Pune Institute of Computer Technology
Dhankawadi, Pune

A SEMINAR REPORT
ON

SINGLE IMAGE SUPER-RESOLUTION FOR AERIAL IMAGES

SUBMITTED BY

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DEPARTMENT OF COMPUTER ENGINEERING
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DEPARTMENT OF COMPUTER ENGINEERING
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CERTIFICATE

This is to certify that the Seminar report entitled

"EVALUATING THE PERFORMANCE OF A DEEP CONVOLUTIONAL NETWORK FOR AERIAL IMAGE SUPER-RESOLUTION"

Submitted by
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has satisfactorily completed a seminar report under the guidance of Prof. M.S.Takalikar towards the partial fulfillment of third year Computer Engineering Semester II, Academic Year 2020-21 of Savitribai Phule Pune University.

Prof. M.S.Takalikar
Internal Guide

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Place:
Date:

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Abstract

One of the greatest challenges while dealing with UAV datasets for computer vision applications is the poor resolution of captured images. Super-resolution, the class of techniques that focus on improving the resolution of imaging systems, can be applied to UAV images to improve the performance across object detection, segmentation and surveillance applications. This work attempts to apply a deep learning based method of single-image super resolution with the goal of enhancing the resolution of drone captured images. The super resolution model returns a high resolution image through mapping that is represented as a deep convolutional neural network. The evaluation of the applied methodology was carried out using eight image quality metrics, and the results show promise for the future of deep super resolution enhanced aerial images.

Keywords

Single Image Super-Resolution, Convolutional Neural Networks, Image Enhancement, Aerial Imagery

1 INTRODUCTION

Modern computer vision applications ranging from social distancing tools to security surveillance systems often combine hardware technologies with image processing software to provide solutions for commonly faced problems in the society including waste management, epidemic monitoring and criminal activity surveillance. These applications may take input from regular devices like Raspberry Pi, cameras, sensors to advanced drone-mounted cameras and automated driving vehicle sensors. The images captured by such devices, in particular the drone mounted cameras, contain important content that is processed and utilized for innumerable applications, including object detection, terrain analysis, activity recognition, human detection, anomaly detection and more.

Unfortunately feeding these images directly to computer vision models does not always deliver the expected results in spite of their large quantity. Several problems hinder the development of such applications and lower the performance of the deployed models. Due to the limitations of cameras, in size of pixels, optics, speed of drones, expensive hardware and instability during flight, the captured data is usually of low resolution and may fail to produce meaningful information at the other end of the processing pipeline. This issue can be solved by utilizing high end cameras like the digital SLR camera or using high resolution sensors, however this upgradation can increase the expenditure of projects immensely and are often not suitable for accident prone cameras like the ones mounted upon drones for aerial photography. Another important obstacle to high quality image data is the variable lighting conditions in the environments surrounding the drones. As it is not possible to equip the landscapes covered by the drone with adequate lighting conditions, the images produced are difficult to mine useful information from.

Super Resolution is an umbrella of techniques and algorithms designed to deliver high resolution images from low resolution input images, and is being used extensively for enhancing vision datasets. To counter the limitations of poor quality data without compromising the quantity of data needed to provide good results, super resolution is a helpful tool and contributes to sharper results due to the enhanced clarity of images. Although many researchers have proposed innovative super resolution methods over the past decades, super resolution remains an ongoing challenge for computer vision researchers who are searching for a perfect technique that can enhance images without losing the core information. Single Image Super Resolution, which is the focus of our work is a type of super resolution, named after the process that works on delivering a high resolution image from a single low resolution image. Previously SISR has shown remarkable results in restoring detailed high frequency information, specifically useful in applications like healthcare and surveillance. [14]

2 MOTIVATION

As discussed above, poor resolution in drone captured images is a great challenge and due to the scarcity of UAV datasets, the need for good quality data is important to aid the development of autonomous vehicles. In this work, we employ a deep CNN based approach that performs single image super resolution for enhancing UAV images. [3, 2] This approach has proved to work well on ImageNet datasets for enhancing the resolution of images using a lightweight model structure. The key feature of this technique is the implicit mapping of LR and HR images via the hidden layers of the network. Previously this technique has been employed successfully to enhance object detection datasets like ImageNet, infrared imagery and we will now test its performance on an UAV image dataset, and observe how the technique is able to adapt to the diversity of scales, object types and resolutions in drone captured images.

