Journal of Engineering Sciences
Vol 11, Issue 5,May/2020
ISSN NO:0377-9254

Repairing of Images Using Machine Learning

Neha Mangla[1], Nikitha[2], Priya B[3], Yogesh G Naik[4]
[1]*Atria Institute Of Technology, ISE, VTU, neha.mangla@atria.edu, India*
[2]*Atria Institute Of Technology, ISE, VTU, nikithareddy131999@gmail.com, India*
[3]*Atria Institute Of Technology, ISE, VTU, priyajamunababu@gmail.com, India*
[4]*Atria Institute Of Technology, ISE, VTU, yoheshnaik1998@gmail.com, India*

***Abstract*— The main aim of image inpainting technique is to make visual improvement to the image as a whole by repairing missing or damaged pixels, some of issues which cause imperfections in the pixels of an image. Here in this paper we concentrate on three issues. First, removing blurriness in an image. The main reason for blurred images are imperfection in capturing pictures, low intensity during taking pictures through smartphones, camera etc. and atmospheric problems. Blurriness occurs during motion or while converting videos into images. Second, removing the text or words on the image. When people needs the image but any word or text is present on their wanted image that can be removed. Third, the main and the important issue in computer vision is to generating the missing region in an image. All these problems will overcome by training the model several times to achieve the outcome for the chosen dataset.**

***Keywords*— Noise, object removal, Motion blur, image Restoration.**

1. INTRODUCTION

Inpainting is the process of restoring its original information related to the image, i.e. the quality of an image should be enhance with the given information in an image. Its application includes enhancing the visual quality of the image, like removing blurriness in an image, removal of text or characters presented in an image or restoring the missing or lose parts of the given image. As in this paper we concentrate on three objectives

[1] Removal of blurriness occurred in different situation such as motion blur, low intensity during taking photos, etc.

[2] In removal of text on the image using inpainting technique where the image can be converted into binary format i.e. black and white where the text are detected and the position presented under the text of character are produced using surrounding information present around the text.

[3] Generating the missing parts or position or pixels are done using the surrounding information. All these are
Done when we train the model which does all the above mentioned applications.

In this paper as we mentioned three applications of image inpainting technique. One among them is removing the motion blur. Here the blurriness is considered as noise. The main aim of this model is to remove the noise present in the image while removing the noise we use filter to remove.

Image deconvolution attempts to recover a sharp image from a blurred image and a blur kernel. Assuming that the camera motion was spatially invariant this problem can formulated as y=k*x+n where y is blurred image, x is the sharp image, k is the blur kernel and n is additive noise. Our goal is to recover x from y.

In this work, learning [11] [12] based approach to image deconvolution could enhance conventional deconvolution technique. Using Weiner Filtering with various definitions, the hypothesis reconstructions of the same blurry image stacks them into a tensor, takes them into deep neural networks to non-linearly merge them and results in a new reconstructed version.

As second application removal of text from images, that requires no user interaction. This system is important because the selection of the area to be inpainted has been done manually by previous inpainting systems detection and recognition of text done automatically, after removal fill-in the resulting gaps via inpainting methods.

In third application, restoring the missing pixels or parts in an image patches are nothing but the missing pixels are constructed according to training given to the model. In this paper patch

based image inpainting is done by replacing the missing area by similar patches of the area.

2. PURPOSE OF WORK

The main purpose of doing this project is restoring the images from some defeats. This defeats may occur in different cases. As in some situations we may need some images for critical purpose where we won't be getting chance of taking such images, in such cases we can use all these techniques. These are used very much to get back the perfect images as we need. As in the case of removing blurriness, the images such as numbers or any other important features in the images can be restored. Similarly in text removal when unwanted text or characters or the watermarks are present that can be removed.

3. METHODOLOGY

3.1 Blur Removal Process

Blurring is a type of reduction of the image bandwidth due to incomplete image creation. It can be caused by relative motion between the camera and the initial image, or by out-of-focus optical device.

