iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 9 **Issue:** III **Month of publication:** March 2021

DOI: https://doi.org/10.22214/ijraset.2021.32796

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue III Mar 2021- Available at www.ijraset.com

A CNN Denoiser using Image Restoration

Niya E C[1], Aiswarya T R[2], Prof. Ani Sunny[3]
[1, 2]Department of Computer Science and Engineering Mar Athanasius College of Engineering, Kothamangalam, Kerala, India
[3]Professor, Department of Computer Science and Engineering Mar Athanasius College of Engineering, Kothamangalam, Kerala, India

Abstract: The objective of image reclamation is to remake the first picture that has been corrupted. Unlike image restoration is an object process rather than a subjective process. That is optimizing the goodness criteria rather than the subjective process . We model the degradation by a process and add some random noises .We train the images according to the model. Using the images with motion blur and noises and uses Mathematical approach to the process .The paper mainly compares with Half quadratic splitting method which leads the image restoration recently. Using PDE method the result were shown. It is the point of this proposed strategy to introduce some traditional PDE-based strategies for rebuilding, attempting to follow as per the pattern in which where they showed up in the writing. The images used were trained with CNN. At the end the result is tremendously surprising. The blur the noises were removed immensely. The algorithm shows the result as the comparison between the original and noise and blur removed image. Compared to the contemporaneous algorithms new proposed algorithm is very effective.
Keywords: Image restoration, deblur, denoise, CNN

I. INTRODUCTION

Image restoration is problem for any decades. New methods are still in search against existing technologies. The objective of picture reclamation is to remake the first picture that has been corrupted. For the recent years MATLAB helps and always helped for improving the image enhancement projects. Connecting Convolutional neural network and trained dataset with MATLAB improves efficiency of the system. Here the image is restored using CNN image denoisor. We model the degradation by a process and add some random noises .We train the images according to the model. Using the images with motion blur and noises and uses Mathematical approach to the process .The paper mainly compares with Half quadratic splitting method which leads the image restoration recently. Using advanced PDE method the result were shown.

Degradation can be due to in maybe image sensor noise, blur due to misfocus, blur due to motion, noise from transmission channel, blur due to transmission channel. according to different IR tasks, mainly they are image denoising, image de- blurring, image super-resolution.in the case of image denoising when H act as an identity matrix, in image deblurring when H is a blurring operator, and in the case of image super- resolution when H is a composite operator of blurring and down-sampling.

Model-based optimization method and discriminative learn- ing method, these are the main two strategies for solving the various image problems. In the case of model-based optimization method, main advantage is it is flexible for solving the different inverse problem like image denoising, image de- blurring, image super-resolution, it is good performance when it is compare to discriminative learning method. Advantage of discriminative learning method is that it have high test- ing speed as it is compare to the model-based optimization method and it is separately train different model for each level, and the main disadvantage is that the application range is greatly restricted by specialized task. for example, model-based optimization methods such as NCSR are flexible to handle inverse problem of denoising, super resolution and deblurring, whereas discriminative learning methods uses such as MLP , SRCNN, DCNN are designed for those three tasks. specific task such as denoising, model-based optimization methods (e.g., BM3D and WNNM) can handle different noise levels, in discriminative learning method of separately train a different model for each level. both these two kinds of methods have their respective advantages and disadvantages, so we integrate of these two methods leverages their respective merits.

Variable splitting techniques are there , such as alternating direction method of multipliers (ADMM) method and halfquadratic splitting (HQS) method ,this is deal with fidelity term and regularization term separately , and particularly, the regularization term only corresponds to a denoising sub problem , Consequently, this permits an integration of any discriminative denoisers into model-based optimization meth- ods. The main base of the work is based on [2] by Kai Zhang, Wangmeng Zuo, Shuhang Gu and Lei Zhang. However, to the simplest of our knowledge, the study of integration with discriminative denoiser remains lacking.

Many groups have gone through the PDE method adapted and implemented through their project.Main one is mentioned in [6].But the paper has some disadvantages. Our paper aims the extension and more advanced method of PDE equations with more accuracy.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue III Mar 2021- Available at www.ijraset.com

The method adopt Convolutional Neural Networks (CNN) to learn the denoisers, so as to take advantage of re- cent progress in CNN as well as the merit of GPU computation. Particularly, several CNN techniques, including Rectifier Linear Units (ReLU) , batch normalization, Adam, dilated convolution are adopted into the network design or training. As well as providing good performance for image denoising, the learned set of denoisers are plugged in a model- based optimization method to tackle various inverse problems.