We propose to apply Single Image Super Resolution using a convolutional neural network based approach [3, 2] to enhance the resolution of UAV images and analyze the performance of the technique using quality metrics. Our main contributions to the work are:

- Conducting experiments to test the performance of CNN based Single Image Super Resolution on the Visdrone 2019 dataset split into low and high resolution subsets.

- Evaluating the performance of the Single-Image Super Resolution technique on the UAV dataset using 8 image similarity metrics: PSNR, SSIM, FSIM, RMSE, SAM, SRE and UIQ.

Figure 1: Data Sample: Left hand side picture is the original high resolution image. Right hand side picture is the picture after applying blur effect.

3 LITERATURE SURVEY

The progress of Super Resolution algorithms in computer vision has been a topic of interest since several decades and is gaining popularity due to the rise in use of UAVs and automated applications. This work focuses on the challenge of Single Image Super Resolution, which has been classically treated using four categories of approaches: patch-based methods, prediction models, edge-based methods and statistical methods, all of which have been summarized in a study [17] and tested across benchmark datasets using multiple image similarity metrics. Prediction models base the transformations on a mathematical formula, and not on training data. In this group of models, interpolation methods work well in creating smooth regions and are very fast but the IP method [7] is better at generating enhanced contrast at edges. Patch based methods learn mapping functions based on patches taken from the training data [5] or external sources. Statistical methods work on exploiting different characteristic properties of images, like the sparsity of large gradients and total variation for generating high resolution images. [9]. Edge based methods mostly work by using edges to regulate priors and generate high quality images, but often fail in other aspects like textures. [4] Inspired by the comparison of the sparse coding methods to a traditional CNN architecture, which were proposed in [8], using CNNs for single image super-resolution was proposed in [3], which is known as SRCNN (Super-Resolution Convolutional Neural Network). Our implementation on drone captured images uses this deep learning based approach proposed for single image super resolution which showed good performance on the Imagenet and object datasets. [3] Multi-Channel SRCNN a variation of this technique was discovered later and takes multi channel inputs unlike the single channel input of SRCNN. [18] Following the success of specifically designed CNN architectures, deep learning generative models soon began gaining popularity, to deal with the loss of texture- like high-frequency details while focussing on minimizing MSE. The SRGAN performed better in maintaining the high frequency details and showed improved image fidelity.

For the Visdrone dataset in particular, some works have applied super resolution for different applications and achieved interesting results. A new data enhancement technique was used to enhance the Visdrone dataset, called scale adaptive image cropping (SAIC) and improved the accuracy by 9.65%. [21] In a proposed new architecture for object detection(PENet), a coarse anchor-free detector(CPEN) achieved 15.1% increase in mAP over the baseline on the Visdrone dataset. The model carried out the process of first finding low-resolution image chips from the original images then applying detectors and finally combining the results. [15] For a similar purpose of object detection, an up-scale feature aggregation framework was proposed along with an upsampling method that showed 6.0% gain in AP on the Visdrone dataset. [11] We observe that most research works focus on the Visdrone dataset from an object detection perspective, and not to enhance the visual appeal of super resolution in general. In this work we shall focus on quantifying the effect of Single Image Super Resolution using image similarity metrics that measure resolution change observable to the human eye.

4 DATA DESCRIPTION

The dataset used for this study is obtained from the Visdrone 2019 dataset of drone captured images. [22, 12] The images which are captured by various drone-mounted cameras, were taken from 14 different cities in China), in both urban and country environments, containing multiple objects including pedestrian, vehicles, bicycles in both sparse and crowded scenes. They were collected in different scenarios, and under various weather and lighting conditions. For the purpose of training, we used 500 images from the Visdrone 2019 test dev dataset which were split into sizable chunks for the model, bringing a total of 144,710 images for the training with 72,355 in low resolution and 72,355 in high resolution. The performance of the model was tested on 18,089 images, extracted from 500 original different images from the same Visdrone data and the performance was also evaluated on 1610 images with Gaussian and average blurring applied.

5 METHODOLOGY

This study involves 2 key components: the application of the CNN based SISR model, and the evaluation of enhancement using image similarity metrics. This section is divided into two parts, each focussing on the way the method is implemented, parts are calculated and results are obtained.

