Image Super-Resolution Restoration Instance-Based Learning and Iterative Kernel Regression

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Abstract. This paper proposes an image super-resolution restoration algorithm based on example learning and iterative directional kernel regression, which is used to solve the problem that the existing super-resolution restoration algorithm based on example learning cannot effect the restored image has a small degree of matching with the sample library and the problem of image restoration in the presence of noise. Among them, the example learning can achieve basic image restoration. In the directional kernel regression, the estimated smoothing matrix can obtain the minimum mean square estimation after multiple iterations, and further optimize the super-resolution restored image. Simulation results show that the improved algorithm improves the robustness and edge preservation characteristics of the super-resolution restoration image. Compared with the classical algorithm, the algorithm has better visual effects and the root mean square error can be improved over 15%, and reflect the effectiveness of the algorithm.

Keywords. Super-resolution restoration; Markov random field; BP algorithm; iterative kernel regression.

1. Introduction

The basic idea of image super-resolution restoration is to reconstruct the information beyond the cut-off frequency of the imaging system while improving the image quality, so as to achieve the image higher than the resolution of the imaging system without changing the imaging system. The biggest advantage of this technology is that it reduces the cost of acquiring high-definition image, which can still be used for the existing low-resolution imaging systems, and increases the utilization rate of acquired resources.

The main technologies of super-resolution restoration include reconstruction-based super-resolution restoration and learning-based super-resolution restoration. In the existing methods, the super-resolution restoration technology based on reconstruction mainly includes iterative back projection algorithm [1] and maximum posterior probability method [2]. However, these algorithms can not effectively learn the mapping relationship between high and low resolution images, especially in the era of increasing data volume, the performance of the algorithm will not be further improved with the increase of data volume. Learning-based super-resolution restoration techniques mainly include example-based method [3], sparse representation method [4]. At the same time, with the continuous maturity of machine learning and deep learning techniques, there are also researchers who introduce machine learning and deep learning algorithms into image super-resolution restoration domain, such as support vector machine [5], convolution neural network [6], deep self encoding learning [7], RBM dictionary learning [8], generative adversarial networks [9]. The learning-based method has strong nonlinear mapping ability. It can fully tap the mapping relationship between high and low resolution based on large amount of data, and is very suitable for image super-resolution...
restoration. Because the method of example learning is one of the most basic prototypes of image super-resolution restoration using the learning method, this paper mainly studies the image super-resolution restoration based on the example learning. The basic idea of image super-resolution restoration based on the example learning method is to comprehensively consider the similarity of different images in high-frequency details, and construct a prior knowledge point by learning the relationship between low-resolution image and high-resolution image to carry out super-resolution restoration. Therefore, the acquisition of prior knowledge points is a key factor to restrict the performance of image super-resolution restoration based on example learning. Prior knowledge points are obtained by training a large number of similar images, and high-resolution images are obtained by supplementing the input image information with the knowledge obtained in the learning process. However, there is a critical problem. The processing effect of the image with small correlation information in the training sample is not ideal, and the processing effect of the noise in the acquired image is not significant. Therefore, this paper mainly focuses on the above two problems, and proposes an image super-resolution restoration algorithm based on example learning and iterative directional kernel regression, which can effectively improve the performance of image super-resolution restoration when the test samples are different from the training samples and there is noise. The proposed algorithm for image super-resolution restoration based on example learning and directional kernel regression is as follows: firstly, the ksvd algorithm is used to train data to get a pair of high-resolution and low-resolution information sample database; secondly, the matching block of input low-resolution image is obtained by using Markov random field theory. Because there are serious stitching traces when the matching block is directly stitched. It is necessary to use the confidence propagation algorithm to optimize the image globally to get the high-precision difference graph. Finally, the image is processed by the iterative directional kernel regression algorithm to get super-resolution restored image. Simulation results show that the proposed algorithm is more robust than the original algorithm, and the performance is improved by more than 15%.

2. Image Degradation Model
In the process of image acquisition and transmission, each process may cause the degradation of image quality, such as the aberration of optical system, the nonlinear distortion of imaging system, the relative motion between object and camera, the scattering of imaging light source and ray, the pollution of various noise, etc. The key of image restoration is how to build image degradation model. Figure 1 shows a general model of image degradation.

![Image Degradation Model](image-degradation-model.png)

Figure 1. Image degradation model.

The process of image degradation can be described as follows from figure 1: the original high-definition image \( f(x, y) \) is degraded to image \( g(x, y) \) after passing through a system \( H[\cdot] \) and external additive noise \( n \). System \( H[\cdot] \) is a complex system, which is a function that integrates all degenerate elements. In fact, the inverse process of image restoration is essentially a process of prediction and estimation. The degradation function \( H[\cdot] \) is estimated by the existing degraded image \( g(x, y) \), so that the original high-resolution image \( f(x, y) \) can be restored approximately.