The main contribution of this work is summarized as follows:

1) We trained a set of fast and effective CNN denoisers. us- ing PDE Method, the powerful denoisers can bring strong image prior into model-based optimization method.
2) Learned set of CNN denoisers are plugged in as a modular part of model-based optimization methods to tackle other inverse problems,like deblurring,denoising etc.
3) The paper mainly compares with Half quadratic splitting method which leads the image restoration recently

II. RELATED WORKS

Designed and trained a CNN denoiser for image denois- ing, using HQS splitting technique.(Kai Zhang,2017) This is plugged into the the learned denoiser prior into a model- based optimization Method,and it is different from other conventional model-based optimization methods. These are usually time-consuming with sophisticated image priors for the purpose of achieving good results. this main highlights of this work is that the potential benefits of integrating flexible model based optimization methods and fast discriminative learning methods. In addition is that this work has shown that learning expressive CNN denoiser prior is a good alternative to model image prior.

In (A.Danielyan,2012), the creators utilized Nash harmony to determine an iterative decoupled deblurring BM3D (ID- DBM3D) technique for picture debluring. This work proposed build investigation and afterward union the edges, formalizing the BM3D picture demonstrating and utilize these edges to create novel iterative deblurring calculations. consider two unique definitions of the deblurring problem:that's are one given by minimization of the single target work and another it depends on the Nash balance parity of two target capacities. The outcomes in a calculation where the denoising and deblur- ring tasks are decoupled. The union of the created calculations is demonstrated. Reenactment tests show that the decoupled calculation got from the Nash balance detailing exhibits the best numerical and visual outcomes and shows prevalence with deference over the best in class in the field, affirming a significant capability of BM3D-outlines as a n propelled picture demonstrating apparatus.

Thinking about the speed and execution, shading picture earlier or denoiser is additionally a key factor that should be taken into account. These days the greater part of the pictures taken by present day cameras or communicated on the web and these are in RGB design. Because of the relationship between various shading channels, it has been together taking care of the shading channels will in general produce preferable execu- tion over freely managing each shading channel(A.Foi,2006)

.

III. PROPOSED WORK

CNN stands for a convolution neural network. In deep learning, a convolutional neural network (CNN, or ConvNet) is a class of deep neural networks, CNN most commonly Used to analyzing visual imagery. it is also known as shift-invariant artificial neural networks or space invariant artificial neural networks (SIANN). They have applications in image and video recognition, recommender systems, image classification, med- ical image analysis, natural language processing, and financial time series.

CNN uses relatively little pre-processing compared to other image classification algorithms. This means that the network learns the filters that in traditional algorithms were hand- engineered. This independence from prior knowledge and human effort in feature de- sign is a major advantage. In the case of image restoration speed and performance, color image prior to or denoiser is also a key factor. most of the images Taken by using modern cameras and that's being transmitted on the internet are in RGB format. Due to the correlation be- tween different color channels, it has been jointly handling the color channels and that tends to produce better performance than independently dealing with each color channel. However, existing methods mainly focus only on modeling a gray image prior and there are only a few works concentrating on mod- eling color image prior. the most successful color image prior modeling method is CBM3D. It first decorrelates the image into a luminance chrominance color space by a hand-designed linear transform and then applies the gray BM3D method in each transformed color channels. While CBM3D is promising for color image denoising, it has been pointed out that the resulting transformed luminance chrominance color channels still remain some correlation and it is preferable to jointly handle RGB channels. Consequently, instead of utilizing the hand-designed pipeline, using discriminative learning methods to automatically reveal the underlying color image prior would be a good alternative.

According to the speed, performance and discriminative color image prior modeling CNN denoiser efficient than oth- ers. we choose deep CNN to learn the discriminative denoisers. The main reasons of using CNN are four-fold.

1) First fold contain the inference of CNN is very efficient because of the parallel computation ability of GPU.
2) Second, CNN exhibits powerful prior modeling capacity with deep architecture.
3) Third, CNN exploits the external prior which is comple- mentary to the internal prior
4) Fourth fold is great progress in training and designing CNN have been made during the past few years and we can take advantage of those progress to facilitate discriminative learning.

