

Different Implemented Techniques of Super Resolution Imaging.

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Abstract : Resolution plays a major role for interpretation and analysis of an image. Super Resolution is a technique to enhance the resolution of an image from single or multiple low resolved images, which gives detailed information present in an image. In this paper, we describe several methods for Super Resolution (SR) that enhances the quality of an image. Mainly the methods are divided into frequency domain and spatial domains. Here, we stated comparison of different approaches, challenges and issues for SR and applications of SR in practical world e.g. in medical imaging, satellite imaging, and forensics. We have approached SR using learning based techniques. We present a novel self-learning approach with multiple kernel learning for adaptive kernel selection for SR. The Multiple Kernel Learning is theoretically and technically very attractive, because it learns the kernel weights and the classifier simultaneously based on the margin criterion. With theoretical supports of kernel matching search method and Optimization approach (Gradient) are proposed our SR framework learns and selects the optimal Kernel ridge regression model when producing an SR image, which results in the minimum SR reconstruction error.

General Terms : Low Resolution, High Resolution, Super Resolution.

Keywords : Self-learning, sparse representation, super-resolution, support vector regression.

1. INTRODUCTION

In most image processing applications, an image is required to be highly resolved. It is mainly required for better pictorial view for human interpretation or for machine perception for making better decisions. Resolution is mainly concerned with the number of pixels per inch (ppi) or dots per inch (dpi) the image possesses. If the number of pixels is less than the image produces will be of low resolution (LR) and offers very less information. As the pixel density increases the image quality as well as the information offering by the image increases. But as the number of pixels increases the light on the sensors decreases which results in shot noise. Usually, the sensor limits the quality of an image due to its physical characteristics like size and density of detectors [2]. The degradations in an image quality are caused at the recording process such as optical distortion, motion blur caused by limited shutter speed, noise and aliasing effects.

Figure 1 shows the common image acquisition system, where different factor affects the image quality like over the air (OTA), charge-couple device (CCD), preprocessors and environment. *Optical Blur* is a non-symmetric design of the lens and an aperture before or behind the optic center of the lens lead to image distortions. *Motions blur* results when the image being recorded changes during the recording of a single frame, either due to rapid movement or long exposure. *Noise* in an image is an undesirable by-product of image capture that adds spurious and extraneous information.



Figure 1: Common image acquisition system

Aliasing effects refer to an effect which can create confusion between different signals when sampled. Due to these, the final observed image is blurred and noisy. One way of producing a high resolution (HR) image, is by installing a high resolution sensor. But it is not very feasible to do so. It results in increase of a cost as well as increase in power consumption. A simple example of this is satellite imaging system or a medical imaging system, where it is infeasible to use a high resolution sensor. So, to come over these, post processing is required to develop a better resolved image that holds more information. One of the promising approaches for this is signal processing techniques to obtain HR image from multiple LR images. Nowadays such approach is more active in research area, and is called Super Resolution (SR) or Resolution Enhancement [2].

2. IMAGE SUPER RESOLUTION

Super Resolution is a technique that enhances the image resolution and makes it clearer for human as well as for machines in view for better information extraction which are not visibly cleared in LR image. Super resolution can be acquired either by processing multiple low resolved images as input and generating a high detail containing a single super resolved image as output or enhancing the details in a single low resolved image and generating a high resolved image for analysis. In SR from multiple LR images, it is a construction of HR image from several LR images, thereby increasing the high frequency components. The basic idea behind this is to combine non-repetitive information contained by multiple LR images. While in SR from single LR image, resolution of the image can be increased either by enhancing the edges of the objects present in an image or by patch redundancy technique, where each LR patch is replaced by its corresponding HR patch. The main benefit of SR approach is that, a HR image can be obtained even with the existing LR imaging with lower cost and less power consumption. In SR reconstruction from multiple LR images, the basic assumption is that the LR should have enough shifted in viewing the same scene. If LR has minor shift then the HR reconstructed image will not contain any new information. Suppose that four images are taken and one image out of four can be taken as reference and other be shifted horizontally, vertically or diagonally to a scale of half pixels. By taking that one image as reference, other three image pixels can be interleaved and a higher resolved image can be generated.

