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Image Reconstruction Using Super Resolution and Back-propagation Neural Networks

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ABSTRACT: Super resolution (SR) is a technique that aims at enhances the resolution of the captured Low resolution image to high resolution using different algorithms and techniques. In this paper we are proposing Image Reconstruction system using patch extraction, super resolution and non-linear mapping techniques.

KEYWORDS: Multi-target tracking Online learned CRF.

I. INTRODUCTION

In most electronic imaging applications, images with high resolution (HR) are desired and often required. HR means that pixel density within an image is high, and therefore an HR image can offer more details that may be critical in various applications. For example, HR medical images are very helpful for a doctor to make a correct diagnosis. It may be easy to distinguish an object from similar ones using HR satellite images, and the performance of pattern recognition in computer vision can be improved if an HR image is provided. For example, people want an inexpensive HR digital camera/camcorder or see the price gradually reduce, and scientists often need a very HR level close to that of an analogy 35 mm film that has no visible artefacts when an image is magnified. Thus, finding a way to increase the current resolution level is needed.

Super-resolution is based on the idea that a combination of low resolution (noisy) sequence of images of a scene can be used to generate a high resolution image or image sequence. Thus it attempts to reconstruct the original scene image with high resolution given a set of observed images at lower resolution. The general approach considers the low resolution images as resulting from resampling of a high resolution image. The goal is then to recover the high resolution image which when resample based on the input images and the imaging model, will produce the low resolution observed images. Thus the accuracy of imaging model is vital for super-resolution and an incorrect modeling, say of motion, can actually degrade the image further.

Methods for SR can be broadly classified into two families of methods: (i) The classical multi-image super-resolution, and (ii) Example-Based super-resolution. In the classical multi-image SR a set of low-resolution images of the same scene are taken. Each low resolution image imposes a set of linear constraints on the unknown high resolution intensity values. If enough low-resolution images are available, then the set of equations becomes determined and can be solved to recover the high-resolution image. Practically, however, this approach is numerically limited only to small increases in resolution. These limitations have leaded to the development of Input image various scales of I. Source patches in I are found in different locations and in other image scales of I.

The high-res corresponding parent patches provide an indication of what the high-res parents of the source patches might look like. “Example-Based Super-Resolution” also termed “image hallucination” example-based SR, correspondences between low and high resolution image patches are learned from a database of low and high resolution image pairs (usually with a relative scale factor of 2), and then applied to a new low-resolution image to recover its most likely high-resolution version. Higher SR factors have often been obtained by repeated applications of this process. Example-based SR has been shown to exceed the limits of classical SR. However, unlike classical SR, the high

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resolution details reconstructed by example based SR are not guaranteed to provide the true (unknown) high resolution details.

II. Related Work

Daniel et.al [1], there approach is based on the observation that patches in a natural image tend to redundantly recur many times inside the image, both within the same scale, as well as across different scales. Recurrence of patches within the same image scale (at sub pixel misalignments) gives rise to the classical super-resolution, whereas recurrence of patches across different scales of the same image gives rise to example-based super-resolution. There approach also attempts to recover at each pixel its best possible resolution increase based on its patch redundancy within and across scales.

Neeraj Kumar et.al [2], in this paper a novel learning based technique for single image super resolution (SR) is proposed. We model the relationship between available low resolution (LR) images and desired high resolution (HR) image as multi-scale markov random field (MSMRF). They are re-formulating the SR problem in terms of learning the mapping between LR-MRF and HRMRF, which is generally non-linear. Instead of learning MSMRF parameters we use artificial neural networks to learn the desired mapping. The results compare favorably to more complex stat-of-the art techniques for 2 × 2 and 3 × 3 SR problem. They also solve the SR problem using optical zoom as a cue by the proposed algorithm as well. The results on experiments with real data are presented

Chao Dong et.al [3], proposed a deep learning method for single image super resolution (SR), method directly learns an end-to-end mapping between the low/high-resolution images. The mapping is represented as a deep convolutional neural network (CNN) that takes the low resolution image as the input and outputs the high-resolution one. Further showed that traditional sparse-coding-based SR methods can also be viewed as a deep convolutional network. But unlike traditional methods that handle each component separately, proposed method jointly optimizes all layers. Deep CNN has a lightweight structure, yet demonstrates state-of-the-art restoration quality, and achieves fast speed for practical on-line usage.