3. Markov Random Field
Generally, a matrix is used to represent an image when it is processed in a computer. Set \( I^H \) (\( P=1, 2 \) N) represents high resolution image, \( I^L \) represents low resolution image. The low-resolution image is
obtained from high-resolution image through blur and down sampling, and the number of high-resolution image blocks is the same as that of low-resolution image blocks, so a set of high-resolution $T_L$ and low-resolution set $T_H$ is obtained, as shown in equations (1) and (2).

$$T_L = \{ I_L^p[i, j], i = 1, 2, 3, ..., I; j = 1, 2, 3, ..., J \}_{p=1}^n$$ (1)

$$T_H = \{ I_H^p[i, j], i = 1, 2, 3, ..., I; j = 1, 2, 3, ..., J \}_{p=1}^n$$ (2)

Among them, $I_L^p[i, j]$ is the block form of $I_L^p$, $I_H^p[i, j]$ is the block form of $I_H^p$.

If a low-resolution image block similar to the sample library is imputed, the corresponding high-resolution image block can be found in the sample library, and then image restoration can be realized.

The Markov random field is based on Bayesian theory, which can estimate the maximum posterior of image. The Markov Random Field model only considers the relationship between a certain pixel and its neighboring pixels, which can well represent the statistical characteristics of the image. By using Markov random field theory, we can use the neighborhood system and conditional probability to divide the correlation between one pixel and another in the image. The specific judgment method is to meet the three conditions of integer probability, Markov and singularity, that is to say, to meet the correlation.

4. Belief Propagation Algorithm

The principle of belief propagation algorithm is to use the mechanism of message transmission and belief transmission to realize the global energy minimization, while the process of finding the maximum probability distribution of Markov random field is the process of finding the global energy minimization of stereo matching. In this paper, the confidence propagation algorithm of segmented region is used. It can be seen from literature that the definition of global energy function is as shown in equation (3):

$$E(f) = \sum_{s \in R} (C(s, f(s))) + \sum_{(s_i, s_j) \in S_{ij}} V(s_i, s_j)$$ (3)

$C(s, f(s))$ is data items, $V(s_i, s_j)$ is interregional smoothing term.

If $m^t_{s_i \rightarrow s_j}$ is used to represent the information transmitted between regions in the $t$-th iteration, the inter region information update is as shown in equation.

$$m^t_{s_i \rightarrow s_j}(f(s_j)) = \min_{f(s_j)} (C(s_i, f(s_j)) + V(s_i, s_j) + \sum_{s_0 \neq f(s_j)} m^t_{s_0 \rightarrow s_j}(f(s_j)))$$ (4)

The confidence degree of the $s_i$ region obtained after $T$ iterations is shown in equation (5):

$$b^T_{s_i}(f(s_i)) = C(s_i, f(s_i)) + \sum_{s_J \in N(s_i)} m^T_{s_i \rightarrow s_J}(f(s_j))$$ (5)

The minimum value of the confidence is the optimal disparity map of the $s_i$ region.

5. Kernel Regression Algorithm

The principle of classical kernel regression is to assign a weighted function to each sampling point, that is, the kernel function; the kernel function assigns weights to other sampling points according to distance [10], as shown in figure 2.
Previous experimental studies have shown that the selection of kernel has little effect on the accuracy of estimation, so this experiment selects a differentiable and relatively simple Gaussian kernel.

5.1. Adaptive Kernel Regression
The adaptive kernel regression function regards the affine kernel as the local gradient estimation of a pixel in a neighborhood. The image restoration process is as follows: First, the image structure is initially estimated, then the local kernel is controlled according to the estimated result, so that the local kernel forms a similar ellipse contour, which can spread along the direction of the local edge structure adaptively, so that the high-frequency information of the image can be better maintained while the noise is suppressed. The adaptive kernel regression not only depends on the sampling density, but also considers the edge characteristic according to the neighborhood sample value. Therefore, the size and extension direction of the kernel can be adapted to the local structure in the image. Figure 3 shows this property.

5.2. Iterative Directional Kernel Regression
Because the estimation of smoothing matrix in directional kernel regression is related to data, it is sensitive to noise. In this case, the iterative regression method can be used, specifically: for noisy images, the classic kernel regression is used to get an initial estimate; during the iteration, the output image of the last iteration is used to estimate a new and more reliable smoothing matrix for the next iteration. The results show that the least mean square estimation can be obtained after several iterations. The advantage of iterative solution is that estimation and denoising can be completed in the same process.

6. Process and Results of Super Resolution Restoration
The flow chart of super-resolution restoration based on example learning and directional kernel regression image is shown in figure 4.

