# Improved Single-Image Self-Learning Super-Resolution Reconstruction Method (Postprint)

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## Abstract

To address the limitations of traditional super-resolution reconstruction methods based on sparse representation that rely on large training sample dictionaries, this paper proposes an improved self-learning super-resolution reconstruction method for single images, leveraging the weak sparsity characteristics of the $l_2$ norm. First, a non-pyramidal ladder-style training image set is established through self-learning. Subsequently, a customized approach is employed to extract feature patches and feature pixel values from low-resolution images and their corresponding high-resolution counterparts in the training set, respectively. Finally, a multi-layer super-resolution mapping model is learned by integrating collaborative representation (CR) theory based on the $l_2$ norm with support vector regression (SVR) techniques. Experimental results demonstrate that the proposed super-resolution method is not only feasible and effective, but also achieves an average PSNR improvement of 0.06~3.92 dB and an average SSIM improvement of 0.0024~0.0348 when compared with traditional single-image super-resolution methods, thereby validating the superiority of the proposed method from both objective numerical metrics and subjective visual perspectives.

## Full Text

## Preamble

### Improved Super-Resolution Reconstruction Method for Self-Learning of Single Images

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**Abstract:** Traditional super-resolution reconstruction methods based on sparse representation rely heavily on large training sample dictionaries, which presents a significant limitation. To address this issue, we propose an improved self-learning super-resolution reconstruction method for single images that leverages the weak sparsity characteristics of the $\ell_2$ norm. First, we establish a non-pyramid, stepped training image set through self-learning. Then, we employ a custom method to extract feature blocks and feature pixel values from low-resolution (LR) and corresponding high-resolution (HR) images in the training set. Finally, we learn a multi-layer super-resolution mapping model by combining collaborative representation (CR) theory based on the $\ell_2$ norm with support vector regression (SVR) techniques. Experimental results demonstrate that the proposed method is not only feasible and effective but also achieves average PSNR improvements of 0.06–3.92 dB and SSIM improvements of 0.0024–0.0348 compared with conventional single-image super-resolution methods. Both objective metrics and subjective visual quality confirm the superiority of our approach.

**Keywords:** single-image super-resolution; $\ell_2$ norm; collaborative representation (CR); support vector regression (SVR)

## 0 Introduction

In recent years, computer vision and image processing have garnered widespread attention, with digital image super-resolution reconstruction remaining a persistent research focus. Super-resolution (SR) reconstruction refers to the process of recovering a high-resolution (HR) image from one or multiple low-resolution (LR) images [1–9]. Based on input/output configurations, SR problems can be categorized into reconstruction-based SR, video SR, and single-image SR. According to the availability of training samples, single-image SR can be further divided into edge-enhanced SR without training samples and learning-based SR with training samples [2]. This paper investigates learning-based single-image super-resolution.

Learning-based single-image super-resolution represents a major breakthrough in SR algorithm research. It primarily employs machine learning methods to learn the mapping relationship between LR and HR images, thereby predicting the high-frequency detail information lost in test images and reconstructing SR images. Current learning-based single-image super-resolution techniques mainly establish HR-LR relationships through two approaches: (a) constructing projection matrices for HR and LR image patch features via redundant dictionaries [3–6]; and (b) establishing functional relationships between LR image patches and corresponding HR image pixel values through regression models [5,7–9], including support vector regression (SVR), anchored neighborhood regression (ANR), and ridge regression (RR) models.