The CNN contain mainly seven layers with three different blocks,the three blocks are first layer is “Dilated Convolu- tion+ReLU” block, “Dilated Convolution+Batch Normaliza- tion+ReLU” blocks in the middle layers, and “Dilated Convo- lution” block in the third and last layer. here ReLU Means it is a Rectifier linear unit,it is a activation function,with out the ReLU It is very hard to in back propagation for training.

Mainly four steps are associated in this methods.that’s are,

A. Enlarge Receptive Field

Using Dilated Filter to Enlarge Receptive Field. the first step is acknowledged that the context information provide the reconstruction of the corrupted or unclear pixel in image denoising. In CNN is used to capture the context information, then it will successively enlarges the receptive field through the forward convolution operations.receptive field means any point take an convolution filter passing through various part of im- age,and each part will generate a single value output.receptive field is nothing but that is the part of image convolution the kernel operate on image at particular time t.

Generally, there are two basic ways to enlarge the receptive field of CNN. the first way is to increasing the filter size and next is increasing the depth. increasing the filter size it is not practical,need to introduce more parameters and also increase the computational burden.

Consider the input image,and it is the noisy image that means it is effected by some image inverse problem like image deblurring,image denoising or image super-resolution etc.imagine just look at the one perspective of first filter/kernel. the noisy image patches 3*3 section of image and then con- voluted using the convolution filter,and get the output value.

B. Accelerate Training

Using Batch Normalization and Residual Learning to Accel- erate Training.The advanced gradient optimization algorithms can accelerate training and improve the performance, the architecture design is also an important factor. CNN archi- tecture designs Adopt the Batch normalization and residual learning which are main two most influential architecture design techniques.it has been pointed out that the combination of batch normalization and residual learning is particularly helpful for Gaussian denoising since they are beneficial to each other. To be specific, it not only enables fast and stable training but also tends to result in better denoising performance. In this paper, such strategy is adopted and we empirically find it also can enable fast transfer from one model to another with different noise level.

C. Avoid Boundary Artifacts

Using Training Samples with Small Size to Help Avoid Boundary Artifacts. CNN may introduce annoying boundary artifacts without proper handling. There are mainly two ways to resolve this,

1) Symmetrical padding
2) Zero padding.

Adopt the zero padding strategy and Adding the exta rows and columns and all elements are filled with zeros.in this way we get the same input size as the output.if n*n is image and f*f is a filter,and the equation of output size is become,

$$outputsize = (n - f + 1) * (n - f + 1) \qquad (1)$$

Using training samples with small size can help avoid boundary artifacts. The main reason is that, rather than using training patches of large size, cropping them into small patches can enable CNN to see more boundary information. For example, by cropping an image patch of size 70*70 into four small non-overlap patches of size 35*35, the boundary information would be largely augmented. We also have tested the performance by using patches of large size, we empirically find this does not improve the performance. However, if the size of the training patch is smaller than the receptive field, the performance would decrease.

D. Learning Specific Denoiser Model with Small Interval Noise Levels

The iterative optimization framework needs various denoiser models with different noise levels, the main problem is that how to train the discriminative models thus should be taken into consideration. Various studies have shown that if the exact solutions of sub problems are difficult or time-consuming to optimize, then using an inexact but fast sub problem solution may accelerate the convergence. In this respect, there is no need to learn many discriminative denoiser models for each noise level. On the other hand, although is a denoiser, it has a different goal from the traditional Gaussian denoising. The goal of traditional Gaussian denoising is to recover the latent clean image, however, the denoiser here just acts its own role regardless of the noise type and noise level of the image to be denoised. Therefore, the ideal discriminative denoiser should be trained by the current noise level. As a result, there is a tradeoff to set the number of denoisers. In this paper, we trained a set of denoisers on noise level range [0, 50] and divided it by a step size of 2 for each model, resulting in a set of 25denoisers for each gray and color image prior modeling. Due to the iterative scheme, it turns out the noise level range of [0, 50] is enough to handle various image restoration problems. Especially noteworthy is the number of denoisers which is much less than that of learning different models for different degradations

