A New super-resolution restoration method with Generated Adversarial Network for underground video images in coal mines

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Abstract: The computer can be used in Super-resolution reconstruction (SR) to process low-resolution images to obtain high-resolution images. Aiming at solving problems of complex underground video image acquisition environment, uneven brightness, blurred images etc, this paper adopts the idea of deep learning to perform super-resolution restoration of underground video images in coal mines, and proposes a generational confrontation network to super-resolution underground video images in coal mines. The experiment proves that Generated Adversarial Network (GAN), while being compare with Super-resolution Deep Convolutional Neural Network (SRCNN), Efficient Sub-Pixel Convolutional Neural Network (ESPCN), Deeply Recursive Convolutional Network (DRCN) the effect of GAN method is better, because it can better realize the super-resolution restoration of underground video images in coal mines and provide preliminary support for the subsequent and further application research of underground images in coal mines.

1. Introduction

Analysis of underground video images in coal mines can provide good data support for intelligent monitoring in underground coal mines. However, due to the influence of imaging systems, external conditions and imaging technology, underground video images of coal mines retain degraded traces such as motion blur and noise, and the spatial resolution is low. In order to get a better image analysis effect, it is necessary to study the technology of surveillance image restoration [1].

Many scholars have conducted research on the restoration of underground video images in coal mines. Niu Kangli [2] proposed a dual-channel night vision image restoration method based on deep learning for the problems of weak night scene light, low visibility, low night vision image signal-to-noise ratio, and poor imaging quality. Two kinds of convolutional neural networks based on a fully connected multi-scale residual learning block (FMRB) respectively perform multi-scale feature extraction and hierarchical feature fusion of infrared night vision images and low-light night vision images to obtain reconstructed infrared images and enhanced low-light images. Xiaowen Liu [3] aimed at solving problem of image degradation caused by the scattering of water mist and coal dust in coal mines, combined the characteristics of images collected by wireless multimedia nodes in coal mines, and proposed a dark Primary Color Transcendental Theory defogging model base on regularized Laplacian matrix. According to the Dark Primary Color Transcendental Theory, the fog-free image database from
underground coal mines is counted, and the physical model of underground coal mine imaging is established. The model was used to estimate the media propagation function and the underground light illuminance, and then the defogging dust model was restored to obtain a clearer image. Super-resolution Reconstruction (SR) processes low-resolution images to obtain high-resolution images by computers [4]. In terms of deep learning for image restoration, Hu Chuanping first introduced the research of image super-resolution algorithms based on deep learning. Through adjusting the size of the convolution kernel and adding a pooling layer, etc, Xiao Jinsheng et al reduced the dimensionality and the number of deep network parameters and improved the training speed. These 4 methods, including Super-resolution Deep Convolutional Neural Network (SRCNN), Efficient Sub-Pixel Convolutional Neural Network (ESPCN), Deeply Recursive Convolutional Network (DRCN) and generative confrontation network (GAN), were used to analyze the image data obtained from coal mine surveillance video. The final result verifies that the GAN algorithm can better realize the super-resolution restoration of underground video images in coal mines.

Various existing image super-resolution restoration methods still have many shortcomings. For example, SRCNN obtains the mapping relationship between LR and HR through end-to-end learning, but it has not fully developed the image Transcendental information, and there is a phenomenon of loss of detailed information [7]. Existing recognition methods based on deep learning had almost no learning of resolution features [8]. In short, the current deep learning-based image super-resolution restoration methods have the following shortcomings: (1) The effective feature information extraction of the image is insufficient. (2) There are many model parameters, a large amount of calculation, and the PSNR index-oriented method is not good in visual perception. [9]

2. Image super-resolution restoration algorithm was based on generative confrontation network

Goodfellow et al, proposed a Generative Adversarial Network (GAN) in 2014 [5]. This model is composed of two networks, one is a generator, which generates new data instances; the other is a neural network called a discriminator, which is used to each of its checks whether the data instance is a real training data set. The model structure of the super-resolution image based on the generative confrontation network is shown in Figure 1.

Figure 1 Schematic diagram of the network model structure based on GAN
The low-frequency part of the network extracts structural features using a 4-layer convolutional network. Each layer in the convolutional network contains a 64-core 9x9 convolutional network and a ReLU activation function. The low-frequency features of the image are obtained by using a filter with a size of 9x9 by convolution. The high-frequency part of the network is realized by an 8-layer convolutional network, in which the convolution kernel is 3x3. The receptive field is enhanced by more convolutional layers and smaller convolution kernels, so the image block can be decomposed in more detail and more delicate information can be processed. Through nonlinear mapping, 1*1 convolution and reconstruction, the final high-resolution image is reconstructed:

The loss function generally adopts the minimum mean square error (MSE), which is shown in formula (1):

\[ I_{MSE}^{SR} = \frac{1}{r^2WH} \sum_{x=1}^{W} \sum_{y=1}^{H} (I_{x,y}^{HR} - G_{\theta_G}(I_{x,y}^{LR}))^2 \]  

(1)

Where \( I_{x,y}^{HR} \) represents the original \( I_{x,y}^{LR} \) represents the reconstructed image, \( W \) represents the number of rows of the image, and \( H \) represents the number of columns.