III. PROPOSED SYSTEM

Figure 1 shows the block diagram of proposed system, the proposed system consists of different modules; they are Input image, pre-processing, clustering, patch extraction non-linear mapping and image reconstruction.

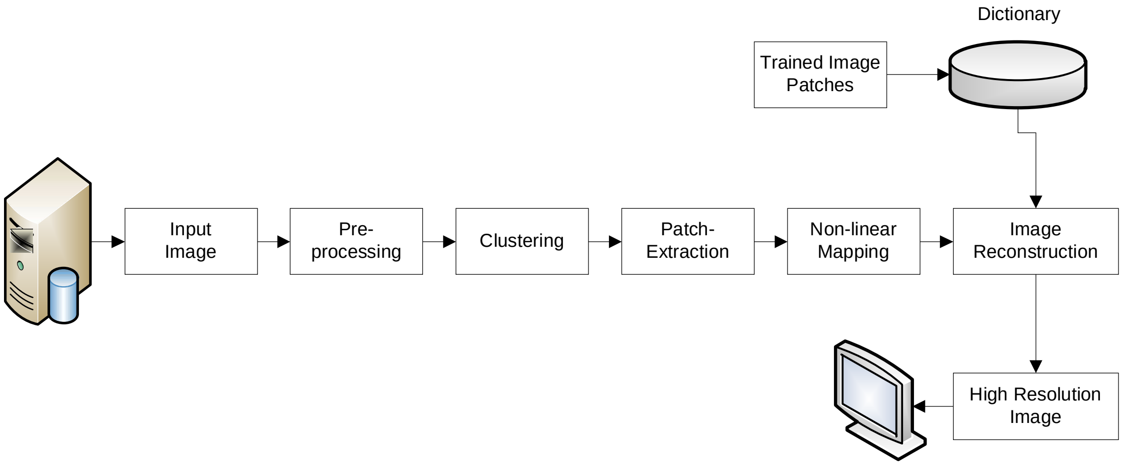

Figure 1: Block Diagram of Proposed System

1. Input Image:

Collects low resolution of images in the database.

2. Pre-processing:

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The main aim of pre-processing is an improvement of the image data that suppresses unwanted distortions or enhances some image features important for further processing. Here we are resizing the input image to a fixed dimension.

3. Clustering

We are applying k-means clustering for input image.

Let us consider an image with resolution of$x \times y$ and the image has to be cluster into k number of cluster. Let p(x, y) be an input pixels to be cluster and $c_k$be the cluster centres. The algorithm for k-means clustering is following as:

- Initialize number of cluster k and center.
- For each pixel of an image, calculate the Euclidean distance d, between the center and each pixel of an image using the relation given below.
- d= $\|p(x, y) - c_k\|$ (1)
- Assign all the pixels to the nearest center based on distance d.
- After all pixels have been assigned, recalculate new position of the center using the relation given below.
- $c_k = \frac{1}{k}\sum_{y\epsilon c_k}\sum_{x\epsilon c_k} p(x, y)$ (2)
- Repeat the process until it satisfies the tolerance or error value.
- Reshape the cluster pixels into image.

4. Patch Extraction

To ensure that the patches cover all the information in the input image, we should decompose the image into patches systematically. Here we extract square patches of the same size column by column, then row by row. To avoid obvious artifacts near the boundaries of the patches, neighboring patches should have some overlap. There are cases when the last patch in a row reaches the right boundary of the image, or the last patch in a column reaches the bottom boundary, so that it is not complete. We handle these cases by mirroring, that is, pretend that there are mirror images about the image boundaries technique gives us meaningful boundary patches.

5. Non-linear mapping

This operation nonlinearly maps each high-dimensional vector onto another high-dimensional vector. Each mapped vector is conceptually the representation of a high-resolution patch. These vectors comprise another set of feature maps.

6. Neural Network Training

The responsibility of the training phase is to train the coupled dictionary and the neural network, and record the data for later use. To get the LR and HR patch pairs used for training, we first downscale the training images to produce the low-resolution counterparts, and then randomly sample LR and HR patches simultaneously. When training the coupled dictionary and the neural network, we use two independent set of training patches, both randomly sampled from the training images. This is because we want the two components to capture different aspects of the relationship between LR and HR, and in practice it accelerates the training of the neural network. The training of the neural network uses the standard Back Propagation algorithm. The architecture of the neural network consists of one input layer, one hidden layer, and one output layer. Because the task considered here can be regarded as regression, we use sigmoid units in the hidden layer and linear units in the output layer.The HR “template” patches, as well as the LR patches, become the input to the neural network. Combining these two parts is straightforward because patches are stored as vectors internally. The neural network propagates the input values to the output layer via the hidden layer, and generates the output HR patches.