E. PDE Based Methods

In the previous methods , the approach considered a class of approach that consists in setting the best energy according to our needs. The equations that were to be solved numerically were the Euler–Lagrange equations associated with the mini- mization problems. Another possibility is to work directly on the equations, without thinking of any energy. It is the aim of this section to present some classical PDE-based methods for restoration, trying to follow the chronological order in which they appeared in the literature.

$$u(0,x) = u0(x)(\textit{initial condition}) \qquad (2)$$

Where u(t,x) is the restored version of the initial degraded image u0(x). As usual, u and 2u stand respectively for the gradient and the Hessian matrix of u with respect to the space variable x. Let us comment. One of the main difference, with the equations encountered up to now is the presence of the parameter t.Starting from the initial image u0(x) and by running (3.43) we construct a family of functions (i.e., images)u(t,x)t¿0 representing successive versions of u0(x). As t increases we expect that u(t,x) changes into a more and more simplified image, or in other words, structures for large t constitute simplifications of corresponding structures at small t. Moreover, no new structure must be created. For these reasons t is called a scale variable. As we will see further, the choice of F in (3.43) is determining, since we would like to attain two goals that may seem a priori contradictory. The first is that u(t,x) should represent a smooth version of u0(x) where the noise has been removed. The second is to be able to preserve some features such as edges, corners, and T-junctions, which may be viewed as singularities. Finally, a natural question is how to classify PDE-based models. The answer is inevitably subjective. Perhaps, the simplest way is to choose the classical PDE classification, namely forward parabolic PDE, backward parabolic PDE and hyperbolic PDEs corresponding respectively to smoothing, smoothing–enhancing, and enhancing processes. Let us follow this classification.

F. Smoothin PDEs

1) *Heat equation:* The oldest and most investigated equa- tion in image processing is probably the parabolic linear heat equation.

Notice that we have here x R2.In fact,we consider that u0(x)is primarily defined on the square [0,1]2. By symmetry we extend it to C =[1,+1]2 and then in all of R2 by periodicity . This way of extending u0(x) is classical in image processing. The motivation will become clearer in the sequel. If u0(x) extended in this way satisfies in addition C —u0(x)— dx ¡ +, we will say that u0 L1

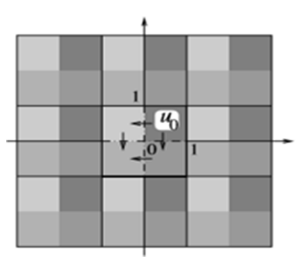


Figure 1. Extension of u0 primarily defined on [0,1]2 to R2 by symmetry and periodicity

The motivation to introduce such an equation came from the following remark: Solving (3.44) is equivalent to carrying out a Gaussian linear filtering, which was widely used in signal processing. More precisely, let u0 be in L1 (C).

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue III Mar 2021- Available at www.ijraset.com

Where G(x) denotes the two-dimensional Gaussian kernel. Convolution by a positive kernel is the basic operation in linear image filtering. It corresponds to low-pass filtering. This formula gives the correspondence between the time t and the scale parameter of the Gaussian kernel.

$\sigma = 0$ $\sigma = 5$ $\sigma = 20$

Figure 2. Examples of the test image at different scales

The convolution by a Gaussian is a low-pass filter that inhibits high frequencies (oscillations in the space domain).As we can observe in Figure 2, the smoothing is isotropic: It does not depend on the image, and it is the same in all directions. In particular, edges are not preserved.In fact, if we introduce two arbitrary orthonormal directions D1 and D2, we have u = uD1D1+uD2D2. If we rewrite this equality with the directions D1 = N = u/—u— and D2 = T with T ·N = 0,—T— = 1, then u = uNN + uTT. The isotropy means that the diffusion is equivalent in the two directions. As will be shown in the sequel, most of the diffusion operators can be decomposed as a weighted sum of uNN and uT.To set the properties satisfied by u(t,x), we either can use the fact that u is a convolution product or we can deduce these properties from the general theory of uniformly parabolic equations. Choosing the latter approach, we summarize below some of the main properties of u(t,x)

a) Gray-level shift invariance: Tt(0) = 0 and Tt(u0 + c) = Tt u0 + c, for any constant c.
b) Translation invariance: Tt(h u0) = h (Tt u0), where h is the translation h(f)(x) = f (x+h).
c) Scale invariance: Tt(H u0) = H(Ttr u0) with tJ = t2, where (Hf)(x) = f (x).
d) Isometry invariance: Tt(R u0) = R(Tt u0), for any orthogonal transformation R of R2 where (Rf)(x) = f(Rx).
e) Conservation of average value: Tt(M u0) = M (Tt u0), where Mf = f (x) dx. C
f) Semigroup property: Tt+s u0 = Tt (Ts u0). Comparison principle: If u0 v0 then (Ttu0) (Ttv0).