The cost function based on adversarial learning is shown in formula (2):

\[ I_{Gen}^{SR} = \sum_{n=1}^{N} - \log D_{\theta_D}(G_{\theta_G}(I_{LR}^{LR})) \]  

(2)

\( D_{\theta_D} \) is the probability that an image belongs to a real high-resolution image.

\( G_{\theta_G}(I_{LR}) \) is a reconstructed high-resolution image.

The GAN algorithm flow is as follows:

Step 1: Scale the image to get a low resolution image;
Step 2: Generator pre-training;
Step 3: Formal training;
Step 4: If the loss function is less than 0.5, then output the result, otherwise go to Step3;
Step 5: Data output;
Step 6: End.

The process of the GAN algorithm is: firstly zoom the image to get a low-resolution image; define the generator and train; define the discriminator and train; perform formal training, use the data of the generator and the discriminator; define the switching strategy, which is the callback device decides when switching between the discriminator and the generator. If the loss function value is less than 0.5, output it, otherwise, continue the confrontation between the generator and the discriminator; finally generate a high-resolution image.

3. Experimental results and analysis

The algorithm has been tested and written on the TensorFlow2.0 and Fastai1.0.60 platforms in this paper, and using an image data set obtained from a coal mine surveillance video. There are 3206 pictures in data set.

Hardware configuration for training and testing: Windows 10 operating system, NVIDIA GeForce GTX 1080 Ti graphics card, Intel(R) i7CPU processor, 8G memory, 4G video memory.

The GAN algorithm is compared with three algorithms for the effect of image super-resolution restoration in this article. These four algorithms are based on Super-resolution Deep Convolutional Neural Network (SRCNN), Efficient Sub-Pixel Convolutional Neural Network (ESPCN), and Deeply Recursive Convolutional Network (DRCN), and the image super-resolution restoration algorithm based on Generative Adversarial Network (GAN). The training time and PSNR of those algorithms are compared as shown in Table 1.
Table 1 Comparison of four algorithms

| Algorithm name | SRCNN  | ESPCN  | DRCN   | GAN   |
|----------------|--------|--------|--------|-------|
| Training time  | 10h    | 8h     | 15h    | 16h   |
| PSNR           | 20.38  | 21.56  | 30.23  | -     |

The training time of GAN is the longest, because it contains the pre-training process. The training time of DRCN is the second, due to it performs continuous recursion and the network is deeper; SRCNN is longer than ESPCN training time because of the difference the convolutional neural network input. The input of SRCNN is the image amplified by bicubic interpolation, while the input of ESPCN is directly the original low-resolution image, so the convolution calculation burden of SRCNN will be relatively large, the training time will be relatively long.

The larger the PSNR value is, the better the recovery effect is. DRCN has the best recovery effect for using the deepest network, SRCNN and ESPCN PSNR values are similar, the effect is not much worse. The loss function of GAN is not comparison together, for lack of using PSNR. It can be seen from the loss function shown in Figure 3. As the number of iterations increases, the effect of training and the effect of testing is getting closer and closer.

![Figure 2 GAN loss function](image)

The experimental results are shown in Figure 3.

![Figure 3 Algorithm effect diagram](image)

In Figure 3, the left column is the original image, and the right column is the processed image.
4. Conclusion
This paper proposes a coal mine underground video image super-resolution restoration algorithm based on generative confrontation network (GAN), and test it by the image data set obtained by a coal mine monitoring video. The experiment result shows that GAN can better perform high resolution images. The restoration of the coal mine provides preliminary support for the subsequent and further application research of underground coal mine images. At present, video image super-resolution restoration has made a lot of achievements, but there are still many unsolved problems: first of all, the network needs to be optimized. The current video image super resolution restoration algorithm has excellent performance, but the model is large and the speed is not high. The second aspect is super resolution image/video quality evaluation method. The widely used indicators are PSNR and SSIM. However, the evaluation method of PSNR may lead to excessive smoothing of reconstruction results. SSIM is evaluated in terms of brightness, contrast, and structure, but still cannot accurately measure the image perception quality, so more accurate measurements are needed to evaluate the reconstruction quality.

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