Image Super-Resolution based NCSs Model with Packet Loss

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Abstract. There are many ways to super-resolution reconstruction of a single image. This method require the association between low-resolution images and high-resolution images, and has achieved good results in different applications. This article also pursues the correlation between low-resolution images and high-resolution images, but we combine images with linear networks to explore the possibilities of combining the two domains. In order to achieve the purpose of restoring image details, we used a method of combining image and network, different from the traditional single-picture super-resolution, we using network delay and packet loss compensation, fully retain the data packets before and after, and find the internal similarity from low-resolution images. Experiments show that inputting images into a network system is affected by system packet loss and has a large impact. It also shows that it is feasible and effective to combine images with network packet loss in the networked control systems model, and specific image effects will be shown in the paper. Our algorithm has achieve a certain expected effect, by superimposing the image super-resolution reconstruction is more extensive, and it is also convenient for future research based on image super-resolution.

1. Introduction

An understanding of an image of image super-resolution is that the higher the pixel of a given image, the closer the image quality is to the original image. If you zoom in on a low-resolution image to a certain degree, the image will become very blurred. If you want to make the image fresh, the technology you need is super-resolution reconstruction. Super-resolution reconstruction now has many implementations, such as Sparse coding [1], Bayesian [2], Pyramid-based [3], and Deep learning [4]. These methods have been proven to be effective and have achieved good results.

1.1. Subject of this article

In the image super-resolution study, multiple images can be processed, or a single image can be processed. For single image super-resolution is a common problem in computer vision. For such problems, the same internal similarity in the image is usually used, or the low-resolution and high-resolution learning mapping function is used to solve the related problem. Our research is also based on the same internal similarities in the image, but we have tried to introduce the network control system into the image super-resolution, which has achieved the effect of restoring pictures lost due to network packet loss.
1.2. General thinking
It is well known that Network Control Systems (NCSs) are closed-loop feedback control systems that can transmit data and commands over digital communication networks. Network latency and packet loss can have an impact on system stability. As an important reason for the performance degradation of NCSs, packet loss has become an important aspect of NCSs research. However, combining NCSs network packet loss with images is also a research direction, which is the starting point for this article. In the case of poor communication conditions, problems such as network delays may occur, and many data inevitably result in packet loss. Then, for the image, the pixel is treated as a data packet. After the NCSs, there will also be a packet loss problem. In other words, the image will lose some details. How to recover the image that loses detail due to packet loss can also become a new idea for super-resolution reconstruction.

1.3. Order of papers
In this paper, we refer to the paper [5], the stochastic stability controller based on packet loss, we only care about the problem of image and packet loss. The structure of this paper is as follows. In the second part, we will briefly introduce the model used and the handling of packet loss in the third part. In the fourth part, we will show the experimental results and analysis the experimental results. In the fifth part, the experiment will be summarized.

2. Model
For the sake of understanding and understanding, here is a brief introduction to the network control model used in this article. This paper considers the situation after the image passes through the packet loss network. It is hoped that the control network can maintain system stability at the same time in the case of random data input. Then the choice of control network model has become the key to the success of this experiment.

2.1. Model selection
In general, few people pay attention to networked linear systems with random data loss, while also taking into account the saturation in the case of random data [6]. This model is a good solution to this problem. Reference is made to a class of network structures based on \( H_\infty \) control problems, taking into account data loss and actuator saturation issues in linear systems. The saturation related problem is improved by introducing an auxiliary matrix. Then design the \( H_\infty \) controller based on state feedback to effectively ensure the stability and safety of NCS [7]. Among them, the method for correcting the CCL effectively solves the problem of the non-convex feasible design controller and proves to be effective. The selected network model is shown in Figure 1.

![Networked control system](image)

Figure 1. Networked control system.

The system is based on state feedback \( H_\infty \) controller. This design not only ensures the stochastic exponential stability of the system, but also performs well in anti-interference suppression attenuation.
performance. The non-convex matrix inequality is transformed into the minimum problem and is constrained by LMI.

