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A Review on Image Super Resolution Using Deep Learning Network

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Abstract

The process of obtaining great resolution copy from a low resolution image is known as image resolution. Image super resolution is one of the recent techniques for improving the resolution of an image. The application is to give an improved visual result after resizing a given digital image for printing or display. In the range of medical imaging, solo image super resolution (SISR) has an extensive range of applications. The learning based methods have an ample range of attention because of their ability in calculating the high frequency parts which might be absent in short resolution images. This paper offers a review on utmost of the effort done to improve the image resolution by means of Deep Convolutional Neural Networks.

Keywords: Image SR, CNN, HR image

1. INTRODUCTION

SISR provides high resolution images (HR) from a little resolution image (LR). Various techniques are used to explain an SISR problem, they are classified into three categories. They are reconstruction based, interpolation based and example based methods. [1] The first method is quite straight forward, but it will not offer any supplementary data for reconstruction and thus the gone frequency can't be reinstated. In case of restoration based approaches, it generally introduces certain information in a converse restoration problem. Example centered approaches tries to renovate the past information from a huge total of inside or external LR HR patch pairs, provides the deep knowledge techniques. This paper emphasis mostly on deep learning grounded resolution approaches and provides an introduction to the field of SISR.

Example based algorithm aims to improve the firmness of LR images by knowledge from additional dissimilar LR-HR couple samples. To recover the HR version of an LR image, the link among LR and HR was useful to an unnoticed LR image. Sample centered approaches are categorized into two forms. Inside knowledge founded approaches and exterior learning centered approaches. [2] In internal knowledge based approaches the self resemblance stuff of natural image will inclines to reappear several times in both the identical rule or through dissimilar rules inside the image. In case of exterior knowledge based approaches it tries to find the related evidence frompatches or additional images

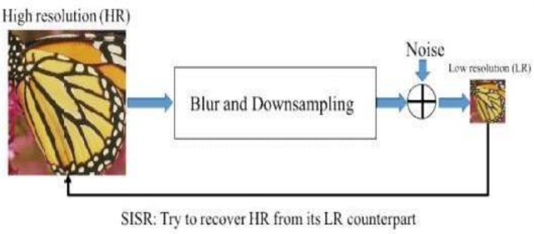

Figure 1. SISR structure

One of the learning algorithm known as locally linear embedding (LLE) follows the idea that the by using some underlying parameters a high dimensionality can be represented. This algorithm finds a set of nearby neighborhood of individually and every topic which describes that particular fact as a lined grouping of its neighbors.

Another important method which is used on behalf of the SR of copy is sparsity based approaches. In this method the image or pixels be represented as a lined grouping of thin features which are taken after an properly whole dictionary. Nearly all super resolution algorithms emphasis ongray rule or distinct network image SR.

2. MACHINE LEARNING- ARTIFICIAL NEURAL NETWORKS- DEEP LEARNING

Machine learning are motivated by artificial neural networks, generally called deep learning which uses a group of methods and procedures which enables the machines to realize complex shapes in data set. Using deep learning approach a huge verity of problems related to computer vision, robotics and language modeling can be solved. The convolutional neural network enables computers to recognize the required objects in images and the performance is also high [4]. For wide verity of machine vision uses, the deep learning algorithms are used. Deep knowledge algorithms are commonly used for image processing applications, and also other areas like language processing, analysis of unstructured type data, speech recognition and synthesis etc.

Computers with machine learning background are able to solve problems by learning from experiences. Mathematical models can be created and trained in such a way that useful outputs are to be produced when inputs are applied. The first and foremost step is to give training and thus gain the experience [5]. From the learned experience, the algorithm can provide a correct prediction for a new input. Depends upon the category of inputs applied, machine learning algorithms are of different types. One important type of classification is supervised and unsupervised learning. In controlled learning, the machine has been specified a group of previously annotated or branded facts and directed to generate accurate labels. But in case of unsupervised learning the computer is asked to find out the patterns in the information without users guidance. Machine learning can be divide into different sub arenas, out of which deep knowledge is the technique commonly used for research applications nowadays [6]. Deep learning techniques are commonly applied nowadays in case of medical image processing and applications.

3. ARTIfiCIAL NEURAL NETWORKS

One among the mainly important and renowned machine learning models used is the artificial neural networks. In neural networks it contains a numeral of associated evaluation units known as neurons, which are organized in layers.

This network consists of an input layer through which the input data is entered, tailed by single or additional unseen layers which transforms the information before ending in the output layer which performs the network predictions. Training is given to predict the output by recognizing patterns in a group of labeled training information [7]. Good prediction occurs when the training given strengthen each neurons. This network is used for predicting on unseen or new data, when the network once learned the patterns.