First, input a large number of high-resolution training images similar to the image to be restored, and use the training data of KSVD algorithm to get the learning dictionary, i.e., generate a sample library, which stores high-resolution and low-resolution sample blocks. Figure 5 shows a pair of high and low resolution information in the sample library.

Then, input the low-resolution image to be restored, take the classic image Lena as an example, add the additive Gaussian white noise with PSNR = 15, process the low-resolution image to obtain the high-frequency information of the low-resolution image, as shown in figure 6, and then perform histogram matching.

Then a Markov network is constructed. The low-resolution block of L = 7 and the high-resolution block of H = 4 are used, and the pixel sampling interval is 3. The high-resolution matching block is searched in the sample database. As shown in figure 7b, the obtained high-resolution image is globally optimized by using the confidence propagation algorithm, and the energy is minimized and iterated through the message transmission and confidence transmission mechanism. When the number of times
is 30, the energy reaches the minimum and a high-precision difference map is obtained. At this time, the image obtained through learning can be obtained as shown in figure 7c. Finally, iterative directional kernel regression processing is carried out. The processing process is described in Section 4.1. The parameters of classical kernel regression processing are as follows: the smooth parameter $H = 0.8$, using local quadratic estimation, the window size is 7; the parameters of the iterative directional kernel regression processing are as follows: smooth parameter $h=2.5$, window size 11, structure sensitive parameter 0.5, regularization parameter 1, iteration number 400. Finally, a high-resolution image is obtained as shown in figure 7e (the number of iterations at this time is 220). The experimental results are measured by root mean square error (RMSE), as shown in figure 8. Table 1 lists the RMSE comparison results obtained in different stages of image processing.

The same processing method processes the image Mandi, and the results are shown in figure 9. The RMSE values obtained in different stages of image processing are shown in table 1.

From the performance test results, we can be seen that subjectively, from the graphs (a), (b), (c), (d), and (e) in figure 7, the restoration effect is significantly improved. The image is smoother and the noise is reduced, and the improved algorithm has richer detail than the super-resolution restoration algorithm based on example learning. For example, Lena image of hair, hat edges and mandi picture of clothes, hair and other parts. On an objective basis, it can be seen from table 1 that the RMSE value of Lena image example learning processing is 16.2342. When the number of kernel regression iterations is 220 in the improved algorithm, the RMSE value reaches the minimum 13.8034, the RMSE value of Mandi’s image learning processing is 101673, and the RMSE value reaches a minimum 7.8005 when the number of kernel regression iterations is 220 in the improved algorithm. The result of the improved algorithm is also better than that of the example-based learning method, which fully demonstrates the effectiveness of the improved algorithm.

![Flowchart of super-resolution restoration algorithm.](image-url)

**Figure 4.** Flowchart of super-resolution restoration algorithm.
(a) high frequency information of HR image  
(b) high frequency information of LR image

**Figure 5.** Paired samples.

![High frequency information for low resolution images of Lena.](image)

**Figure 6.** High frequency information for low resolution images of Lena.

(a) Low resolution images (128×128)  
(b) algorithmic processing results  
(c) The processing results of belief  
(d) results of classical kernel regression  
(e) Iterative Directional Kernel

**Figure 7.** Lena super resolution restoration process chart.

![Root mean square error of kernel regression in Lena image.](image)

**Figure 8.** Root mean square error of kernel regression in Lena image.
Figure 9. Mandi super resolution restoration process graph.

| Image | Example learning processing | Belief Propagation Algorithm | Classical kernel regression processing | Iterative Directional Kernel Regression Processing |
|-------|-----------------------------|------------------------------|----------------------------------------|-----------------------------------------------|
| Lena  | 16.2342                     | 15.3570                      | 15.3550                                | 13.8034                                       |
| Mandi | 10.1673                     | 9.6252                       | 9.6245                                 | 7.8005                                        |

Table 1. RMSE value comparison.

7. Conclusion
In order to solve the problem that the existing super-resolution restoration algorithms based on example learning can not effectively deal with the image restoration under the condition that the matching degree between the restored image and the sample library is small and there is noise, this paper proposes an image super-resolution restoration algorithm based on example learning and iterative directional kernel regression, and the proposed algorithm can realize the basic image restoration by example learning. The estimation smoothing matrix in the directional kernel regression can get the least mean square estimation after much iteration, which improves the performance of the whole algorithm. The experimental results show that the proposed algorithm improves the robustness and edge preserving performance of the super-resolution restoration algorithm. Compared with the classical algorithm, the improved algorithm gets better visual effect, and the root mean square error can be increased by more than 15%. How to improve the operation speed and further optimize the algorithm is the focus of further research.

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