2.2. Parameter introduction
The system is an indeterminate linear NCS with data loss and actuator saturation. The input data is random, where input saturation and constraints are added to the actuator and the data is lost on the way from the sensor to the controller, as follows

\[ x(k + 1) = (A + \Delta A)x(k) + (B + \Delta B)\text{sat}(u(k)) + D\omega(k) \]
\[ z(k) = C_1x(k) + D_1\omega(k) \]
\[ y(k) = C_2x(k) \] (1)

Where \( A, B, D, C_1, D_1, C_2 \) are known real matrix, the specific value is the empirical value, \( x(k) \in \mathbb{R}^n \) is the state vector, \( u(k) \in \mathbb{R}^m \) is the input of the control part, \( y(k) \in \mathbb{R}^p \) is the measurement output of the measurement end, and \( \omega(k) \in \mathbb{R}^q \) is the interference output. Sat is the standard saturation function, we define it as \( \text{sat}(u) = [\text{sat}(u_1), \text{sat}(u_2), \text{sat}(u_3), \ldots, \text{sat}(u_m)]^T \). We also introduce parameter uncertainty, denoted by \( \Delta A, \Delta B \) and follow the format standards below

\[ [\Delta A \Delta B] = ZF(k)[E_1 \ E_2] \] (2)

With \( Z, E_1, E_2 \) is the same as \( A, B \) above, it is a real matrix, with appropriate dimensions, and the value is the empirical value. \( F(k) \in \mathbb{R}^{q_1 \times q_2} \) is Lebesgue measurable elements satisfying

\[ F^T(k)F(k) \leq I \] (3)

When the above formulas (2) and (3) are satisfied, \( \Delta A \) and \( \Delta B \) are satisfied. In the reference literature, the stability analysis and controller synthesis problems of the model are considered and reasonable. This ensures that the closed-loop network system has random exponential stability and also guarantees the stability of incorporating images into the system.

3. Related work
In this section, we will introduce our algorithm ideas.

3.1. Experimental procedure
After the image data passes through the NCS, the packet is lost and the desired resolution image cannot be achieved. Considering a low resolution image \( X \) as the input to the system, in order to achieve the size of the output target image \( Y \), we first upgrade it to the required size using a bicubic interpolation algorithm. The pre-processing of the input image \( X \) has now been completed. The input image \( X \) used herein is a grayscale image and the size is \( 256 \times 256 \), and the final output image \( Y \) is a \( 512 \times 512 \) grayscale image.

Then, the preprocessed images are sequentially input into the system in a \( 2 \times 1 \) matrix until the image input is completed. We use \( \alpha \) to indicate the system packet loss situation. The packet loss is divided into three different phases. The value of \( \alpha \) can be 0.8, 0.9, 0.95, which in turn represents 20\%, 10\%, and 5\% of the packet loss. This packet loss is referenced to [8]. The image after the packet loss is shown in Figure 2. It can be seen that in the case of stable system [9], packet loss has a great influence on the image.

Next, how to compensate for the missing pixels becomes the problem considered in this article. By analyzing the lost data, it can be found that the system lost data and the data discarded when the system is unstable become factors that affect the image quality. Considering the internal correlation of the image, the relationship between adjacent pixels is relatively large, and several common interpolation algorithms are compared, and the effects are not ideal. In this paper, the system loss compensation method is applied, and the image information can be restored as much as possible.

For packet loss compensation, we consider the most commonly used Bernoulli packet to deal with related problems. For data loss, it can be described as

\[ x_c = \alpha(k)x(k) \] (4)
Figure 2. Impact on images with different packet loss.

Where $\alpha(k)$ is the Bernoulli process, $\alpha(k) = 1$ data transmission is completed, and $\alpha(k) = 0$, and data is lost. $\alpha(k)$ in the Bernoulli process satisfies the following conditions:

$$prob(\alpha(k) = 1) = E[\alpha(k)] = \bar{\alpha}$$
$$prob(\alpha(k) = 0) = 1 - \bar{\alpha}$$

In addition, we define $\bar{\alpha} = \alpha(k) - \bar{\alpha}$, we have

$$E[\bar{\alpha}(k)] = 0$$
$$E[\bar{\alpha}(k)\bar{\alpha}(k)] = \bar{\alpha}(1 - \bar{\alpha})$$

We will analyze and compare the experimental results. In the experiment, the model is more effective for images with strong texture, and it is not suitable for images with little difference in texture and excessive edge effect [10].

