Robust Method for Individual Image Super Resolution via nonlocal Sparse Representation

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Abstract:- **Image super resolution is a well explored topic in the field of image processing. In the past several decades, the progress made in image super resolution has benefited from the improved modelling of natural images. In this paper, we introduce a new method for image super resolution using sparse representation. The main aim here is to suppress the sparse coding noise. Thus the image nonlocal self-similarity is exploited to obtain the good estimates of the sparse coding coefficients of the original image and then centralize the sparse coding coefficients of the observed image to those estimates. To this end, a robust algorithm for image super resolution using sparse representation is proposed which outperforms the existing algorithms in terms of improved super resolution performance.**

Index terms - Nonlocal similarity, sparse representation.

INTRODUCTION

Super-resolution (SR) image reconstruction is currently a very active area of research, as it offers the promise of overcoming some of the inherent resolution limitations of low-cost imaging sensors (e.g. cell phone or surveillance cameras) allowing better utilization of the growing capability of high-resolution displays (e.g. high-definition LCDs). Such resolution-enhancing technology may also prove to be essential in medical imaging and satellite imaging where diagnosis or analysis from low-quality images can be extremely difficult. Sparse representations of signals have drawn considerable interest in recent years. Sparse representation codes an image patch as a linear combination of few atoms chosen out from an over-complete dictionary. Sparse representation based image super resolution have shown good results in image high resolution applications such as remote sensing, medical imaging, surveillance, entertainment, etc. For an observed image $\boldsymbol{y}$, the problem of estimation of original image $\boldsymbol{x}$ can be generally formulated as

$$\boldsymbol{y}=\boldsymbol{H}\boldsymbol{x}+\boldsymbol{v} \qquad (1)$$

Where **H** is a degradation matrix and $\boldsymbol{v}$ is the additive noise vector. Assume that $\boldsymbol{x}$ has a sparse representation

Over the dictionary, i.e.X=Φα, where Φ is an over-complete dictionary and $\boldsymbol{\alpha}$ is the sparse coding coefficient. Since the observed image is noisy, it is very challenging to recover the true sparse code α_x of the original image $\boldsymbol{x}$ from the observed image $\boldsymbol{y}$. To faithfully reconstruct the original image $\boldsymbol{x}$, the sparse code α_y of the observed image $\boldsymbol{y}$ should be as close as possible to the sparse code α_x of the original image. In other words, the difference $v_x = \alpha_x - \alpha_y$ which is called as sparse coding noise should be reduced.

To reduce the sparse coding noise, we centralize the sparse codes to some good estimation of α_x by exploiting nonlocal similarity in the observed image and centralize the sparse coding coefficients by means of K-means PCA, block matching and iterative shrinkage algorithm. The proposed NCSR model can be solved effectively by conventional iterative shrinkage algorithm, which allows us to adaptively adjust the regularization parameters from a Bayesian viewpoint.

RELATED WORK

Super resolution approach is based on machine learning techniques, which attempt to capture the co occurrence prior between low-resolution and high-resolution image patches. Example based learning strategy that applies to generic images where the low-resolution to high-resolution prediction is learned via a Markov Random Field (MRF) solved by belief propagation.

By using primal sketch priors to enhance blurred edges, ridges and corner. Nevertheless, the above methods typically require enormous databases of millions of high resolution and low-resolution patch pairs, and are therefore computationally intensive. Locally Linear Embedding (LLE) from manifold learning, assuming similarity between the two manifolds in the high resolution and the low-resolution patch spaces. Their algorithm maps the local geometry of the low-resolution patch space to the high-resolution one, generating high-resolution patch as a linear combination of neighbors. And using nonlocal self similarity many approaches has been developed for image reconstruction.

PROBLEM DESCRIPTION

In the past decades, extensive studies have been conducted on developing various image super resolution methods for image restoration purposes. Due to the ill-posed nature of image restoration, the regularization-based techniques have been widely used by regularizing the solution spaces. In order for an effective regularize, it is of great importance to find and model the appropriate prior knowledge of natural images, and various image prior models have been developed.

The classic regularization models, such as the quadratic Tikhonov regularization and the TV regularization are effective in removing the noise artefacts but tend to over smooth the images due to the piecewise constant assumption. As an alternative, in recent years the sparsity-based regularization has led to promising results for various image high resolution problems. Several algorithms are used for image high resolution using sparse representation.