# 1 Related Work

In 2008, Yang et al. [3] first proposed a super-resolution method based on sparse representation that establishes projection matrices between LR and HR images from a compressed sensing perspective. In 2009, Yang et al. [4] improved upon this work by introducing a dual-dictionary sparse representation approach with separate LR and HR dictionaries. In 2013, Yang et al. [7] combined sparse representation with SVR to propose a self-learning approach to single-image super-resolution (SLSR). This method first employs sparse representation theory and redundant dictionaries to sparsify features from the training image set, obtaining sparse coefficients of image features. It then uses SVR theory to establish a regression mapping model between LR image features and HR image pixels, achieving super-resolution reconstruction. Experimental results demonstrate that the SLSR method, which combines sparse representation and SVR, outperforms the sparse representation approaches of Yang et al. [3,4] that rely on external image databases. However, these sparse representation-based SR reconstruction methods indicate that the key to successful reconstruction lies in achieving sufficiently sparse coefficients for representing image features, and such strong sparsity depends heavily on the constructed redundant dictionary.

## 1.1 Sparse Representation Theory with $\ell_0$ and $\ell_1$ Norms

Consider an image signal $\mathbf{x}$ and a dictionary $\mathbf{D} = [\mathbf{d}_1, \mathbf{d}_2, \dots, \mathbf{d}_k] \in \mathbb{R}^{m\times k}$. The $\ell_0$ norm-based sparse representation model is:

$$\min_{\alpha} \|\mathbf{x} - \mathbf{D}\alpha\|_2^2 + \lambda\|\alpha\|_0 \quad (1)$$

where $\lambda$ is the regularization parameter. Solving Eq. (1) yields an approximate solution $\hat{\alpha}$ of the image signal $\mathbf{x}$ over dictionary $\mathbf{D}$, where $\alpha$ is a sparse vector containing multiple zero elements. Let $\mathbf{A} = [\alpha_1, \alpha_2, \dots, \alpha_n] \in \mathbb{R}^{k\times n}$ denote the coefficient matrix.

Since solving Eq. (1) is an NP-hard problem, Efron et al. [11] improved the $\ell_0$ norm sparse representation by proposing the $\ell_1$ norm-based model:

$$\min_{\alpha} \|\mathbf{x} - \mathbf{D}\alpha\|_2^2 + \lambda\|\alpha\|_1 \quad (2)$$

This model offers better optimization properties while enabling recovery of the image signal $\mathbf{x}$ through the obtained sparse coefficient $\alpha$.

## 1.2 Collaborative Representation Theory with $\ell_2$ Norm

Given the computational expense of $\ell_0$ and $\ell_1$ norms in sparse representation [10], Zhang et al. proposed a collaborative representation method combining least squares with the $\ell_2$ norm, which has lower complexity and higher computational speed than sparse representation.

Let test image data be $\mathbf{x}$ and dictionary samples be $\mathbf{D}$. Adding $\ell_2$ norm sparsity constraints, the collaborative representation model becomes:

$$\min_{\alpha} \|\mathbf{x} - \mathbf{D}\alpha\|_2^2 + \lambda\|\alpha\|_2^2 \quad (3)$$

where $\|\cdot\|_2$ denotes the $\ell_2$ norm and $\lambda$ is the penalty parameter that balances the relationship between least squares and the $\ell_2$ norm of $\alpha$, ensuring stability of the least squares solution while introducing a certain degree of sparsity to coefficient $\alpha$ to improve computational speed.

### 1.3 Support Vector Regression Theory with Linear Kernel

Support vector regression (SVR) extends support vector machines (SVM) for regression tasks. Its objective is to find the optimal regression function $f(\mathbf{x}) = \omega^T\mathbf{x} + b$, where $\omega$ is the normal vector and $b$ is the bias term. The optimal regression function corresponds to a hyperplane in the feature space. Given a training set $\{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \dots, (\mathbf{x}_m, y_m)\} \subset \mathbb{R}^n \times \mathbb{R}$, the primal SVR optimization problem [12] is:

$$\begin{aligned} \min_{\omega, b, \xi, \xi^*} \quad & \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{m}(\xi_i + \xi_i^*) \\ \text{s.t.} \quad & y_i - \omega^T\mathbf{x}_i - b \le \varepsilon + \xi_i, \quad i = 1, 2, \dots, m \quad (4) \\ & \omega^T\mathbf{x}_i + b - y_i \le \varepsilon + \xi_i^*, \quad i = 1, 2, \dots, m \\ & \xi_i, \xi_i^* \ge 0, \quad i = 1, 2, \dots, m \end{aligned}$$