7. Image Reconstruction

The HR patches are then stitched together to reconstruct the HR image, which is exactly the inverse process of the first stage. As in patch extraction, there are patches that fall on the image boundaries. Here we just discard those pixels that are out of bound. We also need to appropriately handle the overlap regions. After the above processing stages, the overlap region from one patch may not be consistent with that from another neighboring patch. We handle this inconsistency by averaging the overlapped pixels..

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III. RESULTS AND DISCUSSION

In This section explains the output of the proposed system.
Here, Figure 1 shows how the neural network would be trained.Figure2: Shows the input image i.e., low resolution image which has to convert into high resolution image. Figure 3,4 &5 explains the clustering results using K-means algorithm. Figure 4 shows the output of our proposed system.

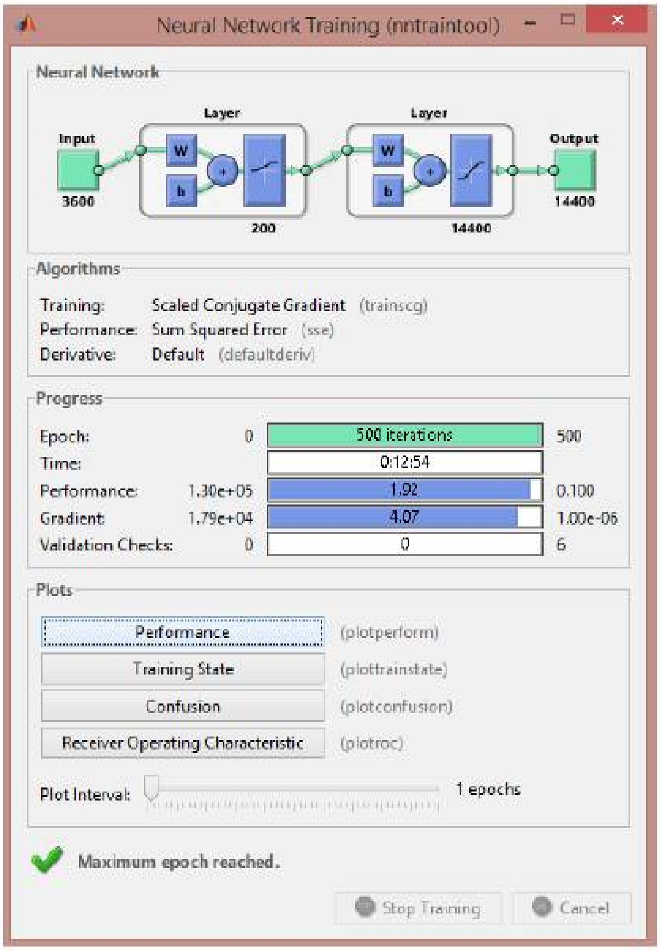

Figure 2 Figure1: Neural Network Training

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Figure2:Input image.

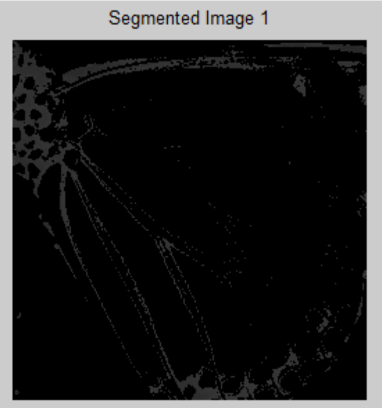

Figure 3: Clustering image at stage 1

Figure 3: Clustering image at stage 2

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Figure 3: Clustering image at stage 3

Figure 4: Reconstructed Image.

IV. CONCLUSION

In this paper, we have studied the relationship between low resolution image (patch) and corresponding high resolution image (patch) .We proposed that the non-linear mapping between LR-image and HR-image can be effectively learnt by neural networks. Our results confirm that proposed algorithm has outperformed the state-of-the art SR techniques. We performed experiments on diverse set of natural images for qualitative performance evaluation of our algorithm. We show that our method is efficient in computation and accurate in performance.

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