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Paper Authors

Beebi Naseeba, Dr.Jhansi Rani Singothu

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Hybrid Inpainting-Enhanced Resize Sampling Algorithm

Beebi Naseeba[1], Dr.Jhansi Rani Singothu[2]
[1]Research Scholar, Dept. of Computer Science and Systems Engineering, Andhra University College of Engg. (A), Andhra University, Visakhapatnam, Andhra Pradesh, India.
[2]Asst. Professor, Dept. of Computer Science and Systems Engineering, Andhra University College of Engg. (A), Andhra University, Visakhapatnam, Andhra Pradesh, India.
[1]bnaseeba@gmail.com,[2]dr.jhansiraniaucsse@gmail.com

Abstract— The burning issues in image processing to overcome the problem occur in object removal, image restoration, manipulation, re-targeting, compositing, and image-based rendering. The focus of image inpainting is to retrieve the missing image region with the help of existing image area. This technique repairs the old and damaged images. This will also works on removing the Wrinkles, dust and black spots of an image, high resolution, correction of red/blue eye, deletion of objects in digital images. This can be applicable to one area of the image. Various traditional models such as CIICA, Deep Generative Models (DGM) are proposed. Among all these methods, the blurred images results are identified. To overcome this issue, the proposed system Enhanced Resize Sampling Algorithm (ERSA) with improved results such as PSNR, SSIM is shown.

Keywords: DGM, image inpainting, CIICA, ERSA.

INTRODUCTION

Image processing is most widely used for processing and segmentation of various complex and complicated images that are available from the many sources. Image inpainting is the technique used to retrieve the missing or damaged part of the image region and also maintains the quality of the images. Nowadays images are capturing with the help of high resolution cameras, mobile phones with high megapixels are used. Processing of these high resolution images becomes more complicated with the traditional algorithms. Images are very helpful for encryption, processing, authentication, sharing etc. Image inpainting is used by various mobile apps and also using in social networking sites. Due to the extra part or distortion sometimes useful images get damaged or deleted. Restoring the images or painting are very natural as its actual version a super

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resolution (SR) algorithm is very useful for predicting and filling in the lost image information. For every image, the lost image area is highlighted and algorithm starts working to retrieve the missing content with the available content. There is more efficient algorithm is a Super-resolution algorithm which can produce very efficient.

Wide range of applications are using for the digital face images and are in the field of face recognition [1], facial performance capture [2], facial three-dimensional (3D) animation modeling [3], and face fusion [4], and these are mainly focusing on present research scenario to increase the application expectations. If the shooting equipment failure with the interference of human, and also the encoding and decoding done during transmission, the actual digital image is significantly defective [5], this may loss the features of the facial image and also effects the face recognition accuracy. Thus, it is known that the re-development of damaged image is required with better technique.

Image inpainting is actual called as traditional graphics issue, which is based on physical and mathematical methods. Based on the available existing information the image restoration is done to the defective part of the image. Segmentation plays the major role in finding the defective or damaged area. Segmentation is used to segments the image according to the size and resolution of the image and finds the area of the actual image which are consider the eyes, nose, mouth and ears [6]. The output of the image after the implementation of image inpainting techniques some issues such as blurred images can be seen. Based on the different types of methods inpainting is classified into two types: structural propagation methods based on partial differential equations (PDEs) [7] and texture synthesis methods based on sample block [8].

Especially in this paper, the proposed Ensemble technique such as Enhanced resize sampling algorithm is used to process the images with high resolution and without losing the image quality and maintains the default image size. In deep learning or in machine learning many image repairing algorithms are discussed very widely such as convolutional self-coding [9], generative adversary network (GAN)-based repair methods [10], and recurrent neural network (RNN)-based repair methods [11].

The organization of the paper as follows section 2 discussed about the literature survey. Section3 about the

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proposed methodology, algorithm steps and dataset description and results are incorporated in section 4. Conclusion and references are as follows.

Literature Survey

The author Gatys et al. [12] explained about the featured based which responses in higher layers of VGG [13] is used to capture the features such as semantic and textures information of an image with the integration of content presentation and the gram matrix features. The utilization of perceptual loss function for training of the image transformation process is explained by the Johnson et al., [14] and same results can be shown in order to get rapid output [12]. The author Chen [15] explained about how the photographic images can be synthesized from semantic layouts by a single feed-forward network trained with only perceptual loss.

Early image inpainting mainly relies upon at the information from the prevailing locale inside the statistics pictures. The TV primarily based totally techniques that don't forget the perfection belongings are an critical calculation to denoise photograph through explaining the amazing estimation of a capacity. By growing a version that wires in advance low function community and explaining the version, LR primarily based totally techniques can properly enhance the consequences of denoising and deblurring errands. Criminisi, which appears for comparative patches from the non-lacking district of the information photograph, can be a conventional calculation, but it is confined to the inpainting of the floor and foundation. Numerous strategies which are like Criminisi cannot be implemented to semantic photograph inpainting through coordinating and replicating similar patches from a solitary photograph.