5.1 Convolutional Neural Networks for Single Image Super Resolution

The process of converting the low resolution input image to a high resolution image using convolutional neural networks is broken into three fundamental operations that transform the data and map the vectors between the layers as shown in figure 2.

1. Patch Extraction and Representation

   In this stage, patches are extracted from the input image [Y], and each patch is represented as a multi-dimensional vector. The operation returns vectors that contain a set of feature maps, whose count is equal to the dimensionality of the vector and can be defined by 1.

   $$F_1(Y) = max(0, W_1 * Y + B_1) \tag{1}$$

   where W_1 and B_1 represent the filters and biases respectively. Y is Low Resolution input image and $\star$ is the convolution operation. Rectified Linear Unit (ReLU) was chosen as the activation function.

2. Non- linear Mapping

   The first layer extracts an n1-dimensional feature for each patch and in the second operation we map each of these n1-dimensional vectors into an n2-dimensional one. The operation can be defined by 2.

   $$F_2(Y) = max(0, W_2 * F_1(Y) + B_2) \tag{2}$$

   where W_2 and B_2 denotes the filters and biases respectively.

3. Image Reconstruction

   This operation aggregates the HR patch wise representations to generate the final HR image through 3.

   $$F(Y) = W_3 * F_2(Y) + B_3 \tag{3}$$

   where W_3 and B_3 refer to the filters and biases respectively in the third layer.

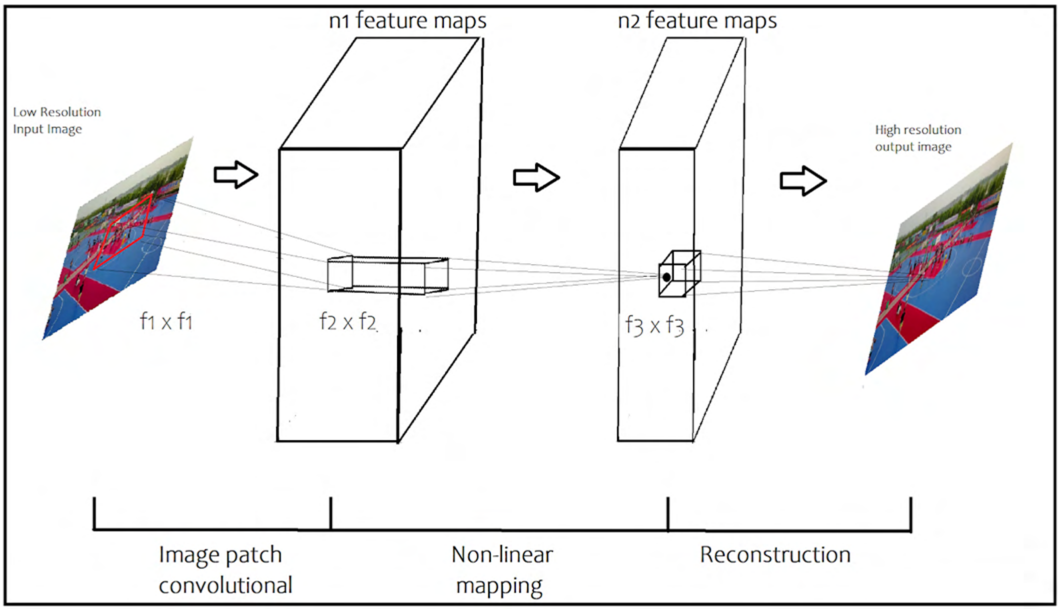

Figure 2: Model Architecture

Our goal is to learn the mapping by minimizing the loss between the reconstructed HR image and the true one. Here the loss is MSE given by 4.

$$L(\Theta) = 1/n \sum_{i=1}^{n} ||F(Y_i;\Theta) - X_i||^2 \tag{4}$$

where n is the number of training examples.

CNN uses stochastic gradient descent for optimization. Here, the weight matrices of convolution kernel are updated as per 5.

$$\Delta_{i+1} = 0.9.\Delta_i - \eta.\frac{\delta L}{\delta W_i^l}, W_{i+1}^l = W_i^l + \Delta_{i+1} \tag{5}$$

where $l \epsilon \{1,2,3\}$ and i are the indices of layers and iterations,η is the learning rate, and $\frac{\delta L}{\delta W_i^l}$ is the derivative.