These in-variance properties are quite natural from an image analysis point of view. For example, the gray-level shift in- variance means that the analysis must be independent of the range of the brightness of the initial image. The other geometric properties express the in-variance of image analysis under the respective positions of percipiens and perceptum. Are these properties sufficient to ensure correct qualitative properties for Ttu? The answer is no. Though the heat equation has been (and is) successfully applied in image processing, it has some drawbacks: It is too smoothing. In fact, whatever the regularity of the initial data, u(t, x) is C in x, t ¿ 0: Edges are lost. We sometimes say that the heat equation has infinite speed of propagation. Of course, this instantaneous regularity is not a desirable property, since in particular, edges can be lost or severely blurred.

G. Weickert's Approach

1) The diffusion tensor D = (dij) belongs to C(S2, S2), where S2 denotes the set of symmetric matrices (i) The diffusion tensor D = (dij) belongs to C(S2, S2), where S2 denotes the set of symmetric matrices Then for all u0 L( ) equation (3.69) has a unique solution u(t,x) satisfying

$$u \in C\left([0,T]; L^2(\Omega)\right) \cap L^2\left([0,T]; W^{1,2}(\Omega)\right), \qquad (3)$$

$$\frac{\partial u}{\partial t} \in L^2\left((0,T); W^{1,2}(\Omega)\right). \qquad (4)$$

2) *Edge-enhancing anisotropic diffusion:* If one wants to smooth preferably within each region and aims to preserve edges,then one should reduce the diffusivity 1 perpendicular to edges all the more if the contrast µ1 is large. This behavior may be accomplished by the following choice:

$$\lambda 2 = 1 \qquad (5)$$

3) *Coherence-enhancing anisotropic diffusion:* If one wants to enhance flow like structures and close interrupted lines, one should smooth preferably along the coherence direction v2 with a diffusivity 2 that increases with respect to the coherence (µ1µ2)2. This may be achieved by the following choice of the eigenvalues of D(J):

$$\lambda 1 = \alpha \qquad (6)$$

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue III Mar 2021- Available at www.ijraset.com

IV. DESIGN

MATLAB Tool is tremendously good tool for image enhancement techniques. Different noises that can be added to a image is given below in figure 3.

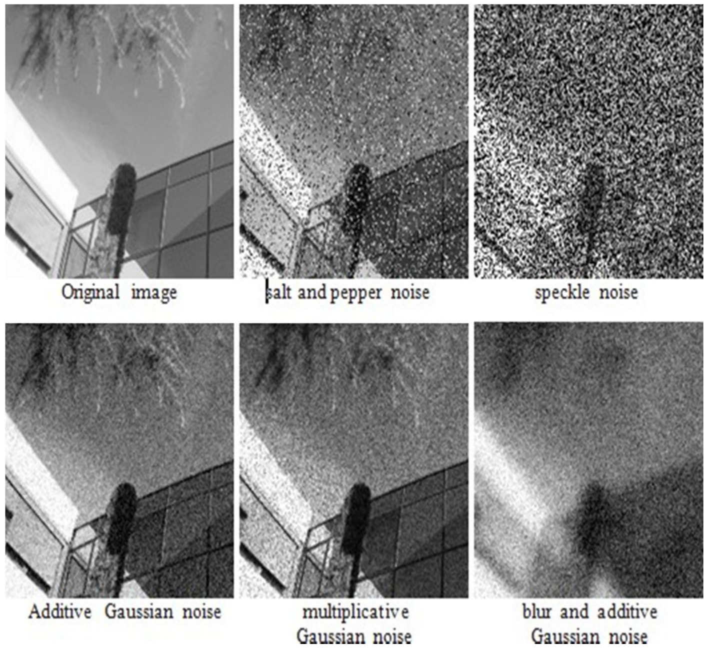


Figure 3. Examples of degradation in the top left-hand side corner of the “Borel building” image.

