             % Eq. 3
        end
    end

    x = DDID_(x, y, sigma2, 31, 16, 0.6, 2.16);
end
```

The parameters,that we use in this process is found empirically and also to be same for all noise levels. We use N = 30 iterationswith a temperature decay rate of $\alpha^{-1} = 1.533^{-1}$and gradient step size $\lambda = 0.567 \log\alpha$.The initial scale factor for the range scale is γ_r=988.5,and for the spatial scale γ_s=2/9. The window radius is r = 15,and we use a reference spatial sigma of σ_s = 7. For the final DDID step, we use a larger kernel size with window radius r = 31 and spatial sigma $\sigma_s = 16$. The range and frequency domain parameters are γ_r= 0.6 and γ_s = 2.16.



We used 30 iterations, where the intermediate imagesare taken snapshots after 10, 20, and 30 iterations. Usually,an iteration of denoising output cannot be used as an input for next iteration.further, the output pixels are correlated and estimating the variance would require expensive covariance tracking.But, in our case, correlated noise in the spatial domain is decorrelated in the frequency domain and covariance tracking is not necessary.this allows iteration to proceed further without getting stuck at any point and the local minima is obtained.



Finally,the (PSNR),peak signal noise ratio is graph is drawn,to visually have a significant note about how the noise signal is decreasing fast at the beginning and slows down as the noises becomes smaller,with the MSE calculation.Ourmerthod works well for natural images,with the properties of gradient smoother,edgessharper,tips are clearer,and text as crisper.Coming on to artifactsstudy,otherdenoising methods are biased towards natural images,where the PSNR results are close to theoretical limits.Compared to DDID,PID uses more number of iterations,for best results and quality of the image.

V. CONCLUSION

In contrast to current state-of-the-art denoising methods, our algorithm is short. Despite its simplicity,PIDalgorithm delivers high-quality results, in denoising synthetic images and produce best results compared to other methods.though many methods works well for natural images ,we performed a new challenge in denoising synthetic images.we focused on quality and simplicity rather than performance,which remains a terrain to explore acceleration in denoising process. Finally, we believe that our contribution is not limited toimage denoising. Several analysis were made to find out how our denoising approach impacts related problems like artifact removal, superresolution, and hole filling. Our denoisingformulation is agnostic of dimensionality of the signal. We therefore expect that our contribution to be of interest to the signal processing community at large and to many domain
specific applications.

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