Here is a brief description of the changes in the system. In order to effectively analyze system performance and controllers, there are changes in the following forms:

$$sat(u(k)) = \sum_{s=1}^{2^m} \eta_s (D_2Kx_c(k) + D_\omega Hx_c(k))$$

Where $\eta_s > 0, s = 1, 2, ..., 2^m$ and $\sum_{s=1}^{2^m} \eta_s = 1$. We use Bernoulli packet loss to simulate network packet loss. Combined with Equation 4-7, the closed-loop network uncertain linear system model becomes as follows:

$$x(k + 1) = (\bar{A} + \bar{\alpha}(k)\bar{B})x(k) + D\omega(k)$$
$$z(k) = C_1x(k) + D_1\omega(k)$$
$$y(k) = C_2x(k)$$

Where

$$\bar{A} = A + \Delta A + \bar{\alpha}\sum_{s=1}^{2^m} \eta_s (B + \Delta B)(D_2K + D_\omega H)$$
$$\bar{B} = \sum_{s=1}^{2^m} \eta_s (B + \Delta B)(D_2K + D_\omega H)$$

3.2. Effect comparison

Combined with Figure 2 and Figure 3, we can see that data packet loss has a great impact on the transmission of a single image, and the image is not only lost in texture information. As a whole, as long as data occurs, the integrity of the image is difficult to preserve. Here is a short description. For Figure 2, we can see that the image loss part is in the horizontal bar. The reason is mentioned above. In order to better obtain the internal correlation of the image, the purpose of this is to The key points can be reserved, which can ensure that when the image is compensated for packet loss, the change of each key pixel point is small, and the upper and lower parts are only supplemented by the surrounding pixel points, so that more information can be obtained, which can effectively compensate. The missing part, Figure 3 proves that the image detail reduction is still very high.

Finally, for the output image $Y$, the pixel points of the region are re-stretched according to the $4 \times 4$ region, and Figure 3 can be obtained. Due to the limited space, the picture in this article only shows the effect of one picture. The rest of the test pictures will be displayed in tabular form.
4. Experimental result
The experimental results are shown in Table 1. And Table 2. Table 1. shows the impact of data network packet loss on different pictures. As can be seen from Table 1, the packet loss has a great impact on the picture and the data is seriously lost. Table 2. shows that the packet loss compensation algorithm used in this paper compensates for the packet loss data.

![Images](a) Original image (b) Bicubic (c) \( \alpha = 0.8 \) (d) \( \alpha = 0.9 \) (e) \( \alpha = 0.95 \)

**Figure 3.** The result of compensating for the lost image.

| Images | Different packet loss situation (PSNR) |
|--------|---------------------------------------|
|        | Bicubic  \( \alpha = 0.8 \)  \( \alpha = 0.9 \)  \( \alpha = 0.95 \) |
| Bird   | 31.76  20.65  22.04  25.32            |
| Butterfly | 24.04  15.87  16.86  18.22        |
| Woman  | 28.04  18.52  20.01  21.97            |

| Images | Compensation effect (PSNR) |
|--------|-----------------------------|
|        | Bicubic  \( \alpha = 0.8 \)  \( \alpha = 0.9 \)  \( \alpha = 0.95 \) |
| Bird   | 31.76  22.15  27.34  32.98            |
| Butterfly | 24.04  17.73  20.37  26.07        |
| Woman  | 28.04  19.82  25.32  29.53            |

Finally, the algorithm is compared with the current mainstream algorithms, and the results are shown in Table 3. It can be seen that the combination of network packet loss and image super-resolution reconstruction is feasible, and the mainstream algorithm can be balanced. For the image with obvious boundary information and strong contrast of texture information, the algorithm has better effect. Before the verification, I guessed it and achieved better results. It also worked very well for the subsequent enhancement of the image super-resolution effect.

5. Conclusion
As can be seen from the renderings, our method can restore the details of the image and is more friendly to the image after the packet loss. However, it is not difficult to see that for the information of the severely lost part, after the compensation, there will be a step effect on the boundary of the image. The experimental results of this paper are analysed, and the effect has been predicted, and the method is also proved effectively.
### Table 3. Algorithm comparison.

| Images  | Algorithm comparison (PSNR) |
|---------|----------------------------|
|         | Bicubic        | SC[11] | K-SVD[12] | AND[13] |
| Bird    | 31.76          | 34.11  | 34.57     | 31.82   |
| Butterfly | 24.04          | 25.58  | 25.94     | 25.90   |
| Woman   | 28.04          | 29.97  | 31.37     | 34.55   |

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