The aim of the patch based techniques are developed to fill the missed area patch-by patch by using the better matching algorithms to replace the image at accurate and exact region. Many methods are discussed for image inpainting by utilizing the patch based method. The authors Ruzic and Pizurica [16] described the method which consists of searching the better matching patch in the surface element by using Markov Random Field (MRF). Jin and Ye [17] developed the annihilation property filter (APF) and low rank structured matrix (LRSM) for the better patch based recovery results. To remove the object from the image the author Kawai et al. [18] developed based on fixing the target object and restrict the search around the target by the background around.

ENHANCED RESIZE SAMPLING ALGORITHM (ERSA)

For small images:

P-Image: The input images initialize the filename, width-height and pixel values;

Input: Image [1….N];

For each Image[i] do

Decode Image[i] to retain its filename, width, height and pixel values;

End for

FOR LARGE IMAGES WITH HIGH RESOLUTION

Large Image: the big file consists of data file and an index file

ID: image filename; Offset: P-Image[i]'s size;

Offset←0;

For each P-Image[i] do

Offset←Offset + the size of P-Image[i];

Insert ID and Offset of P-Image [i] into Large-Image. Index;

Insert P-Image[i] into Large-Image. Data;

ALGORITHM PROCESSING STEPS:

Step 1: Initialize dataset.

Step 2: Training for images

$\{t_1, t_2, t_3 \ldots \ldots \ldots t_n\}$

Step 3: Testing image represents as

$\{i_1, i_2, i_3 \ldots \ldots \ldots i_n\}$

Step 4: select one image as input.

Step 5: matching the image with other content in image

Step 6: Apply ERSA.

Step 7: Results

DATASET DESCRIPTION

The dataset CelebA is used and the proposed algorithm is implemented on this dataset. The dataset consists of 30000 images in 1024 x 1024 resolutions. Among these 100 images are selected for training and 30 images are selected for testing. The dataset is available at https://www.kaggle.com/lamsimon/celebahq

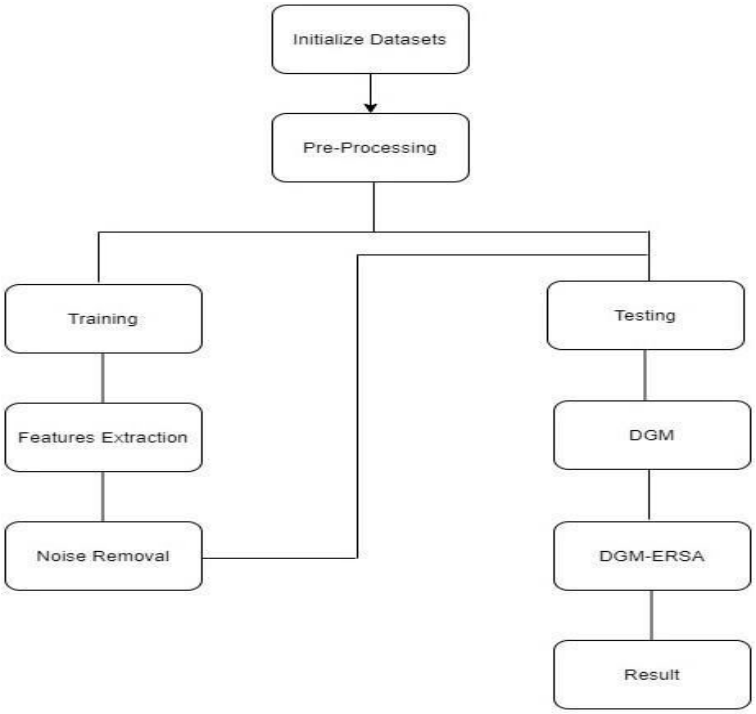

Figure 1: Proposed methodology

Figure 1 explains about the process of proposed methodology which consists of feature extraction, noise removal and integration of DGM-ERSA which adopts image segmentation, patches finding, rectangle area recognition etc.