Artificial neural networks are so malleable and have the ability to solve and model complex problems. One disadvantages of ANN are that it is highly expensive to train. In the area of machine learning artificial neural network has a high role and most intensively studied.

The network is feed with training data in the training phase and asked to make predictions which match the labels which are known. The training is given how to develop the in-between representation to formulate a complex demonstration of the input which ends in precise calculations at the output [8]. For a neural network the training has been given by changing its weights in such a way that it will optimize the output. That is, an optimization algorithm called gradient descent algorithm is applied. The training is done in the following way. When sample data is applied over the system the gradient of the loss function is computed in accordance with each and every weight by means of the chain rule and reduces theloss by altering these weights using gradient descent.

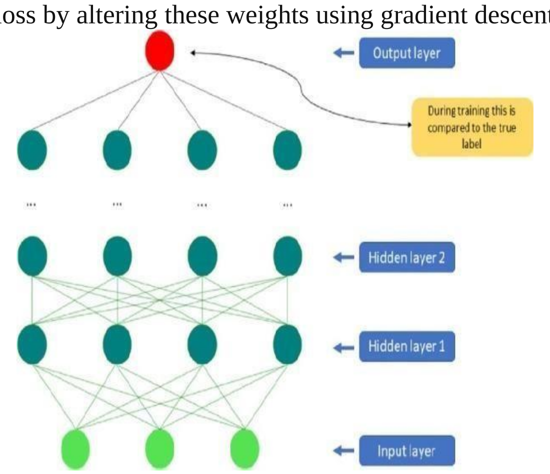

Figure 2. Structure of ANN

4. DEEP LEARNING

In case of machine learning, the models are trained in such a way that they perform some valuable tasks centered on the planned information take out from the raw information. But in case of deep learning, directly from the given raw data computers are able to learn required features and representations automatically. The key variation among DL and ML is that the earlier mainly concentrates on learning representation data automatically [9]. In the arena of medical imaging convolutional NNs are used to trigger learning process in deep learning. CNN is a powerful method to learn different image representations and structured data.

5. DEEP LEARNING FOR IMAGE SR

The CNN used for image super resolution called super-resolution convolutional neural networks (SRCNN). The steps in SRCNN are as follows. Preprocessing is the first step in which the L R image is up scaled to H R image using the technique bicubic interpolation [10]. By using feature extraction technique, the set of attributes are mined from the up scaled LR images. Nonlinear mapping is selected to map the required features among LR image and high resolution image patches. The final HR image is recreated from the HR patches in the final step.

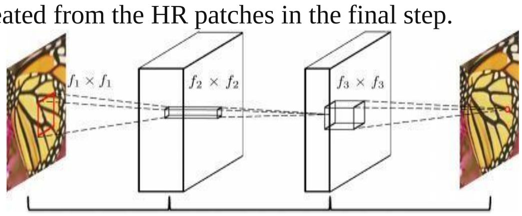

Figure 3. SRCNN model for SISR

After SRCNN, very deep CNN and deeply recursive CNN are implemented. Both VDSR and DRCN network contains 20 convolutional layers. In this case, residual connections are used make the model understand the difference between inputs and outputs [11].

Thus deeply recursive residual networks (DRRN) are generated which uses both global and local residual connections.

Another method of reconstructing HR images is by using deconvolution layers, and it is done in fast super resolution convolution neural network (FSRCNN). FSRCNN is faster with better image quality than the SRCNN model. The steps in FSRCNN are as follows. Feature abstraction, nonlinear mapping, shrinking, deconvolution and expanding. The first step, bicubic interpolation in SRCNN is replaced by a 5X5 convolution. It is called feature extraction. Shrinking is a 1X1 convolution which is done todecrease the amount of feature maps.

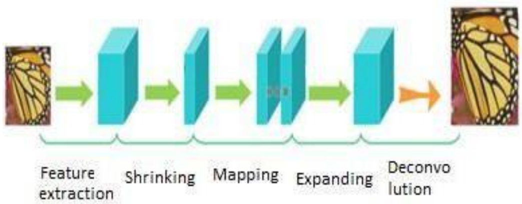

Figure 4. Structure of FSRCNN

FSRCNN is the first network which uses a normal deconvolution layer for rebuilding high resolution images from low resolution features [12]. The main advantage of using deconvolution layer is the reduction in computation.
The problems of conventional super resolution approaches such as SRCNN, FSRCNN and VDSN are as follows. In all the above mentioned techniques, the low resolution images are up scaled or up sampled in the beginning stage itself. Thus all the convolutions done will be based on the up scaled low resolution images [13]. Thus the number of computations increases. To overcome this problem, a new network called efficient sub-pixel convolutional neural network (ESPCN) is proposed.
Instead of improving resolution by resizing feature maps like the deconvolution layer ensures, ESPCN improves the stations of the output datas for keeping the spare ideas to improve perseverance and these are rearranged to acquire the HR output over a detailed planning standard. The deconvolution layer is cut down into the sub pixel convolution in ESPCN [14].
Comparing with the nearest neighbor interpolation, this method is more effective, which can too confirm the efficiency of ESPCN.
This Network is used to convert a low resolution images into a high resolution format for forward appreciation. The alteration is done according to the informations extracted from the input image [15]. By comparing the performance of other image resolution methods, ESPCN is recorded as a high resolution method.