5.2 Pseudo Code

1. Load dataset.

2. Preprocess data. Splitting larger images into chunks for model.

```
for i in range(0, cols - COLS - 1, COLS / 2) do
        for j in range(0, rows - ROWS - 1, ROWS / 2) do
                out <= crop((i, j, i + ROWS, j + COLS))
```

3. Downsample training imagery.

```
for image in allimages do
        temp <= resize((int(ROWS / 2), int(COLS / 2)), Image.BILINEAR)
        temp <= resize((ROWS, COLS), Image.BILINEAR
```

4. Create model.

```
model <= Sequential()
model.add(Convolution2D(activation="relu", shape=(400, 400, 3)))
model.add(Convolution2D(activation="relu"))
model.add(Convolution2D(activation="relu"))
model.compile(optimizer="adam", loss="mse", metrics=["accuracy"])
```

5. Train model using MSE as loss function.

6. Test accuracy on test data.

7. Evaluate performance using image similarity.

5.3 Evaluation Criteria

The essence of all the metrics employed in our analysis is the image similarity. We utilized 8 different metrics to assess the quality of the final images.

1. FSIM - The feature similarity index understands images mainly according to low level features. Should be closer to 1. Higher value is better. [20]

2. ISSM - The Information theoretic-based Statistic Similarity Measure combines information theory with the statistic and has high capability to predict the relationship among image intensity values. Should be closer to 1. Higher value is better. [1]

3. PSNR - Peak Signal-to-Noise Ratio (PSNR) measures the ratio between the maximum possible power of a signal and the power of corrupting noise and operates directly on the intensity of the image. Higher value is better. [6]

4. RMSE - The Root Mean Squared Error measures the amount of change per pixel before and after the operation. Should be closer to 0. Lower value is better. [13]

5. SAM - Spectral Angle Mapper (SAM) determines the spectral similarity between two spectra by calculating the angle between the spectra and treating them as vectors in a space with dimensionality equal to the number of bands. Should be closer to 0. Lower value is better. [19]

6. SRE - Signal to Reconstruction Error ratio (SRE) measures the error relative to the power of the signal. Higher value is better. [10]

7. SSIM - Structural Similar Index Measure (SSIM) focuses on capturing the loss of structure in the image. Should be closer to 1. Higher value is better. [6]

8. UIQ - Universal Image Quality index - Models the image distortion as a combination of the following factors: contrast distortion, luminance distortion and loss of correlation. Should be closer to 1. Higher value is better. [16]

6 RESULTS

For the analysis we use a subset of the Visdrone 2019 test-dev set [22, 12] that consists of 500 images, which was decomposed into a large training set that consists of 144,710 images for the training with 72,355 in low resolution and 72,355 in high resolution. For testing purposes, the model was evaluated on 18,089 images, extracted from 500 original different images from the same Visdrone data. The final performance of the CNN on the 1610 images evaluated using the 8 different metrics has been presented in 1.

The CNN based SISR is showing good performance when tested with image similarity metrics, with almost perfect SSIM score of 0.99, good PSNR of 60 and very low RMSE. As we can see in the figures 2 and 3 the enhancement is visible on the blurred images, and the details of the smaller objects in the images are more well defined.

FSIM	ISSM	PSNR(dB)	RMSE	SAM	SRE(dB)	SSIM	UIQ
0.80244	0	60.41191	0.00096	76.20474	61.14094	0.99888	0.78816

Table 1: Evaluation Criteria Results

Figure 3: Results Part 1. Left picture depicts low resolution input and right picture depicts high resolution output.

Figure 4: Results Part 2. Left picture depicts low resolution input and right picture depicts high resolution output

7 DISCUSSION

In this study we have evaluated the performance of a well established method for single image super-resolution on the Visdrone 2019 dataset that learns end to end mapping between low and high resolution images. We have utilized some of the most popular(PSNR and SSIM) metrics for evaluating the results and also considered 6 other image similarity metrics namely the ISSM, FSIM, RMSE, SAM, SRE and UIQ. The measure of SAM, a metric that is usually insensitive to illumination, shows unsatisfactory performance of our method on Visdrone data. The metric which should be near 0 is giving the value 76.20 for the images. From the figures 2 and 3, we can see how the CNN works well in enhancing the smaller elements and the lines on the court.