V. DESIGN OF PROPOSED SYSTEM

Referenced different mathematical textbooks for finding the solution for Image restoration problem. And using PDE found one solution. The design of the system included installing the required software and finding the hardware components. The high performance system with Intel Core i7 was used to run the code and the result.MATLAB GPU Cuda maxnet versions should be matched for designing the system. Here used the PDE method and versions of MATLAB WAS 2015b and cuda version 8 and Cudnn version 5.1. System was having windows 7 operating system.

1) Download and install visual Studio 2015
2) Download and install Windows SDK
3) Set up the compilers in MATLAB
4) Give path to the max convnet to MATLAB
5) Connect to the GPU
6) Run the Demo code Code is given Below.

a) mex –setup
b) mex -setup:’C:2015b642015.xml’ C
c) mex -setup C++
d) mex -setup:’C:2015b642015.xml’ C++
e) cd ’C:-1.0-beta25’
f) addpath matlab
g) vlcompilenn(’enableGpu’, true, ’cudaMethod’, ’nvcc’, ... ’cudaRoot’, ’C:FilesGPU Computing Toolkitˇ8.0’, ... ’en- ableCudnn’, true, ’cudnnRoot’, ’C:FilesGPU Computing Toolkitˇ8.0’) ;

gpuDevice

VI. RESULT

MATLAB is always better option for doing image enhance- ment projects. Here also it proved. Using MATLAB the results were accurate , and comparison between the original and output was done . Fig 4 is represented as the original image.

Figure 4. Original Image

The Figure 4, Figure 5 and Figure 6 and figure 7 shows the simulation results of MATLAB.

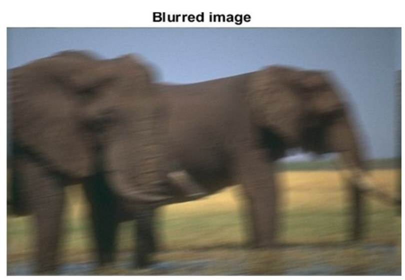


Figure 5. Image with blur

The Image blurring is the one of the image inverse prob- lem.there are mainly two types,motion blur due to the subject movement.next is blur due to the camera shake.

VII. CONCLUSION

Image restoration is one of powerful image enhancement tool In the Image processing. Here using Deep learning training set of images and restored Images using various techniques. Most important one among them was of course image deblurring and denoising. Using the advanced PDE based techniques blurred and noisy image was restored. Image restoration worked very effectively using the PDE technique. Blurred images consist of motion blurred and the later images included was with simulated and additive noises. The work focused on restoration using a better estimate of the noise-to- signal-power ratio. And the result was better and excellent. The images restored than the any restoration algorithms available now. The work ended with comparison between the various image restoration algorithms. The main comparison was be- tween the Half splitting quadratic method. And the results were quite successful.

VIII. ACKNOWLEDGEMENTS

The authors would like to thank The Principal of Mar Athanasius College of Engineering Dr. Mathew K, Head Of the Department of Computer Science and Engineering , Mar Athanasius College of Engineering Prof,Joby George, Class tutor Prof. Neethu Subash and we owe sense of gratitude and sincere thanks to Prof.Ani Sunny for her guidance, constant supervision, encouragement and support throughout the period of this thesis work.

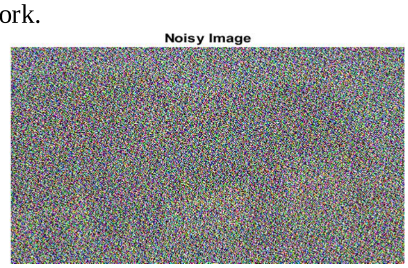


Figure 6. Both noise and blur Image

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue III Mar 2021- Available at www.ijraset.com

Fig 7.3 shows image with both noise and blur.Boisterous picture is additionally the one of the picture converse issue. Picture commotion implies is arbitrary variety of brilliance or shading data in pictures, and it is typically a part of electronic clamor. It very well may be created by the picture sensor, scanner or computerized camera.