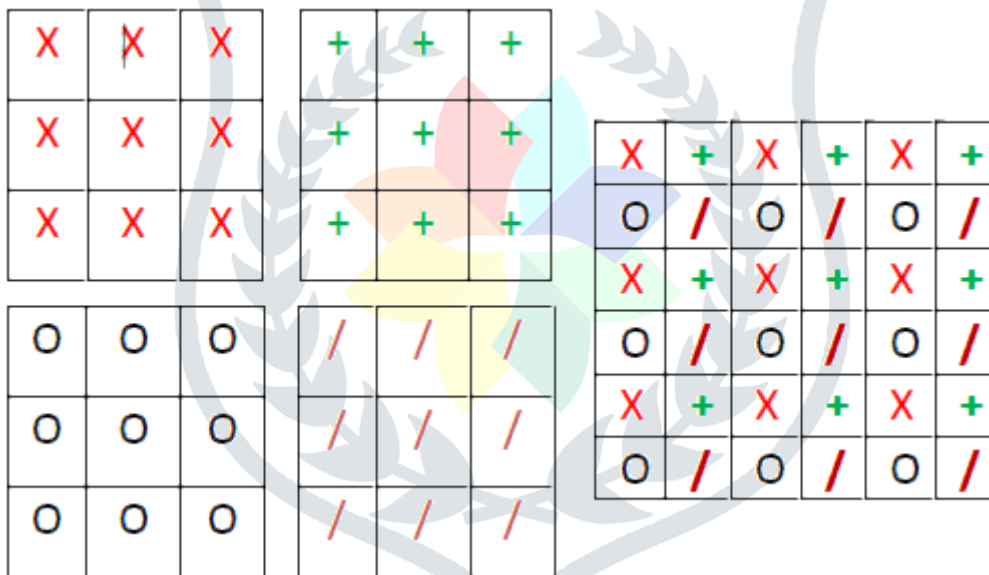


Figure 2: Ideal Super Resolution setup.

(Out of the Four images are taken, first one can be taken as reference and other three images can be considered to be relative shifted to half a pixel in horizontal, vertical, and diagonal directions (left side-four images). These three image pixels can then be added to produce a high resolution image with increase in size of the image (right side-single image)) [1].

Usually, a super resolution method consists of the following basic processing steps: (1) Registration, (2) Interpolation and (3) Deblurring or noise removal.