It is interesting to note that the model performs slightly worse when measured using ISSM, but better according to FSIM and SSIM values. As the SSIM considers the loss of structural information while measuring the degradation of quality, the high SSIM scores indicate the retention of structural information after passing through the SISR network. SSIM and FSIM are considered better metrics in terms of human visual perspective. Thus from a human visual perspective, the CNN method has performed well with 0.99 and 0.8 scores of SSIM and FSIM respectively.

The SRE metric,which is suited to making errors comparable between images of varying brightness, unlike PSNR, but both metrics indicate good performance of the model. The final UIQ metric is very robust at measuring structural distortion during the image degradation process, much better than MSE and has a good score of 0.78, indicating low structural distortion but performance which can be improved. PSNR, RMSE and SRE indicate how different the images are, and thus cannot provide us with a good measure of quality of enhancement. SSIM and FISM do provide us with this measure by taking structure of image into consideration. ISSM and UIQ provide a well rounded perspective of quality using a combination of measures and SAM how reliably the relative spectral distribution of a pixel has been reconstructed. Overall the metrics provide a good idea of the enhancement, with good visual perspective, maintenance of structure and clarity, but the performance still has scope for improvement in terms of overall quality and increasing reliability of reconstruction of relative spectral distribution of pixels.

8 CONCLUSION AND FUTURE WORK

The performance of the deep learning method for single image super-resolution definitely holds promise for future super resolution techniques using deep learning for the enhancement of aerial images. The greater the resolution of the image, the greater detailed information can be obtained from it in numerous applications. The shortcomings of the method in reconstructing the relative spectral distribution of pixels was also noted. Our future work will focus on evaluating the results of the deep learning SISR against State of the Art Methods like deep generative networks, very deep convolutional networks, feature discrimination and testing their performance against the same metrics. We would like to add to this network and propose changes in the architecture that will improve the performance across the weak areas. One could also explore the effect of SISR on detection of objects on different scales to explore the capability of the architecture to enhance multi-scale object detection.

We were able to observe how this approach enhances the UAV images from both a human visual perspective and the maintenance of structure in image enhancement from a technical perspective. Due to the simplicity and robustness of the CNN architecture, this method can be applied to other low-level vision problems, such as image deblurring. The future of super resolution holds opportunity for vast exploration through deep learning and statistical image processing techniques. Due to the soaring demand for drones and satellite captured images, the search for robust super resolution algorithms will parallely support computer vision tasks like object detection, segmentation and tracking.

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27/03/2021	Requirement and Domain Analysis	Explore the domain and decide a relevant idea to implement.	Prof. M.S.Takalikar
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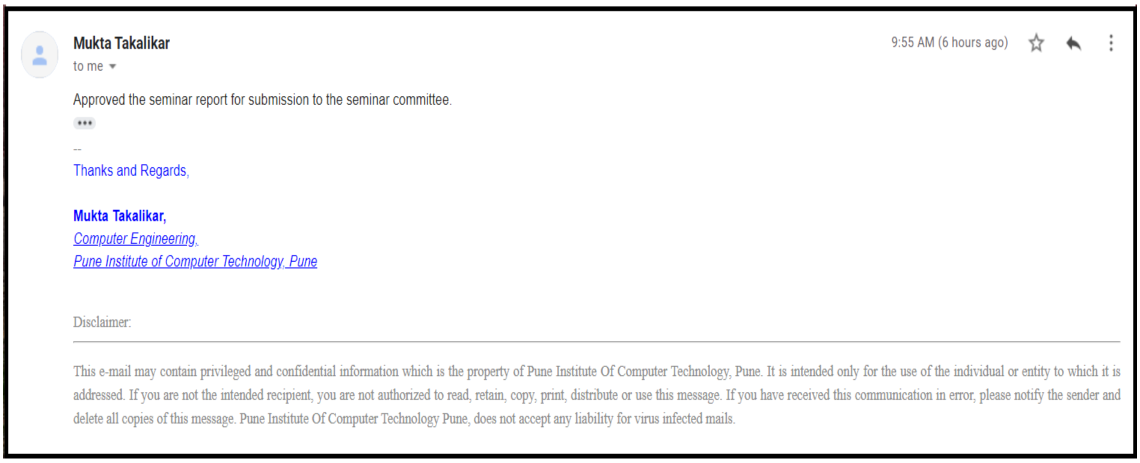

Mukta Takalikar
to me

9:55 AM (6 hours ago)

Approved the seminar report for submission to the seminar committee.

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Thanks and Regards,

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