Restoration of Blurred, Noisy Image

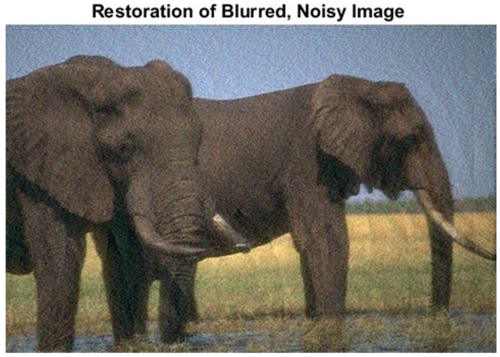


Figure 7. Both noise and blur removed Image

Fig 7.4 shows restoration of blurred and noisy im- age,removing the blurriness means uncleanness of image and also noise are removed.

REFERENCES

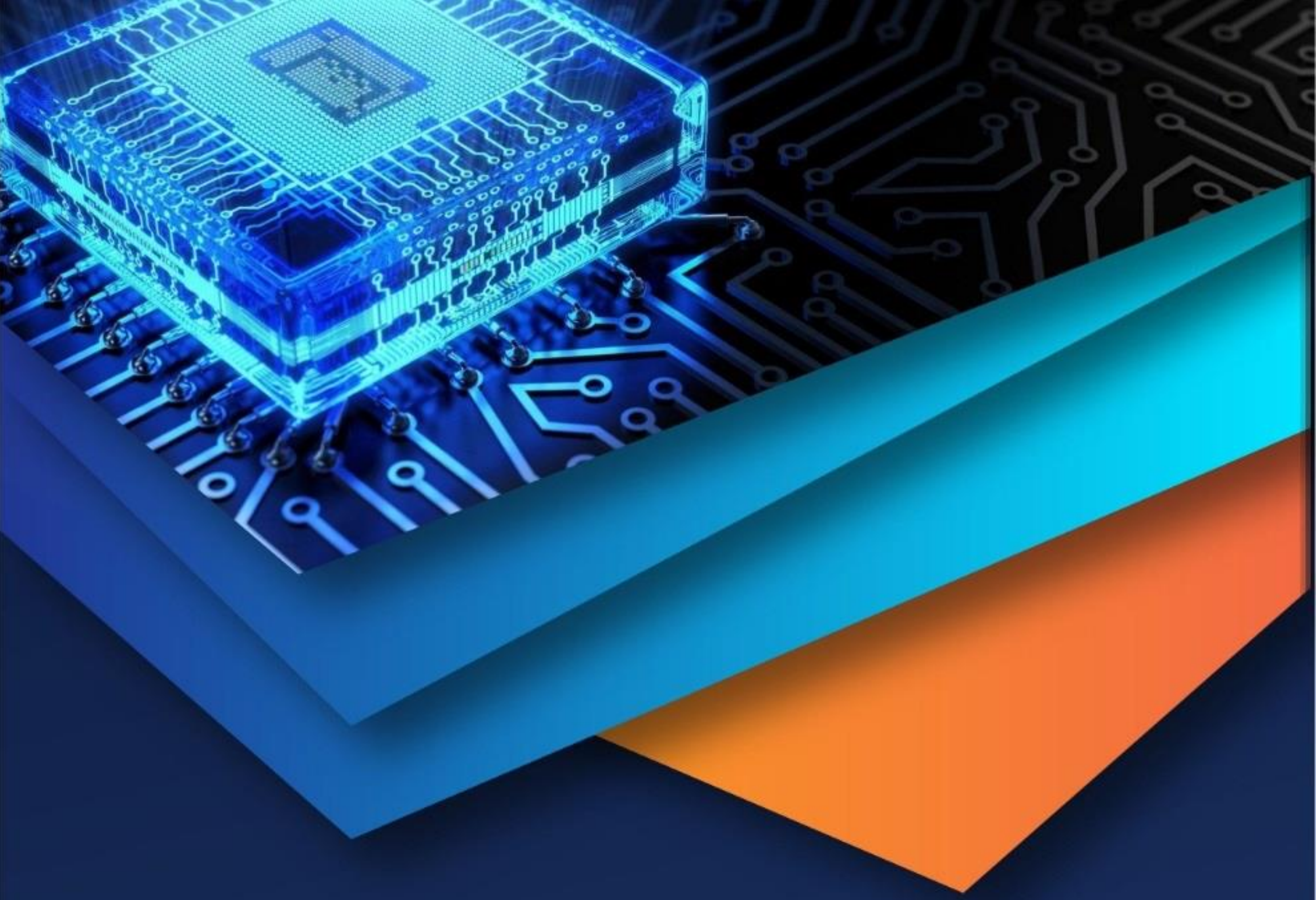
[1] Aubert, Gilles, Kornprobst, Pierre. "Mathematical Problems in Image Processing", Textbook Chapter 4 -Image Restoration
[2] Kai Zhang, Wangmeng Zuo, Shuhang Gu, Lei Zhang."Learning Deep CNN Denoiser Prior for Image Restoration".
[3] A. Danielyan, V. Katkovnik, and K. Egiazarian. BM3D frames and variational image deblurring. IEEE Transactions on Image Processing, 21(4):1715–1728, 2012.
[4] A. Foi, V. Katkovnik, and K. Egiazarian. Pointwise shape adaptive DCT denoising with structure preservation in luminance-chrominance space. In International Workshop on Video Processing and Quality Metrics for Consumer Elec- tronics, 2006.
[5] S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein. Distributed optimization and statistical learning via the alternating direction method of multipliers. Foundations and Trends in Machine Learning, 3(1):1–122, 2011. 2
[6] Ehsan Nadernejad , Hamidreza Koohi, PDEs-Based Method for Image Enhancement Applied Mathematical Sciences, Vol. 2, 2008, no. 20, 981 - 993
[7] M.B. Ould and El Mamoun Souidi ." A Generalization of the PVD Steganographic Method",(IJCSIS) International Journal of Computer Science and Information Security,Vol. 8, No. 8, November 2010
[8] Shin-Jye Lee, Tonglin Chen, Lun Yu, and Chin-Hui Lai "Image Classi- fication Based on the Boost Convolutional Neural Network."
[9] A. Brifman, Y. Romano, and M. Elad. Turning a denoiser into a super- resolver using plug and play priors. In IEEE International Conference on Image Processing, pages 1404– 1408, 2016. 2
[10] A. Buades, B. Coll, and J.-M. Morel. A non-local algorithm for image denoising. In IEEE Conference on Computer Vi- sion and Pattern Recognition, volume 2, pages 60–65, 2005. 3
[11] H. C. Burger, C. J. Schuler, and S. Harmeling. Image denoising: Can plain neural networks compete with BM3D? In IEEE Conference on Computer Vision and Pattern Recognition, pages 2392–2399, 2012. 2, 5
[12] P. Campisi and K. Egiazarian. Blind image deconvolution: theory and applications.CRC press, 2016. 1
[13] A. Chambolle. An algorithm for total variation minimization and ap- plications. Journal of Mathematical imaging and vision, 20(1-2):89–97, 2004. 3
[14] A. Chambolle and T. Pock. A first-order primal-dual algorithm for convex problems with applications to imaging. Journal of Mathematical Imaging and Vision, 40(1):120– 145, 2011. 2