where $\phi$ is a nonlinear mapping function, $C > 0$ is the penalty parameter, $\varepsilon$ is the insensitivity function, and $\xi_i, \xi_i^*$ are slack variables representing upper and lower training error bounds. To solve this optimization problem, we introduce Lagrange multipliers $\beta_i, \beta_i^*$ and transform the primal problem into its dual:

$$\begin{aligned} \max_{\beta, \beta^*} \quad & -\frac{1}{2}\sum_{i,j=1}^{m}(\beta_i - \beta_i^*)(\beta_j - \beta_j^*)K(\mathbf{x}_i, \mathbf{x}_j) - \varepsilon\sum_{i=1}^{m}(\beta_i + \beta_i^*) + \sum_{i=1}^{m} y_i(\beta_i - \beta_i^*) \\ \text{s.t.} \quad & \sum_{i=1}^{m}(\beta_i - \beta_i^*) = 0 \\ & \beta_i, \beta_i^* \in [0, C], \quad i = 1, 2, \dots, m \end{aligned} \quad (5)$$

where $K(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{x}_i^T\mathbf{x}_j$ is the linear kernel function. The final linear kernel SVR function is:

$$f(\mathbf{x}) = \sum_{i=1}^{m}(\beta_i - \beta_i^*)K(\mathbf{x}_i, \mathbf{x}) + b \quad (6)$$

## 2 Super-Resolution Method Based on $\ell_2$ Norm with Same-Size Images

The key to single-image super-resolution reconstruction lies in learning the relationship between LR and HR images. Considering image variability, this paper employs a self-learning approach to construct a training set for each input image. Unlike the pyramid-stepped image set generation methods proposed in [5,7,9], we propose a self-learning method that establishes a training set of same-size images.

### 2.1 Self-Learning Same-Size Image Set

Let the input high-definition original image be $\mathbf{I}$. We simulate the image degradation process to obtain the training image set for single-image super-resolution. First, we blur image $\mathbf{I}$ using a custom Gaussian blur function; then downsample the image by a factor of $z$; finally, we add Gaussian white noise at 40 dB SNR to obtain the LR image $\mathbf{I}_{\text{low}}$ to be super-resolved.

Subsequently, we construct an LR image pyramid from image $\mathbf{I}$ using the same Gaussian blur function and downsampling factor. Using bicubic interpolation (BI), we upsample the LR image pyramid to the original image size, obtaining a training image set $\{\mathbf{I}_1, \mathbf{I}_2, \dots, \mathbf{I}_M\}$ with super-resolution dimensions but progressively decreasing clarity. Here, $\mathbf{I}_i$ has higher clarity than $\mathbf{I}_{i+1}$, and we appropriately define $\mathbf{I}_1$ and $\mathbf{I}_M$ as HR and LR images, respectively. Figure 1 illustrates the overall process of self-learning same-size image sets. The size of image set $M$ is determined by the number of layers in the LR image pyramid, which primarily depends on the downsampling factor and image patch size.

Examining the global view of the multi-resolution training image collection described in Figure 1, we observe that these image sets satisfy a progressive resolution pattern. The goal of super-resolution research is to increase image resolution and clarity during upscaling. Based on this progressive resolution property, we only need to identify the relationship model between adjacent images $\mathbf{I}_i$ and $\mathbf{I}_{i+1}$, then select the optimal model from multiple relationship models to reconstruct the super-resolution image $\mathbf{I}_{\text{sr}}$. The progressively higher-resolution images $\mathbf{I}_i$ and $\mathbf{I}_{i+1}$ satisfy the independent and dependent variable requirements for our subsequent super-resolution mapping model.

### 2.2 Image Feature Extraction and $\ell_2$ Norm Collaborative Representation

Based on the self-learning process described in Section 2.1, the key to our super-resolution reconstruction lies in learning the optimal relationship model between adjacent LR and HR images in the same-size image set $\{\mathbf{I}_i\}_{i=1}^{M}$. As shown in Figure 1, although images $\mathbf{I}_i$, $\mathbf{I}_{i+1}$, and $\mathbf{I}_{\text{low}}$ share the same dimensions, they are generated by interpolating LR images that progressively approximate the real image, resulting in varying clarity levels. Therefore, by learning multiple relationships among these same-size images and selecting the relationship model with minimal error, we can reconstruct the super-resolution image $\mathbf{I}_{\mathrm{sr}}$.

**2.2.1 Feature Extraction** Let the image patch size be $p \times p$. The training HR image set is $\{\mathbf{I}_i^h\}_{i=1}^{N-1}$ and the corresponding LR image set is $\{\mathbf{I}_i^l\}_{i=2}^{N}$. We extract LR image patch set $\{\mathbf{x}_i^l\}_{i=1}^{dN}$ and the center pixel value set $\{y_i^h\}_{i=1}^{dN}$ of corresponding HR image patches using a sliding window with step size 1. Since our reconstruction model is a regression model between LR image patches and HR pixel values, we follow [13] and multiply each $\mathbf{x}_i^l$ by a $p \times p$ weight distribution matrix $\mathbf{G}$, which assigns greater weight values to the center of $\mathbf{x}_i^l$. This yields the updated LR feature set $\{\mathbf{x}_i^l\}_{i=1}^{dN}$, forming the training set for super-resolution image reconstruction: $\{\mathbf{x}_i^l, y_i^h\}_{i=1}^{dN}$.

**2.2.2 $\ell_2$ Norm Collaborative Representation** Since $\ell_0$ norm sparse representation of features $\mathbf{x}_i^l$ yields coefficients $\alpha$ with most elements equal to 0, it actively ignores some extracted image features, potentially introducing errors in the subsequent LR-HR mapping model. In contrast, $\ell_2$ norm collaborative representation produces coefficients $\alpha$ that approach 0 but are not exactly 0, preserving all image features. Building on Zhang et al.'s [10] work comparing $\ell_1$ norm sparse representation and $\ell_2$ norm collaborative representation for face classification, which demonstrated that collaborative representation improves both accuracy and efficiency while reducing computational complexity, we propose a method that combines $\ell_2$ norm with least squares.

For each LR image $\mathbf{I}_j^l$ $(j = 1, 2, \dots, N-1)$, we extract feature set $\mathbf{X}_j = \{\mathbf{x}_i^l\}_{i=1}^{dN}$. Vectorizing each patch matrix into column vectors, the collaborative representation coefficient $\alpha_j$ is obtained by:

$$\min_{\alpha_j} \|\mathbf{X}_j - \mathbf{D}\alpha_j\|_2^2 + \lambda\|\alpha_j\|_2^2 \quad (7)$$

where $\mathbf{D}$ represents the dictionary. To solve Eq. (7), we use regularized least squares to obtain the approximate solution $\hat{\alpha}_j$ of the collaborative coefficients on dictionary $\mathbf{D}$:

$$\hat{\alpha}_j = (\mathbf{D}^T\mathbf{D} + \lambda\mathbf{I})^{-1}\mathbf{D}^T\mathbf{X}_j \quad (8)$$

where $\mathbf{I}$ is the identity matrix. This approach improves both the accuracy of the LR-HR mapping model and reduces computational complexity in the coefficient-based image feature representation process.

### 2.3 Super-Resolution Reconstruction Model

In [3–6], Yang, Tian, and Zhang et al. proposed using custom four-direction high-pass filter operators to extract LR image feature blocks, then establishing super-resolution reconstruction models via $\ell_1$ norm sparse representation or $\ell_2$ norm collaborative representation. This paper employs linear kernel SVR to build a mapping model from LR image features to HR image space for reconstructing the super-resolution image $\mathbf{I}_{\mathrm{sr}}$.

**2.3.1 Reconstruction Mapping Model** We divide each LR image feature set $\{\mathbf{x}_i^l\}_{i=1}^{dN}$ into training set $\{\mathbf{x}_i^l\}_{i=1}^{\mathrm{train}N}$ and test set $\{\mathbf{x}_i^l\}_{i=1}^{\mathrm{test}N}$ based on location parity. The training set constructs the reconstruction mapping model $\mathbf{F}$, while the test set builds the error model $\mathbf{E}$.

For training set $\{\mathbf{x}_i^l\}_{i=1}^{\mathrm{train}N}$, we use Eq. (5) to establish a linear kernel SVR model between LR image features $\alpha$ and HR image pixel values $y^h$, obtaining the mapping model from LR features to HR space:

$$\mathbf{F}: \hat{y}^h = \sum_{i=1}^{\mathrm{train}N} (\beta_i - \beta_i^*) K(\alpha_i, \alpha) + b \quad (9)$$

where $K(\alpha_i, \alpha)$ represents the linear kernel function between $\alpha_i$ and $\alpha$. Similarly, we establish mapping models $\mathbf{F}_j$ $(j = 1, 2, \ldots, N-1)$ for each LR-HR image pair.

**2.3.2 Error Model** Following Yang et al.'s [7] SLSR method, we simultaneously construct an error model $\mathbf{E}$. For each test set $\{\mathbf{x}_i^l\}_{i=1}^{\mathrm{test}N}$ corresponding to training set $\{\mathbf{x}_i^l\}_{i=1}^{\mathrm{train}N}$, we use the reconstruction mapping model from Section 2.3.1 to recover HR pixel values $\hat{y}^h$ for test data $\alpha$. We then apply SVR theory to establish an error model mapping LR image features to HR space:

$$\mathbf{E}: \hat{e}^h = \sum_{i=1}^{\mathrm{test}N} (\beta_i - \beta_i^*) K(\alpha_i, \alpha) + b \quad (10)$$

Similarly, we establish error mapping models $\mathbf{E}_j$ $(j = 1, 2, \ldots, N-1)$ for each LR-HR image pair. Finally, based on the error model built from LR image features, we select the $\hat{y}^h$ from the reconstruction mapping model with minimal error as the HR image pixel value. Figure 2 illustrates the overall flow of our proposed super-resolution image reconstruction model.

## 3 Experiments

All experimental images are downloaded from the University of Southern California (USC) image database [14]. The experimental platform is a 64-bit Windows 7 Ultimate system with an Intel Core(TM) i3-4130 CPU @ 3.40 GHz, running MATLAB R2015a.

### 3.1 Experimental Setup and Parameter Settings

To ensure fairness, we preprocessed the LR images for all comparison methods (Yang et al.'s SCSR [4], Yang et al.'s SLSR [7], Wang et al.'s CSCN [15], Tian et al.'s ANRSR [5], and Zhang et al.'s CCRSR [6], with codes available on the authors' homepages) using our proposed method.

If an image is in RGB color space, we first convert it to YCbCr color space based on human visual sensitivity to luminance differences. We then apply super-resolution methods to the Y component (luminance) while using bicubic interpolation for the chrominance components (Cb and Cr).

During experiments, we set the downsampling factor $z = 2$, Gaussian blur variance $\sigma = 0.1$, and training image set size $M = 5$, where adjacent image patches overlap by 4 pixels. For $\ell_2$ norm collaborative representation, the feature vector dimension is $K = 100$. SVR reconstruction mapping model parameters are obtained using the gridregression.py function from the LIBSVM toolbox [16], with $C = 4$ and $\varepsilon = 0.01$. The LR image weight distribution matrix $\mathbf{G}$ is configured as a $p \times p$ Gaussian function with $p = 5$.