Image repair approaches strategies to improve the accuracy of distorted images. It discusses in particular the retrieval of information that was lost to the human eye through any phase of deterioration A.

We make use of a Degradation Model to help explain the underlying processes:

G (u, v) = H (u, v)* F (u, v) + N (u, v)

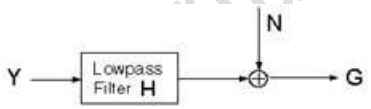

Fig 1: Degradation model

Where G and F are respectively the Fourier transforms the degraded images and the reference image f. H is called the degradation function, and N is an additive value-modeled noise term.

3.1.1 Point Spread Function (PSF)

The amplitude of the observed point image is distributed over multiple pixels.

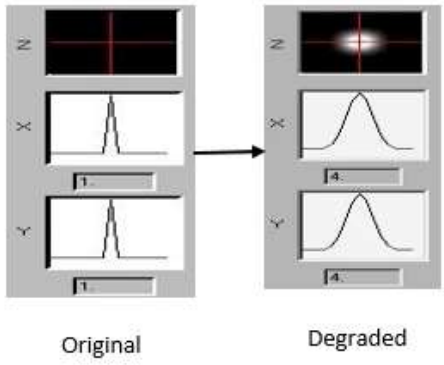

Fig 2: Point spread function

3.1.2 Local image distortion formation

Local distortion formation model representation, let's call one dimension case, i.e. the operation of some PSF on a certain vector {c I I= 1. 4}, which elements are pixel values of a fixed picture.

In particular, in the case of horizontal blurring per pixel as a result of distortion, each pixel value and a value of a preceding (left) pixel are added by the coordinate and divided by two: $c_i^1 = (c_{i+ci-1})/2$ this of the image are missing then that can be restored, where missed information are reconstructed using surrounding information.

Formula results from the following: as far as the left pixel comes on the given pixel during its movement, during exposure both values were able to reflect in the position. We obtain a new distorted image as a result:

$$\frac{(c_1+c_0)}{2}\left|\frac{(c_2+c_1)}{2}\right|\left|\frac{(c_3+c_2)}{2}\right|\frac{(c_4+c_3)}{2}$$

This is the model of ideal distortion

For the next pixel object its intensity function value c (xi, yi) is determined by the scalar vector product v = (τ,τ (1-2τ)) i $\mathbf{F}_i$ = (f (x_i, y_i), f (x_{i-1}, y_i), f_ϕ (x_i, y_i)):

$$c(x_i,y_i)=\mathbf{v}\cdot\mathbf{F}_i.$$

(1) Here $f_\phi(x_i, y_i)$, $f(x_i, y_i)$, $f(x_{i-1}, y_i)$ – Strength function values in given pixels and limit values. Every buffer area point will be calculated by the related scheme intensity function values. The pixel value of the final buffer area will be equal to the value of the intensity function, which will consist of the color value of the background τ.

The regularity obtained for the case of uniform motion can, however, be maintained for the buffer region j pixel and can be written as follows:

$C_j = a_j f_j + (1-a_j)\, b_j$, $a_j = \sum_{i=1}^{j} h_i$

where $j \in [0; m]$; h_i – i-e not null value of discrete PSF h; b_j – value of intensity function of background at the given point; f_j – integrated value of intensity function in pixels of any moving object.

3.1.3 System flow of blur removal

The deblurring method is modeled iteratively in our motion deblurring algorithm where the steps of the latent image prediction, kernel, are centered.

Latent Image Prediction First, edge prediction is performed to predict a latent image, which is used as an initial kernel estimation input. In shock filter the blurred image is applied to pre-sharpen.

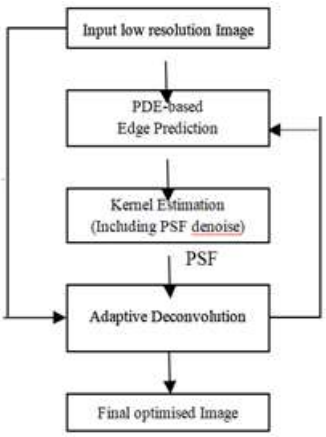

Fig 3: Flowchart of blur removal

PSF is calculated by rapid Fourier transformation, particularly after the predicted image is up-sampled in the multi-scale scenario, noises may be generated. Therefore, after PSF estimation, we further propose to conduct a denoising method for the blur kernel, that is, first let the pixels be zero if their value is less than 1/20 of the maximum pixel. And then delete unconnected components whose kernel size area is less than 1 / D. Here D is calculated by the parameters during each iteration. The refined PSF is our approximate blur-kernel in one iteration after normalization.

Adaptive Deconvolution Our simple deconvolution concept with the kernel estimated in the previous step is to restore the latent image L by minimizing energy function f L from an approximate kernel K and input blurry image B.

3.2 Generating missing regions

3.2.1 The Operation of Dilation

The process of structuring element B on image A and moving it across the image in a way similar to convolution is defined as dilation operation**.** The two key inputs for the dilation operator are the image which is to be dilated and a set of coordinate points known as a structuring factor which describe also as a kernel. The mathematical description of dilation for binary images is the following steps:

1. Suppose that X is the set of Euclidean coordinates that suit the binary image data, and that K is the set of coordinates for the structuring part.

2. Let Kx denote the translation of so that its origin. Then the dilation of X by K is simply the set of all points such that the

3. Intersection of X and K. Kx with X is non-empty. It dilation is defined as set operation. A is dilated by B, written as A ⊕ , is defined as(1):

$$A \oplus B = \{z|(B)_Z \cap A \neq \Phi\} \qquad (1)$$

This includes the empty setΦ, the structural dimension B and the array reflection B.

In Figure (5), note that all the 'black' pixels
In the original image will be preserved in a dilation process, any borders will be extended and minor gaps filled in.

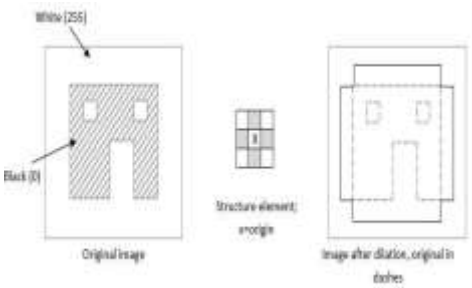

Fig 4: Dilation process

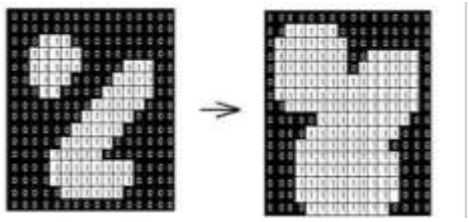

Fig 5: Effect of dilation on binary image using a 3 ×3 square structuring feature.

3.2.2 The operation of erosion

The erosion process is the same the dilation, but the pixels are transformed to 'white', not 'black'. The two main inputs for the erosion operator are the image which is to be eroded and a set of coordinate points known as a structuring element which define also as a kernel. For binary photos the following steps are the mathematical description of erosion:

1. Suppose that X is the set of Euclidean coordinates that suit the binary image data, and that K is the set of coordinates for the structuring part.

2. Let K_X denote the translation of K so that its origin is at x.

3. The erosion of X by K is the set of all X Points x such K_X that is a subset of A is eroded by B, Recorded as AΦ, defined as (2)

$$A \varnothing B = \{z \mid (B)_z \cap A^c \neq \Phi\} \qquad (2)$$

Among them Φ is the empty package B, the structural part and the array complement A.

The only remaining pixels in Figure (6) are those which correspond with the origin of the structuring element where the entire structuring element was embedded within the current entity.

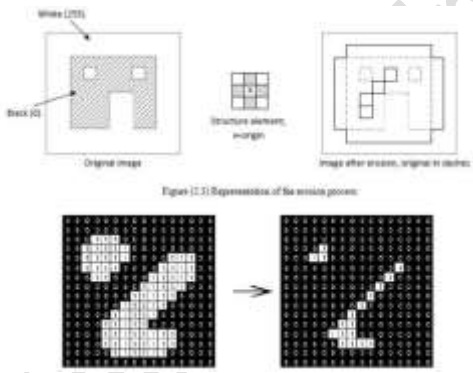

Fig 6: Representation of erosion process

3.2.3 Boundary extraction

The boundary of a set A, denoted by B, can be obtained by first eroding A by B and then performing the set differences between A and its erosion. That is,

Where B is a suitable structuring element. '–'is the difference operation on sets.

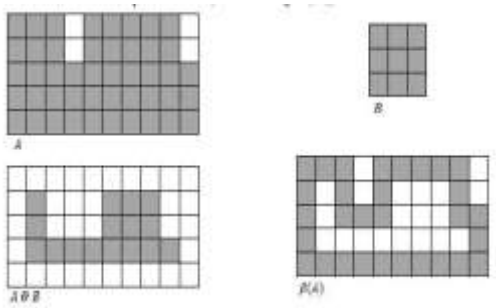

Fig 7: Representation of the Boundary extraction algorithm.

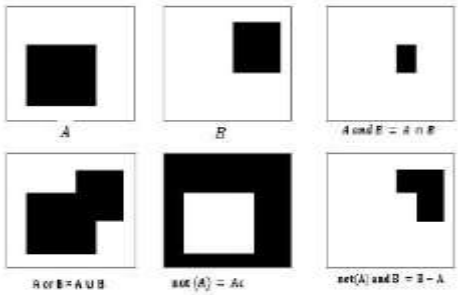

Fig 8: Representation of principle set activities

3.2.4 Region Filling

The area filling algorithm focused on the set dilations, complements, and intersections. The key purpose is to fill the entire field with 'rust' from a point within the border. If we follow the convention, all non-boundary (background) points are called 'white' at first stage and then we assign a 'black' value to p. By the following process fill the area with 'rust',

$$X_K = (X_{X-1} \oplus B) \cap A^C \qquad k= 1,2,3$$

Where,

$X_0 = P$,

B is the symmetric strutting element∩ is the intersection operator the complement of the algorithm terminates at iteration step k if X_k. The filled set and its boundary is contained by the set union of X_k and A.

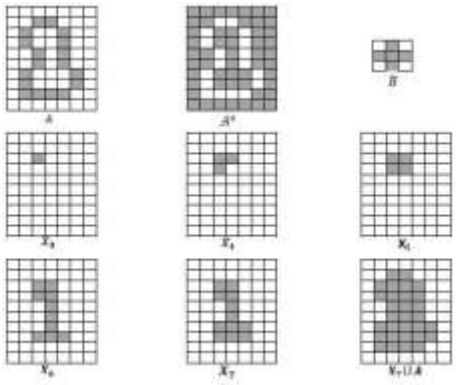

Fig 9: Representation of the region filling algorithm.

4. EXPERIMENTS AND RESULTS

This section is used to show the results of this paper. The images are selected from the data set stored in the database. The result consist of three outcomes of:

4.1 Blur image restoration

In the input image where blur is found in the image of RGB color image is processed and output image is produced.

Fig 10: Input image with blurriness

Fig 11: Step of processed output of the image

Fig 12: Final output where the blurriness is completely removed.

4.2 Text removal from an image

In this we choose the image from the data[13][14][15] set consist of different images and loaded. The next is loading the text on the selected image.

Fig 13: Input is Given with Image and Text

The fig 13 is the original image and the text image is masked on the original image to create the image with text on it as shown in fig 14.

Fig. 14

After applying the algorithm, the final output is shown in fig 15.

Fig .15

4.3 Restoring missing part in an image

In this part the image is selected from the dataset and patches are generated randomly where the missing parts has to be generated or restored. The fig 16 is the raw input given to generate the random patches as shown in the fig 17. After image is processed to generate the missing parts to give the complete image shown in fig 18.

Fig. 16

Fig. 17

Fig. 18

5. CONCLUSIONS

Noise reduction is difficult since the noisy image can be described by multiple noise image pairs, so we need to select the right pair from them. The problem is caused since the blur will differ spatially depending on the relative motion between the camera and the image. This method shows that (i) blur kernel estimates can be determined by evaluating blurred edge profiles, and (ii) a blur kernel from these projections can be computed using the inverse radon transform. As in the removal of text the morphological algorithm was inspired by the opening process of the reconstruction. This algorithm collects all the pixels corresponding to text characters, and its output can therefore be known as the region of that same inpainting. We also developed a program for automatic text removal and image painting by adding then an appropriate method of inpainting.

REFERENCES

[1]Jian-Feng Cai, Hui Ji, Chaoqiang Liu, and Zuowei Shen. Blind motion deblurring from a single image using sparse approximation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2009.

[2] S. H. Chan, X. Wang and O. A. Elgendy, ”Plug-and-Play ADMM for image restoration: Fixed point convergence and applications,” IEEE Transactions on Computational Imaging, Nov. 2016.

[3] Nah, Seungjun, Tae Hyun Kim, and Kyoung Mu Lee. ”Deep multi-scale convolutional neural network for dynamic scene deblurring.” arXiv preprint arXiv:1612.02177 3 (2016).

[4] O. V. Michailovich and D. R. Adam, “Deconvolution of medical images from micro scopicto whole body images,” in Blind image deconvolution: Theory and Applications, P. Campisi and K. Egiazarian, Eds. CRC, 2017, Ch.-5.

[5] S. Dai, M. Yang, Y. Wu, and A. K. Katsaggelos, “Tracking motion blurred targets in video,” in International Conference on Image Processing (ICIP’06), Atlanta, GA, October2006.

[6] Anat Levin. Blind motion deblurring using image statistics. Advances in Neural Information Processing Systems, December 2006.

[7] Qi Shan, Jiaya Jia, and Aseem Agarwala. High-quality motion deblurring from a single image.

ACM Transactions on Graphics (SIGGRAPH), 2018.

[8] Lu Yuan, Jian Sun, Long Quan, and Heung-Yeung Shum. Progressive inter-scale and intra-scale non-blind image deconvolution. In SIGGRAPH '08: ACM SIGGRAPH 2008 papers, pages 1–10, New York, NY, USA, 2018. ACM

[9] R. Kohler, C. Schuler, B. Sch ¨ olkopf, and S. Harmeling. ¨ Mask-specific inpainting with deep neural networks. In German Conference on Pattern Recognition, pages 523–534. Springer, 2014

[10] C.-Y. Lee, S. Xie, P. Gallagher, Z. Zhang, and Z. Tu. Deeplysupervised nets. In Artificial Intelligence and Statistics, pages 562–570, 2015.

[11]Neha Mangla," Bitcoin Price Prediction Using Machine Learning" International Journal Of Information And Computing Science, Volume 6,Issue 5,Pages 318-320,2019.

[12]Neha Mangla," Machine Learning Approach for Unstructured Data Using Hive", International Journal of Engineering Research,Vloume 5, Issue 4, 2016 .

[13]Neha Mangla," A survey paper on big data analytics using map reduce and hive on hadoop framework", International Journal of Recent Advances in Engineering & Technology,Volume 4, Pages 112-118, 2016 .

[14]Neha Mangla," IPB-Implementation of Parallel Mining for Big Data", Indian Journal of Science and Technology,Volume 9, Issue 45, 2016.

[15]Neha Mangla," EPH-Enhancement of Parallel Mining using Hadoop", International Journal of Engineering Research, Volume No.5 Issue: Special 5, pp: 992-1128