AUTHORS PROFILE

Aiswarya T R received Bachelor of Technology degree and specialized in Computer Science and Engineering from Thejus Engineering College, Thris- sur,Kerala affiliated to calicut univer- sity in 2018 and currently pursuing Master of Technology, specializing in Computer Science and Engineering from Mar Athanasius College of Engineering, Kothamangalam affiliated to APJ Abdul Kalam Technological University. Her research interest is in Machine Learning,Image processing and Cloud Computing.

Niya E C received Bachelor of Tech- nology degree and specialized in Com- puter Science and Engineering from The- jus Engineering College, Thrissur, Kerala affiliated to Calicut university in 2018 and currently pursuing Master of Technology, specializing in Computer Science and En- gineering from Mar Athanasius College of Engineering, Kothamangalam affiliated to APJ Abdul Kalam Technological University. Her research interest is in Image Processing and Cloud Computing, and Machine Learning.

Prof. Ani Sunny is currently work- ing as assistant professor in the Depart- ment of Computer Science and Engineer- ing, Mar Athanasius College of Engi- neering, Kothamangalam, Kerala, India. She received her B-Tech Degree in 2011 and M-Tech in 2014 in Computer Sci- ence and Engineering from Mahathma Gandhi university . She is interested in the areas of Hardware and microprocessors, Networks,Image Processing



10.22214/IJRASET

INDEX COPERNICUS 45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY