A Novel Approach for Single Image Super Resolution by Sparse Signal Representation

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Abstract
This paper presents a new approach to obtain a high resolution image from a single image low resolution by a technique of sparse representation. Sparse representation is a way of representing a signal sparsely i.e. with fewer non zero elements. In this method we find the sparse representation of the input low resolution image patches and then use the coefficient of this representation to generate the high resolution image output.

Keywords: Sparse Coding, Sparse Representation, Super Resolution (Sr)

1. Introduction
High Resolution (HR) is the need of the present system. HR deals with increasing the density of pixel in an image leading to more clarity and greater detailing. Applications of the HR image is evident everywhere such as in medical imaging, video surveillance etc. Better results of an image in terms of clarity gives ease of diagnosis for a doctor. Also in video surveillance if a high resolution image is there along with other images it gives easy identification of person, objects etc. Similar is the case with satellite imaging system.

There are ample numbers of ways by which one can increase the spatial resolution of an image first one is by decreasing the size of pixel that is increasing the number of pixels per unit area (pixel density). But the disadvantage of this methodology is that the amount of light available to each pixel also gets reduced so the image gets suffered by shot noise. To increase the pixel density without having suffered the shot noise problem is a difficult process since the present sensor technology has already reached to a level of generating pixel density of 40µm² for a 0.35µm from CMOS process. Another approach of generating a HR image is to increase the chip size but the disadvantage of increasing the chip size is it increases the capacitance and increased capacitance leads to large transfer rate which is not fruitful.

One encouraging technique is to use signal processing technology to obtain high resolution image from single or multiple low resolution images. So Super Resolution is a signal processing technique to get a HR image from an observed one or multi LR images. The word “super” in super resolution is actually describing its super characteristics. The main advantage of this technique is that it is cost effective and is not obsolete technology.

Super resolution is a process of obtaining the ultimate quality of an image via a single LR image or numerous LR images of the same scene. One can use either a single sensor or multiple sensors to obtain LR images from the same scene. SR technology deals with combining the principal attributes of image interpolation and restoration, via the image restoration the image's dimension is changed and from the restoration process the degraded image is recovered.

Now the question is how can we get a HR image from different LR images? Which is nothing but the [A] conventional approach of generating super resolution image? The fundamental assumption for expanding the spatial resolution is accessibility to different LR images. apprehended from the same scene. In the SR scenario, the LR

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images depicts diverse ‘looks’ of the same scene, meaning LR images are first aliased or say sub-sampled and then shifted with sub pixel accuracy. If the shifting is of full integer unit then each and every image will have the same kind of information and so any new sort of information is not obtained. Different looks of the same scene may be acquired from multiple captures from a single camera or by different cameras situated at multiple positions more clarity can be visualized from Figure 1.

Thus Super Resolution is the methodology that deals with reinstating the downgraded image and increasing the size of the image. The major factors that affect the image are aliasing, blurring and noise. The aliasing is said to occur when the sensor’s size is bigger than the optical spot size. Next, blurring is due to limitation in the shutter speed or one can say limitation in the relative movement between the scene and the imaging framework. Noise is an integral part which may occur inside the sensor or may happen throughout the transmission hence diminishes the resolution capability of an image. So there is a need to improve the quality of image. The various effects discussed above can be diagrammatically visualized as in Figure 2.

According to this model, let us assume that, \( x \) is the required HR image of the dimension \( L_1 N_1 \times L_2 N_2 \) which is sampled at or above the Nyquist rate from a continuous scene. If \( x \) is written as \( x = [x_1, x_2, \ldots, x_N] \) then the \( k \)-th observed LR image may be represented as \( y_k \) of size \( N_1 N_2 \times 1 \). As the relative motion between scene and camera is present, the high resolution image should be warped by a motion compensating warping matrix \( M_k \) of size \( L_1 N_1 L_2 N_2 \times L_1 N_1 L_2 N_2 \). In addition, the final image may be blur because of either camera lens or due to fast moving object. Therefore blurring matrix \( B_k \) of size \( L_1 N_1 L_2 N_2 \times L_1 N_1 L_2 N_2 \) should also be considered. If \( D \) is a \( (N_1 N_2)^2 \times L_1 N_1 L_2 N_2 \) sub-sampling matrix and \( n_k \) indicates a lexicographically ordered vector of noise then the observed model can be mathematically represented,

\[
y_k = DB_k M_k x + n_k \quad \text{where} \quad 1 \leq k \leq p
\]

Where, \( p \) represents no. of available low resolution images.

Most of the super resolution method proposed in the study material comprises of three stages as shown in Figure 3: (1) registration (2) interpolation (3) restoration. The stages can be executed either differently or together. Registration refers to estimating the motion effects, in this the shifts between the LR image and a reference LR image is compared and are evaluated with fractional pixel accuracy. Certainly for successful implementation of the algorithm sub pixel accurate motion is the need but practically the shift between the LR images are unpredictable so use non uniform interpolation is performed to get equal spaced images. Last restoration of image is done to the up sampled image for removal of the noise and the blurring effects.

The SR reconstruction is an ill-posed issue due to the less number of input images, poor registration and unknown blurring operators. Regularizations methods proposed in deals with a technique for a better resolution with minimal aliasing effects. Since aliasing
occur in many imaging systems, the limitation of the detector arrays for not proper sampling the scene with the required field of view results in image being severely aliased. In the above paper work, maximum a posteriori (MAP) foundation for estimating the HR image and the registration of image is proposed. Quite a few earlier works were based on having the knowledge of the registration parameters, a priori or utilizing the registration methods not well enough to deal with the seriously aliased images. In this method, the parameters for registration are updated regularly beside the HR image in a cyclic coordinate-descent optimization procedure.

But the disadvantage of the conventional approach is that performance deteriorates when the number of available input images is less or magnification factor is large. The result is the image with excessively smooth effect and non-availability of the high frequency effects. In learning based method, the relationship between an low resolution image and its corresponding high resolution image is examined by a pair of low resolution and high resolution patches. The training data then is used to get the higher-resolution image. In order to apply the super resolution approach in real time, the super resolving time should be reduce. Xie Qinlan et al. proposed an improved example based single-image super-resolution method in.

3. Pseudo Code for the Approach

Input: Take low resolution image as input along with two training dictionaries \(D_h\) and \(D_l\)

For 3x3 patch ‘p’ of \(Y\) take in raster scan order with overlap of one pixel

- \(\hat{a} = \arg\min \lambda\|a\|_1 + \frac{1}{2}\|Da - \hat{p}\|_2^2\)

- place HR patch, \(x = D_h\hat{a}\) in \(S_o\)

End

Use Back Projection. to get the nearest image. to \(X_o\) which fulfills the reconstruction conditions

\[
S^* = \arg\min_s \|s - S_0\|_2 \text{ s.t. } MS = Y
\]

Output: SR Image. \(S\).

4. Result

![Flow chart – SR via sparse Representation](image)

Figure 4. Flow chart of the algorithm.
5. Conclusion

The paper work presents a novel approach of super resolution by jointly training of two dictionaries from the low and high resolution image patches. The effectiveness of sparse as a prior is demonstrated from the result. However, the work done herewith can be further improved with using a state-of-the-art denoising algorithm such as BM3D. So future work of this work lies in increasing the PSNR value by BM3D algorithm.

6. References

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