Single Image Super Resolution Reconstruction Algorithm Based on Deep Learning

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Abstract. Super resolution image reconstruction technology is the core technology in image processing, which provides technical support for most of the intelligent devices for target tracking and target detection. However, the existing image acquisition stage will cause extra high cost to improve the image resolution. Optimization algorithm is one of the best ways to solve this kind of problem. At present, there is no substantial breakthrough in this field in China. Therefore, this paper studies single image super-resolution reconstruction algorithm based on deep learning. In this paper, the application of super-resolution reconstruction algorithm in single image is discussed. The analysis shows that the application of deep learning in this field is shallow and has a large optimization space. Especially for the existing main problems, the traditional algorithm is optimized and improved. According to the demand of resolution reconstruction, combined with the latest deep learning method, the accuracy and robustness of the algorithm are further improved. At the same time, it effectively improves the comprehensive performance of the model. In order to further verify the actual performance of the proposed algorithm, the corresponding comparative experiments are established. The experimental results show that the proposed algorithm has obvious advantages over the traditional fsrcnn algorithm, especially when the PSNR of dataset 4 is 2, 3, and 4 times, it can increase 0.41 dB, 0.58 dB and 0.52 DB respectively. Analysis shows that this algorithm has obvious advantages and achieves ideal results.

Keywords: Super Resolution Reconstruction Technology, Deep Learning, Image Processing, Target Detection

1. Introduction

Super resolution reconstruction (SR) is a technique that uses low quality images to produce high quality images. The improvement of image resolution is beneficial to the observation and analysis of image details, thus providing more useful information for subsequent image processing [1-3]. However, in the image acquisition stage, improving the resolution will greatly increase the cost, and the image quality is not ideal. Therefore, it is more important to improve the image resolution through the algorithm [4-5].

The super-resolution algorithm can be divided into two categories: traditional super-resolution
algorithm for multiple images and super analysis algorithm for single image. The deep learning method can automatically extract features from a large number of data, and because of the complexity of the depth model, it can establish a complex nonlinear transformation [6-8]. It is a powerful tool for super-resolution reconstruction of an image. In recent years, a large number of deep convolution network models have been applied in the field of super-resolution and achieved good results. However, as a rapidly developing discipline, deep learning will be more and more widely used in computer vision, which will also bring more inspiration to the development of super-resolution field [9-10].

This paper deeply studies the current application of deep learning in single image super-resolution reconstruction technology in China, and understands that the application of deep learning in the field of image super-resolution reconstruction is still in the primary stage, and does not give full play to the advantages of deep learning. Aiming at the technical problems of high cost and poor quality of single image super-resolution reconstruction, this paper proposes a single image super-resolution reconstruction algorithm based on deep learning. It is hoped that through the optimization and improvement of deep learning algorithm in this paper, the comprehensive level of single image super-resolution reconstruction technology in China can be improved. Aiming at the problems of high cost, backward algorithm and low image quality, the traditional super-resolution reconstruction algorithm is optimized and improved according to the characteristics of deep learning technology. The improved algorithm has the advantages of simple operation and accurate calculation. Compared with the traditional FSRCNN algorithm, the proposed algorithm improves the PSNR (dB) value while ensuring the image quality. The analysis shows that the performance of the reconstruction model after optimization of the algorithm in this paper has obvious improvement, and has great advantages.

2. Deep Learning and Image Super Resolution Reconstruction Technology

2.1. Deep Learning
Deep learning obtains high-level abstract feature information from the original data, which solves the problem of feature extraction and data classification. The basic structure of deep learning is neuron, which firstly collects the input information transmitted by dendrites, and then transforms the input data by using nonlinear activation function. Multiple neurons are combined to form a hierarchical structure, and a multi-layer network structure is formed by cascading and parallel connection between layers. Deep machine learning data model mainly includes: input layer, hidden information layer and data export.

- **Input layer**: input signal, input data to model.
- **Hidden layer**: it is composed of multiple hidden layer units. The data features are extracted from the original data by multi-layer nested nonlinear transformation.
- **Output layer**: displays data features extracted from hidden layers.

Because of its outstanding performance in feature extraction, deep learning technology has been playing an important leading role in modern computer stereo vision and other computer stereo vision technology fields.

2.2. Image Super Resolution Reconstruction Technology Based on Deep Learning
Deep machine learning analysis is the most important machine deep learning analysis algorithm. It mainly aims to obtain data through multi-layer nonlinear logic transformation algorithm, learn the potential emerging data distribution logic rules, so as to continuously improve the ability of reasonable logical judgment and analysis and prediction of emerging data distribution. With the development of convolutional neural network, more and more researchers try to introduce deep learning into super-resolution reconstruction. In 2014, the three-layer convolution neural network was used for the first time to learn the mapping relationship between low-resolution images and high-resolution images. Since then, super-resolution reconstruction has set off a wave of in-depth research in the field of super learning.

The reconstruction process includes the following steps:
(1) The feature is extracted. The input low resolution image is eliminated and preprocessed, and then the processed image is sent to the neural network to obtain the detailed features of the image.

(2) Design the network structure. The convolution neural network is combined with multiple segments to establish the network model.

(3) Training methods. By reducing the loss function, the ability of model learning is improved.

(4) Verify the model. According to the performance of the training model on the verification set, the existing network model is evaluated and adjusted.

2.3. Evaluation Index of Reconstructed Image Quality
There are different application objects and scenes for image super-resolution reconstruction. How to better combine the super-resolution reconstruction algorithm with the practical application, the performance and operational efficiency of the algorithm itself have become the key factors. The quality of reconstructed image is evaluated mainly by subjective quality evaluation method and objective quality evaluation method.

The subjective quality evaluation method is mainly based on the visual perception of human eyes, and the image edge is clear and heavy. During the implementation of the method, the subjects scored the images according to certain criteria and visual perception. Finally, the arithmetic mean of all scores is MOS value. Although the subjective method is more suitable for the actual production and application, the objective method is the mainstream image quality evaluation method due to its time-consuming and high cost. The unit of PSNR is dB, and its value usually fluctuates in the range of 20 to 40. The higher the value, the closer the reconstructed image is to the original high-resolution image. SSIM is based on the extraction of structural information from human visual system. It evaluates the quality of reference image and reconstructed image from three aspects of brightness, contrast and structure. Although PSNR and SSIM can estimate the quality of the reconstructed image to a certain extent, for most of the current super-resolution algorithms, the advantages and disadvantages of these algorithms are generally combined with simple subjective quality assessment.

2.4. Image Super Resolution Algorithm Based on Convolution Neural Network
The image super-resolution algorithm based on convolution neural network adopts the deep learning method to train and study the low resolution and high-resolution images directly. Srcnn adopts a joint optimization strategy. The learning network structure consists of three convolution layers, which represent the extraction and display of image block features, the nonlinear mapping between LR image block and HR image block, and the reorganization of HR image block.

In this paper, three convolution layers in srcnn based deep learning network are optimized:

\[
Y_1 = \max(0, W_1^R \ast X + B_1^R) \\
Y_2 = \max(0, W_2^R \ast X + B_2^R) \\
Y_3 = \max(0, W_3^R \ast X + B_3^R)
\]

Where \(X\) is the LR sub image, \(Y_i (i=1,2,3)\) is the output of the convolution layer, \(W_i (i=1,2,3)\) and \(B_i (i=1,2,3)\) are the weight matrix and offset of the convolution layer respectively, and \(n_i = (i=1,2,3)\) and \(f_i = (i=1,2,3)\) are the number of filters in the three convolution layers. The mean square error between the output \((Y_i)\) of the third convolution layer and the corresponding HR sub image is used as the driving loss function. In the test process, the input is the LR image to be processed, and the output is the enlarged HR image.

3. Network Training
(1) Experimental platform
The training and testing results of this experiment are run on Linux RedHat rhel7.5 system. The CPU hardware configuration is es-2650 v4@2.20GHz, 128GB of memory and 15GB of video memory available. All paper codes are based on tensor flow and implemented in Python 3.6 in Spyder integrated development environment.
(2) Experimental data

The training data set is composed of timoft data set, and the image content is mainly divided into human, animal and plant. The test data set of the model consists of standard test data sets set3 and SET4, including human, animal and plant.

(3) Training parameters

Like most super-resolution reconstruction networks, this paper mainly uses a mean square network error model function as a network loss model function to analyze and train various network loss model algorithms. At the same time, in the process of network training, Adam is used to optimize and update the network parameters. The exponential decay rate of Adam algorithm is 0.92 for the first-order moment and 0.98 for the second-order moment. Every 1500 steps, the learning rate decays discontinuously with the attenuation coefficient, and the exponential decay rate is 0.97.

4. Discussion

4.1. Analysis of Experimental Results

In the experiment, the scale factors of super-resolution reconstruction are 2, 3 and 4, respectively. The training and test data set information is shown in Table 1. In K90 video card, the training time of various super-resolution reconstruction algorithms based on deep learning is the same order of magnitude, and all training is completed in one day. According to the experimental data of SSIM and PSNR, the corresponding data analysis charts are made, as shown in Figure 1 and Figure 2.

From the analysis in Figure 1, we can see that the performance of the reconstruction algorithm in this paper is the best when the PSNR index is 2, 3, 4 times. Compared with fsrcnn algorithm, the proposed algorithm can increase 0.41 dB, 0.58 dB and 0.52 DB respectively after 2, 3 and 4 reconstructions of test data set 4. In addition, it can be seen from the experimental results in Figure 2 that the reconstruction quality of fsrcnn algorithm is worse than that of this algorithm. For SSIM index, the performance of the reconstruction algorithm is the best. In addition, the performance of the algorithm designed in this chapter is better than that of fsrcnn in large-scale 4-fold reconstruction.

Analysis shows that the original LBP mapping is very sensitive to the change of image texture details, which reduces the robustness of the algorithm. Therefore, the feature extraction operator based on the original LBP spectrum cannot effectively extract structural similarity information from the original image, resulting in poor quality of the reconstructed image. This algorithm can effectively mine the local structure similarity information in the image, and has achieved good results in both subjective quality and objective quality.

Table 1. training / test data set table.

| Data set Param | Number of images | Image format | Spatial resolution | Data format |
|----------------|------------------|--------------|--------------------|------------|
| Training data set | 1 | 100 | png | 75*75 | RGB24 |
| | 2 | 200 | png | 334*435 | RGB24 |
| Test data set | 3 | 10 | png | 256*256 | RGB24 |
| | 4 | 20 | png | 720*576 | RGB24 |
Figure 1. Comparison of PSNR (dB) results of different algorithms

Figure 2. Comparison of SSIM values of different algorithms
4.2. Application Fields of Image Super Resolution Reconstruction Technology

(1) Image compression
When the transmission of real-time video requires a high frame rate, if it is a video conference, the image can be compressed before the video transmission, and then sent to the receiver to decode the image again. By using the high-resolution image reconstruction and recovery technology, the original code image data is restored again, which greatly reduces the image memory space.

(2) Medical imaging
The super high-resolution reconstruction technology of medical phenomenon imaging can greatly reduce the accuracy requirements of medical phenomenon imaging in medical imaging processing environment. Accurate diagnosis of each patient can help surgeons to make a better scientific judgment on each patient.

(3) Remote sensing imaging
Long range sensing is expensive and expensive to develop. Therefore, the researchers put image super-resolution reconstruction technology into this field, so as to better solve this problem and improve the resolution of the observation image.

(4) Public safety
The video collected by monitoring equipment in public places is often affected by weather and other factors, and there are problems such as image blur. Through super-resolution reconstruction of the collected video, more important information can be extracted.

(5) Video perception
Image super-resolution reconstruction technology can improve the video quality and enhance the user's visual experience.

5. Conclusions
With the rapid development of intelligent technology, intelligent technology has been widely used in various fields. Image technology is an important part of intelligent technology, but the existing image super-resolution reconstruction technology is not ideal, which has a great impact on the whole intelligent system, and limits the development of intelligent field. The research of single image super-resolution reconstruction algorithm based on deep learning proposed in this paper further improves the overall performance and robustness of super-resolution reconstruction technology by optimizing the algorithm. After optimization, the improved reconstruction model has good performance, which makes up for the shortcomings in this field. The analysis shows that the research in this paper has achieved ideal results and made a contribution to the research in this field.

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