### 3.2 Influence of Regularization Parameter $\lambda$

Since $\lambda$ affects the approximation coefficients of LR image feature blocks, we investigate its impact by performing multiple super-resolution reconstructions on the same image data (Figure 3(a) 4.1.01) with $\lambda \in [5 \times 10^{-7}, 5]$. Figures 4 and 5 show the PSNR and SSIM variations for different $\lambda$ values.

Analysis of Figures 4 and 5 reveals that when $\lambda \in [5 \times 10^{-7}, 0.1]$, its impact on PSNR and SSIM is negligible. However, when $\lambda > 0.1$, significant fluctuations occur in both metrics. Notably, excessively large $\lambda$ values produce poor visual quality. Based on these findings, we select $\lambda = 5 \times 10^{-4}$ for our experiments.

### 3.3 Experimental Results and Analysis

Following the experimental setup in Section 3.1 and the $\lambda$ analysis in Section 3.2, we reconstruct super-resolution images $\mathbf{I}_{\text{sr}}$ from LR images $\mathbf{I}_{\text{low}}$ of test images using multiple methods, computing their PSNR and SSIM values as shown in Table 1. Figure 6 displays reconstructed images for selected test cases.

Comparing the PSNR and SSIM metrics in Table 1, we observe that except for images 4.1.04, 4.1.06, 4.2.03, 4.2.05, and 5.1.11, our method achieves the highest scores across all other images. For images 4.2.05 and 5.1.11, the SLSR method [7] produces the highest PSNR and SSIM values. This is likely because these images have relatively uniform and simple content, and SLSR's feature extraction focuses on contour edge detection, making it particularly suitable for such cases.

Although Zhang et al.'s CCRSR method [6] shows relatively lower PSNR values, its SSIM scores are higher than other methods, indicating better structural similarity to the original HR images. Notably, images 4.1.04, 4.1.06, and 4.2.03 exhibit particularly prominent SSIM performance. This is because CCRSR employs four-direction high-pass filtering for LR feature extraction and incorporates clustering, which preserves substantial structural similarity within each cluster.

Wang et al.'s CSCN method [15] achieves optimal PSNR for images 4.1.05 and 5.1.13, but only marginally higher than our method (by 0.01 and 0.46 dB, respectively). However, our method's SSIM values for these images are 0.0169 and 0.0406 higher than CSCN, demonstrating superiority over sparse coding and deep network-based approaches.

Figure 6 provides visual comparisons of reconstruction results. The images produced by our method (f) show clearer details, such as the numeral "1" below the "0" on the right side of image 5.1.13, which is not visible in other reconstructions. For image 4.1.08, our result (f) exhibits higher clarity for each bean, with smooth edges and no halos, making it more realistic. For image 4.2.03, while our method (f) does not produce as sharply countable whiskers as some alternatives, it maintains recognizable detail with lower distortion. These subjective observations, combined with objective metrics, confirm the effectiveness and relative optimality of our approach.

## 4 Conclusion

This paper addresses the limitations of traditional super-resolution methods based on sparse representation and the problem of sparse coefficients potentially ignoring critical image features. We propose a super-resolution reconstruction method using $\ell_2$ norm collaborative representation with same-size image training sets. Our approach extracts feature blocks from multiple same-size LR images, redistributes feature magnitudes, and employs $\ell_2$ norm collaborative representation instead of sparse representation to coefficientize LR image features, thereby establishing more efficient linear-kernel SVR models that preserve complete feature information. Experimental results demonstrate that compared with existing super-resolution methods based on sparse representation, collaborative representation, and SVR, our method produces super-resolution images $\mathbf{I}_{\text{sr}}$ with better visual quality and higher evaluation scores, proving its effectiveness and superiority from both subjective and objective perspectives.

Since our current feature selection approach is relatively simple, reconstruction results for images with uniform and simplistic content are not ideal. Future work will focus on improving feature extraction methods to capture and preserve more effective image features, establishing a super-resolution reconstruction model adaptable to diverse image types.

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*Note: Figure translations are in progress. See original paper for figures.*