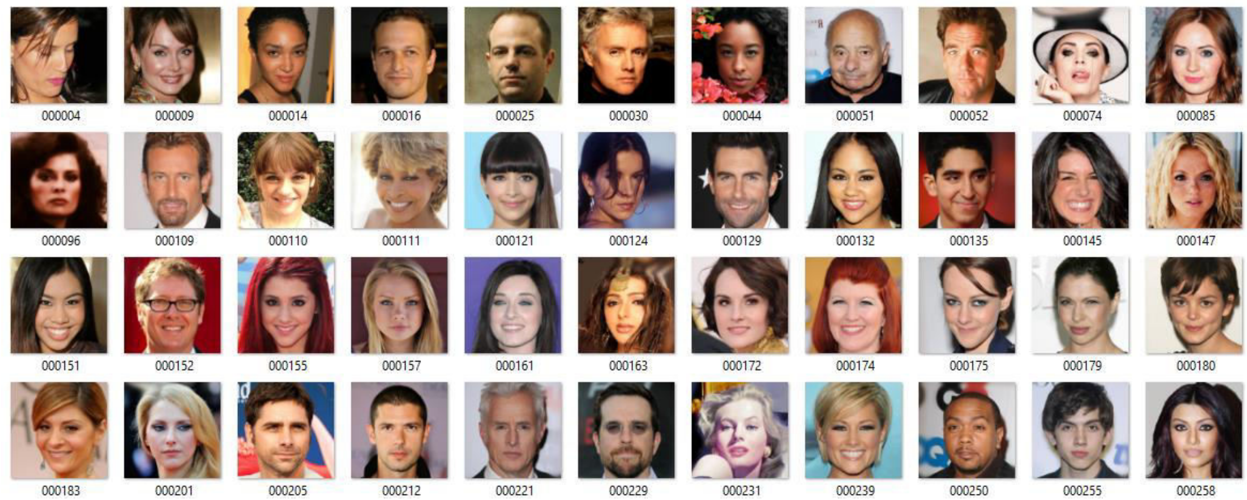

Figure 2: Training dataset celebA HQ

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Figure 3: Testing dataset CelebA HQ

EXPERIMENTAL RESULTS

The experimental results conducted by using python programming language with the installation of different packages and the execution runs by using IDLEX (python IDE). The version of python-3.6.5-amd64 and WinPython64-3.6.5.0Zero are used. The system hardware is with 4 GB Ram and 1 TB hard disk for the execution.

PERFORMANCE METRICS

The performance metrics such as peak-signal-to-noise ratio (PSNR) and structural similarity index measure (SSIM) are calculated in this paper. These are used to show the quality of the images and overcome the issues which are related to noise reduction and similarity index.

The proposed methodology check the undetectable compression operation that needs to calculates the similarity differences. The PSNR starts with the mean squad error. Let there be two images: A and B. With the dimensional size x and y, compresses of z number of channels.

$$MSE = \frac{1}{z * x * y} \sum (A - B)^2$$

$$PSNR = 10 * log_{10} \left(\frac{MAX_A^B}{MSE}\right)$$

The MAXA is the highest valid number for every pixel. For every image the single byte per pixel per channel is 255. If the two input images are same the result is 0 and this is invalid which is dividing by zero operation in the PSNR formula. The result image is improved with 70% to 80% of results for every image.

Instead of using traditional error summation methods, the SSIM is designed by modeling any image distortion as a combination of three factors that are loss of correlation, luminance distortion and contrast distortion. The SSIM is defined as:

$$SSIM = (f, g) = l(f, g)c(f, g)s(f, g)$$

Where

$$l(f, g) = \frac{2\mu_f \mu_g + C_1}{\mu_f^2 + \mu_g^2 + C_1}$$

$$c(f, g) = \frac{2\sigma_f \sigma_g + C_2}{\sigma_f^2 + \sigma_g^2 + C_2}$$

$$s(f, g) = \frac{\sigma_{fg} + C_3}{\sigma_f \sigma_g + C_3}$$

Figure 4: left side image is input image with size (1024x1024) and right side image is CIICA output image (256x256)

Figure 5: left side image is input image with size (1024x1024) and right side image is DGM output image with size (256x256)

Figure 6: left side image is input image with (1024x1024) size and right side image is ERSA output image with (1024x1024).

Algorithm	PSNR	SSIM	Time (Sec)
CIICA	20.47	67.28	6
DGM	18.31	81.28	14
DGM-ERSA	12.37	84.28	12

Table 1 comparison of traditional and proposed methodologies

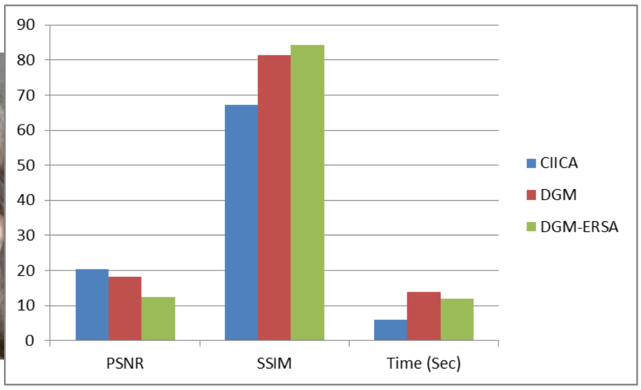

Figure 6: performance shown in terms of parameters.

Conclusion

In this paper, the proposed system Deep Generative model with the integration of Enhanced Resize Sampling Algorithm (ERSA) is implemented to overcome the issues identified in the image inpainting. The DGM-ERSA is the method which improves the quality of the image with the improvement of noise reduction with PSNR and similarity index is calculated with SSIM. As a result, the image inpainting recovers the entire missing image region without any blur images.

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