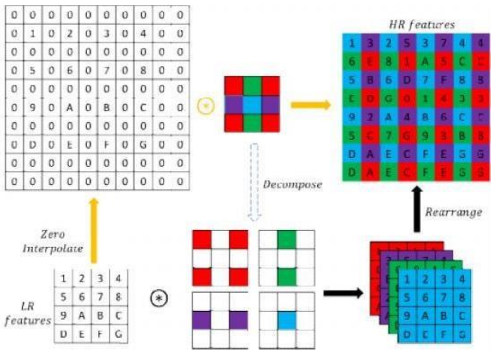

Figure 5. ESPCN architecture

Another classical approach for image super resolution is very deep super resolution or VDSR, which was published in 2016. In SRCNN we have only 3 layers but in VDSR the number of layers is increased to 20.
To train the VDSR model it is required to use a very high initial understanding rate to accelerate resolution. There are two more contributions that VDSR architecture has made. Since the SISR algorithm uses number of scaling factors in which they are having a tough relationship with one another [16]. This is one of the main basic fact of almost all SISR algorithms. Bicubic of low resolution image is taken as the input in VDSR. At the training process VDSR takes the bicubics of low resolution of different scaling factors together and training has been done. The second contribution of VDSR architecture is the residual learning [17]. Deep CNN method is used by VDSR to learn how mapping has been done to obtain residual from the bicubic. It was noticed that residual learning will accelerate convergence and improve performance.

6. Comparison of SISR algorithms

As an overview of the performance of different deep learning based single image super resolution algorithms, a comparison work has been done and listed in figure 6. The parameters which are highly important like peak signal to noise ratio (PSNR) and structural similarity index (SSIM) has been evaluated and performance is compared [18]. The quality of the image reconstructed will be better if the peak signal to noise ratio and structural similarity are high.

Conclusion

This paper provides an assessment of different super resolution methods. This paper mainly focused on SISR methods which uses sample centered learning. It was found that deep learning centered approaches have attained high rate of presentation among all other SR methods. The contributions of each algorithm is analyzed and their advantages and disadvantages are discussed.

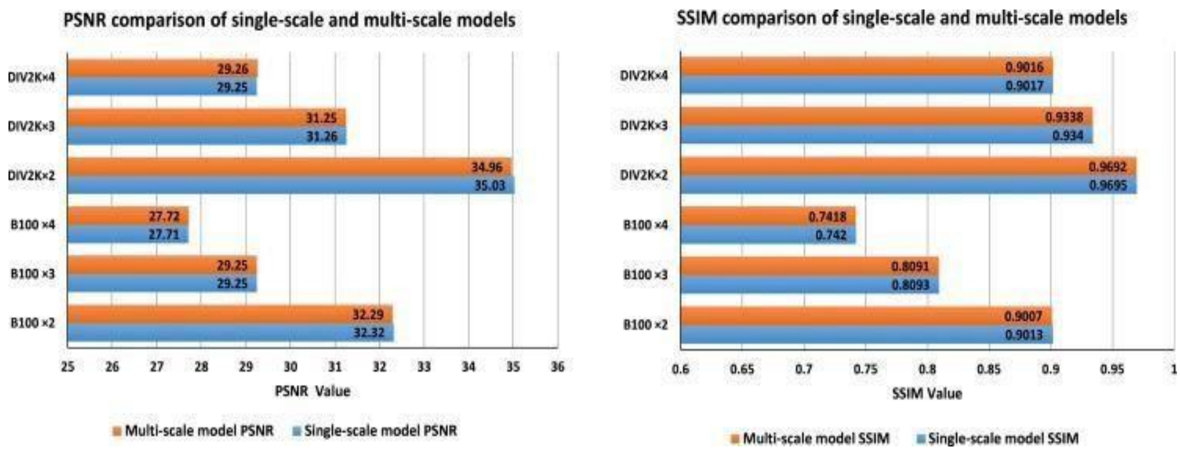

Figure 6. Comparison of PSNR and SSIM values of different SISR models

The reliability of each algorithm is based on the application. An algorithm which is highly applicable for medical imaging will not be effective for remote sensing applications. If is understood that the development of an algorithm is based on the field of application. This review paper has improved the understanding of deep learning centered super resolution processes applied to solo image super resolution, which is used as a leader for the learner and tosses up several queries in necessity of additional analysis.

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