Some of the recently developed algorithms are Block Matching 3D Shape Adaptive Principle Component Analysis (BM3D-SAPCA) algorithm, Learned Simultaneously Sparse Coding (LSSC) method, Expected Patch Log Likelihood – EPLL method, etc. When the noise level is high, the above mentioned methods tend to generate many visual artefacts. The proposed robust algorithm has much less artefacts than other methods and is visually more pleasant.

MOTIVATION

Due to the degradation of the observed image (noisy image), the sparse representations by conventional models may not be accurate enough for a faithful reconstruction of the original image. One important issue of sparsity-based image super resolution is the selection of dictionary. Conventional analytically designed dictionaries such as DCT, wavelet and curve let dictionaries are insufficient to characterize the so many complex structures of natural images. So in our proposed method we are using K means PCA to cluster the patches and learn a PCA sub-dictionary for each patch to code.

METHODOLOGY

In this paper, the reconstruction of observed image can be organized into three levels. In the level 1, the input image is fed through the noisy channel to obtain the noisy image. In the level 2, the proposed technique called robust algorithm of sparse representation for image super resolution is applied to the noisy image so obtained in the level 1 to get the de noised image. The proposed algorithm uses K means PCA to create dictionary of the noisy image and perform block matching to obtain the blocks and then iterative shrinkage algorithm is applied to reduce the sparse coding noise to approximately zero. To this end, we obtain the de noised image of improved image quality. Principal component analysis (PCA) is a widely used statistical technique for unsupervised dimension reduction. K-means clustering is a commonly used data clustering for unsupervised learning tasks. Here we prove that principal components are the continuous solutions to the discrete cluster membership indicators for K-means clustering. Equivalently, we show that the subspaces spanned by the cluster centred are given by spectral expansion of the data covariance matrix truncated at K−1 terms. These results indicate that unsupervised dimension reduction is closely related to unsupervised learning. On dimension reduction, the result provides new insights to the observed effectiveness of PCA-based data reductions, beyond the conventional noise-reduction explanation.

We cluster the patches of image $\boldsymbol{x}$ into K clusters and learn a PCA sub-dictionary Φ_k for each cluster. For a given patch, we first check which cluster it falls into by calculating its distances to means of the clusters, and then select the PCA sub-dictionary of this cluster to code it.

The purpose of a block matching algorithm is to find a matching block from a frame *i* in some other frame *j*, which may appear before or after *i*. This is used to discover temporal redundancy in the image sequence, increasing the effectiveness of interface image compression. Block matching technique consists of three main components: block determination, search method, and matching criteria. Block determination specifies the position and size of blocks in the current frame, the start location of the search in the reference frame, and the scale of the blocks. The search method looks for candidate blocks in the reference frame. The matching criteria are to determine the best match among the candidate blocks.

In image super-resolution the simulated LR image is generated by first blurring an HR image with a 7×7 Gaussian kernel with standard deviation 1.6, and then downsampling the blurred image by a scaling factor 3 in both horizontal and vertical directions. Iterative Shrinkage algorithm is used to solve the l_1 – norm minimization problem.

SIMULATION OUTPUT

Matlab is used for simulation to verify the performance of the proposed algorithm of nonlocal sparse representation we conduct extensive experiments on image super resolution. The basic parameter setting Of nonlocal sparse representation is as follows: the patch size is 7×7 and $K = 70$, $\delta = 2.4$, $L = 5$, and$J = 160$. To evaluate the quality of the restored image peak single to noise ratio is calculated.

Fig.1

Fig 1 is the observed image for which the noise, blur and downsampling is down to get the original image.

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Fig.2

Fig 2 is the original image LR image is generated by first blurring an HR image with a 7 × 7 Gaussian kernel with standard deviation 1.6, and then downsampling the blurred image by a scaling factor 3 in both horizontal and vertical direction.

Fig.3

Fig.3 is reconstructed image for which the peak signal to noise ratio is calculated between observed image and reconstructed image

CONCLUSION

In this paper we presented a robust algorithm for image super resolution for image high resolution applications using sparse representation. The sparse coding noise which is defined as the difference between the sparse code of the unknown original image is minimized to improve the performance of sparsity-based image restoration. The experimental result on image super resolution demonstrated that the proposed method can achieve high performance to other leading super resolution methods.

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