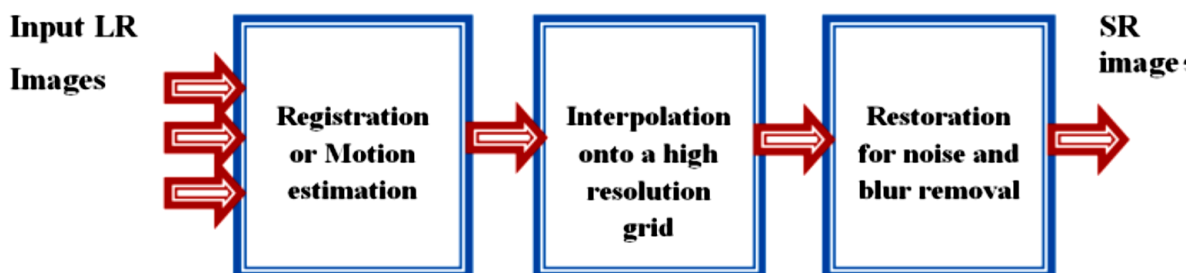


Figure 3: Basic SR reconstruction stages

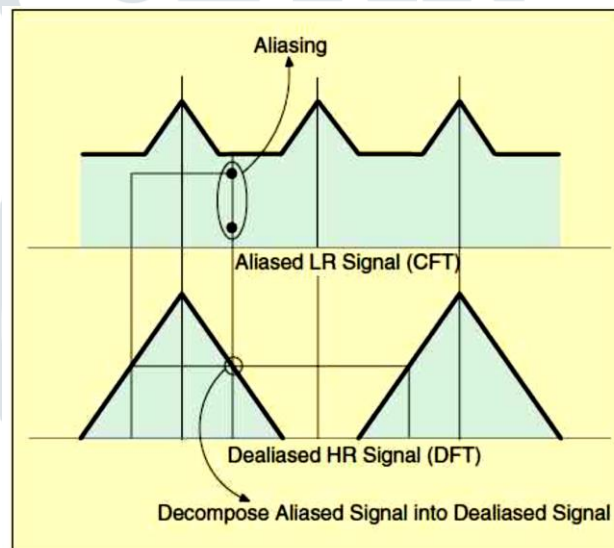
Image registration is the process of overlapping more than one images of the same scene which has been taken from different angles by the sensors. In registration two or more images are align geometrically to obtain the information through image fusion or change detection. Interpolation is a process of estimating the intermediate pixels between the pixel values. When any image is converted from LR to HR, intermediate gaps are introduced and these values have to be estimated and filled with interpolation process. As the process of interpolation introduces some artifacts the resultant image will be blurred or noisy. Through different filters and techniques noise will be removed and finally a super resolved image is generated.

3. EXISTING METHODS

Super-resolution techniques can be classified as (1) Frequency domain approach and (2) Spatial domain approach.

3.1 Frequency domain approach

Tsai and Huang proposed frequency based approach in which they stated to transform the LR image into Discrete Fourier Transform (DFT) domain and combined them according to the relationship between the aliased DFT coefficients of the observed LR images and that of the unknown high-resolution image. The combined data are then transformed back to the spatial domain where the new image could have a higher resolution than that of the input images [3]. The principles of frequency domain approach areas follow: i) what is the shift property of the Fourier transform. ii) The aliasing association between the continuous Fourier transform (CFT) of an original HR image and the discrete Fourier transform (DFT) of observed LR images, iii) the supposition that an original HR image is band limited. Through these properties system equation is derived [4]. Frequency domain approach has some benefits like it is spontaneous way to enhance the details by extrapolating the high frequency information presented in LR images. As well it has lower computational complexity. But the disadvantage is that is incapable of handling the real-world applications.



LR image relationship with HR image [4].

3.2 Spatial Domain Approach

The frequency domain approach has certain drawbacks like it limits the inter-frame motion to be translational. As well it is very difficult in frequency domain to use the prior knowledge. As the main problem is ill-posed image in SR, prior knowledge is required to overcome this. The main benefit of spatial domain is the support for unbind motion between frames and prior knowledge availability for solving the problems. Some of the methods are interpolation, iterative back projection and projection onto convex [4].

3.2.1 Interpolation

Interpolation is the process of transferring image from one resolution to another without losing image quality. In Image processing field, image interpolation is very important function for doing zooming, enhancement of image, resizing any many more. Most common interpolation techniques are nearest neighbor, bilinear and cubic convolution. Digital image is a signal, spatially varying in two dimensions. This signal is sampled and quantized to get values. All these values called pixels of image. When we increase the resolution of image from low to high, it is called up-sampling or up-scaling while reverse is called down sampling or down scaling [5].

(i). Bilinear interpolation

In Bilinear interpolated point is filled with four closest pixel's weighted average. Bilinear interpolation is recommended for continuous data like elevation and raw slope values. The interpolation kernel for linear interpolation is:

$$u(x) = \begin{cases} 0 & |x| > 1 \\ 1 - |x| & |x| < 1 \end{cases}$$

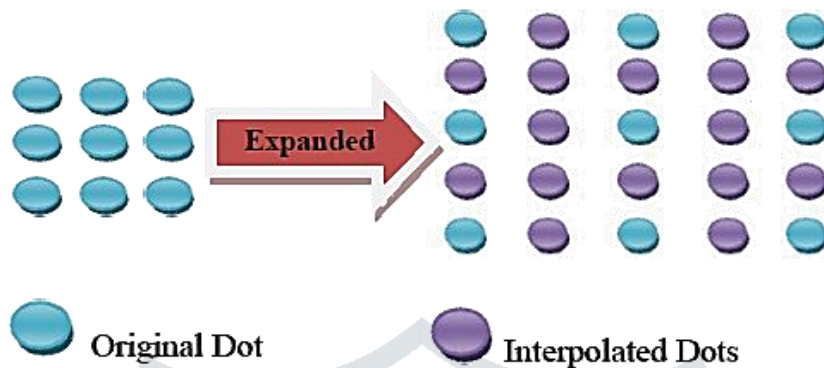


Figure 5: Basic concept of interpolation [5].

(ii). Bicubic interpolation

Looks at the sixteen nearest cells and fits a smooth curve through the points to find the output value. Bicubic interpolation is recommended for smoothing continuous data, but this incurs a processing performance overhead. The interpolation kernel for cubic interpolation is:

$$u(x) = \begin{cases} \frac{3}{2}|x|^3 - \frac{5}{2}|x|^2 + 1 & 0 \leq |x| < 1 \\ -\frac{1}{2}|x|^3 + \frac{5}{2}|x|^2 - 4|x| + 2 & 1 \leq |x| < 2 \\ 0 & 2 < |x| \end{cases}$$

Where x = distance between interpolated point and grid point [5].

(iii). Nearest Neighbor interpolation

In this method, nearest value is copied for interpolation and this technique has less computational complexity. Nearest neighbor interpolation is recommended for categorical data such as land use classification. The interpolation kernel for each direction for this method is:

$$u(x) = \begin{cases} 0 & |x| > 0.5 \\ 1 & |x| < 0.5 \end{cases}$$

Where x = distance between interpolated point and grid point [5]. The resultant image produced by the interpolation technique generally suffers from artifacts.

3.2.2 Iterative Back Projection (IBP)

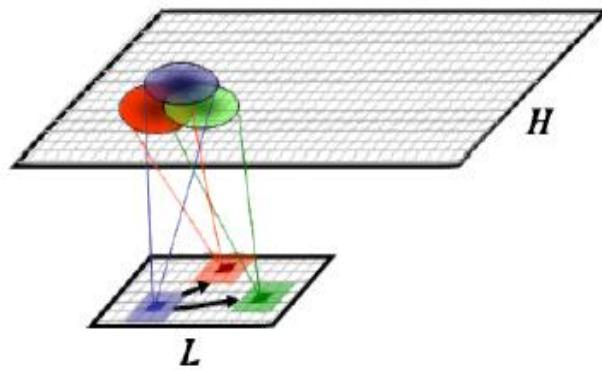
In IBP approach HR image is estimated by back projecting the difference between the simulated LR image and captured LR on interpolated image. This iterative process of SR does iterations until the minimization of the cost function is achieved. Mathematically the SR step to IBP is written as

$$X = X^{(0)} + X_e$$

Where, X - interpolated image; X_e - error correction [6].

3.2.3 Example-Based SR

It is said that nature has repetitions in behavior. In Example-approach, the same rule is applied. This approach is useful only single LR image is available. In this approach, the has small patches that redundantly reappear, both within the well as across the scale. Each LR patch in an image is by its corresponding HR patch to generate the SR image. assumption is that, the image should have enough HR for the correspondence LR patches [8].



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Figure 7: Single Image Multiple Patch [8].

3.2.4 Learning Based SR

It is a concept of machine learning, where the machine is trained to classify LR and its corresponding HR patches. In this approach, both LR and HR patches are divided into different classes. By doing so, the number of comparison reduces, as it has to compare LR with only HR patches. For an image if it is an edge-area of the LR, the routine example-based image SR algorithm can be used to implement the local and fine SR. For the flat regions of the low-resolution, only interpolation algorithm is used for super-resolution. The performance of learning based super-resolution depends on HR patch(es) retrieved from the training data for an input LR patch [7]. Dotted Squares are the HR patches for Solid Square LR patches as shown.

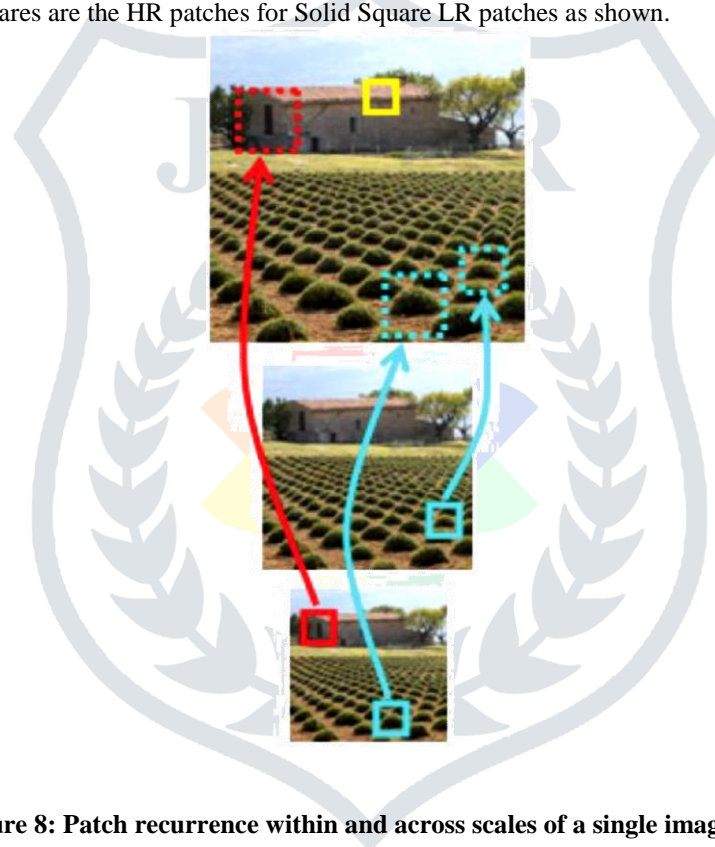


Figure 8: Patch recurrence within and across scales of a single image [8].

4. PROPOSED METHOD

In this section we will describe our proposed unsupervised learning framework for single image SR. In this approach, there is no need to manually and carefully select the training image data which is not practical for real world SR applications. There is no assumption of image patch self-similarity in this framework. Fig. gives the overview of the SR approach. Image I_0 is the input LR image, and ISR is the final SR output. Instead of searching for similar image patches from the different down-scaled versions $\{I_1, I_2, \dots\}$ a relationship is modelled between images from each scale. Once these models are observed for each scale, the best ones are selected to refine each patch S' (up sampled version of I_0) into output ISR . Image sparse representation is used as an effective feature for learning.

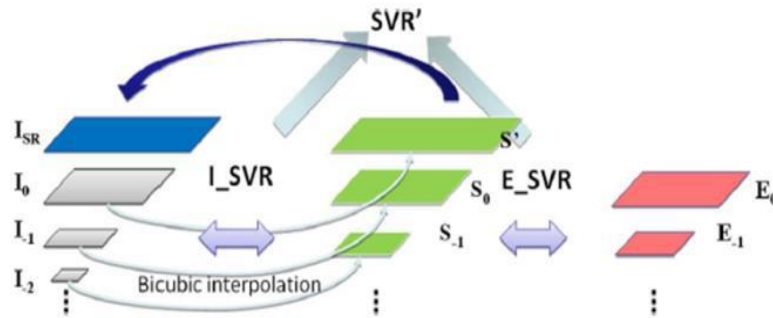


Figure 1 Self-Learning framework for single image SR [11]

1. Learning

of Image Sparse Representation

Bicubic interpolation is used to synthesize input LR image into its HR version. After all 3 x 3 pixel patches are extracted from this synthesized image, proper features need to be selected to describe each patch to learn the SR models. Sparse coding is used to represent the image features. The advantage of using sparse image representation is that training and computation time will decrease as most image feature attributes will be zero. To determine the sparse representation for the patches, an over complete dictionary is learned from the extracted patches and the resulting sparse coefficients are the features of interest. To learn the dictionary, the tool developed by [12] is used to learn the dictionary D and the associated sparse coefficients α for each patch. This is formulated as the following optimization problem:

$$\min_{x \rightarrow 0} \frac{1}{2} \|D\alpha - x\|_2^2 + \lambda \|\alpha\|_1$$

Where x is the image patch of interest, D is the over-complete dictionary, and α is the corresponding sparse coefficient. The Lagrange multiplier λ balances the sparsity of α and l_2 norm reconstruction error. The image patches are divided into high and low spatial frequency ones and their dictionaries are learned accordingly.

2. Support Vector Regression

SVR is an extension of support vector machine (SVM) and has the ability to fit the data in a high-dimension feature space without assumption of data distribution. SVR is capable of predicting the unknown outputs effectively. In training, SVR [13] solves the following problem:

$$\min_{w, b, \epsilon, \epsilon^*} \frac{1}{2} w^T w + C \sum_{i=1}^n (\epsilon_i + \epsilon_i^*)$$

$$s. t. y_i - (w^T \phi(\alpha_i) + b) \leq \epsilon + \epsilon_i^*,$$

$$(w^T \phi(\alpha_i) + b) - y_i \leq \epsilon + \epsilon_i^*$$

$$\epsilon_i, \epsilon_i^* \geq 0, i = 1, \dots, n.$$

In (2), y is the pixel value at the same location as the center of the patch of interest in the HR image, b is the off-set parameter of the regression model, $\phi(\alpha_i)$ is the sparse image representation, n is the number of training patches, w is the norm vector of the nonlinear mapping function, C is the trade-off between the generalization and the training error bounds ϵ_i . And ϵ_i^* , subject to margin. Once the SVR training is complete, the observed SVR is applied to predict the final SR output. As shown in Fig, bicubic interpolation is used to synthesize the HR version from the test input image. Then the sparse representation is derived for each patch and center pixel value is updated using the learned SVR model.

3. Unsupervised Learning of SVR for Image SR

The resolution of the input LR image I_0 is downgraded into low resolution versions $\{I_1, I_2, \dots\}$. Then these images are interpolated to synthesize the associated HR images using cubic spline interpolation. So two image pyramids $\{I_i\}$ and $\{S_i\}$ are obtained. Each image I_i can be regarded as the ground truth image of its interpolated version S_i . Later SVR is applied to model the relationship between S_i and I_i . Then we obtain the set $I_SVR = \{I_SVR_0, I_SVR_1, \dots\}$ as the collection of SVR models observed from different

image scales. SVR is subject to training errors ε_i and i^* with precision. So the predicted result of S_i using I_SVR may not be same as I_i , and the error image ε_i^* is obtained. The pixels of the error image are calculated as:

$$e_{ij} = \|I_{ij} - I_SVR_i(\alpha_{ij})\|, i = 0, -1, -2$$

Where the j -th pixel value in image I_{ij} is, is the sparse representation of the j -th patch in S_i . Once E_i is obtained another SVR regression model E_SVR_i is used to model the relationship between S_i and E_i . To summarize, first the image pyramids I_i and S_i are constructed from a given LR input image. SVR models E_SVR and I_SVR are then observed from different image scales. Then the errors are predicted using E_SVR for each patch in S' to obtain the final SR output I_{SR} . Once the smallest E_SVR_i is determined, then the corresponding I_SVR_i is used for further refining.

5. APPLICATIONS

Several practical areas and applications of SR as follows:

- **Biometrics** – Fingerprint recognition, Face recognition, Character recognition, DNA analysis.
- **Medical Science** – MRI, CT, X-Ray, Ultrasound [1].
- **Satellite Imaging** – Planetary information, Weather forecasting, Target detection, Traffic detection.
- **Surveillance Video** – Zooming region of interest (ROI). E.g. license plate recognition of vehicle, target recognition [1].
- **Entertainment** – HDTV, Photography.
- **Commercial** – Barcode reading.
- **Military** – Tracking and Detecting

6. CONCLUSION

This paper discusses about different techniques to achieve SR image from a single image or multiple LR images. We specified interpolation based, reconstruction based and learning based approaches to achieve the goal. We also include applications and comparison of different SR approaches. In future as per the application requirement such as in medical science and satellite imaging, using some of the above methods of SR, new methods can be derived by extending or integrating them which can generate more detailed containing SR images as result. This paper proposed a novel in-scale self-learning framework for single image SR. We advanced the learning of support vector regression and image sparse representation in our SR method, which exhibited excellent generalization in refining an up-sampled image into its SR version. Different from most prior learning-based approaches, our approach is very unique since we do not require training low and high-resolution image data. We do not assume context, edge, etc. priors when synthesizing SR images, nor do we expect reoccurrence of image patches in images as many prior learning-based methods did. Moreover, by deploying different types of interpolation or SR techniques to up-sample images at intermediate scales in our framework, we confirmed the robustness and effectiveness of our proposed SR framework. Future research will be directed at the extension of our current SVR models to the use of multiple kernel learning for adaptive kernel selection.

7. REFERENCES

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