Super Resolution Image Reconstruction using linear regression regularized sparse representation

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Super Resolution Image Reconstruction using Linear Regression Regularized Sparse Representation

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C E R T I F I C A T E

This is to certify that the thesis entitled ***"Super Resolution Image Reconstruction using Linear Regression Regularized Sparse Representation"*** *by* ***Mr. Saka Harshavardhan****, submitted to the National Institute of Technology, Rourkela (Deemed University) for the award of Master of Technology in Electrical Engineering, is a record of bonafide research work carried out by him in the Department of Electrical Engineering under my supervision. I believe that this thesis fulfills the requirements for the award of degree of Master of Technology.The results embodied in the thesis have not been submitted for the award of any other degree elsewhere.*

Prof.Dipti Patra

Place:Rourkela
Date:

To My Loving parents and Inspiring GUIDE

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Abstract

This thesis addresses the generation and reconstruction of the high resolution (HR) image by using the single low resolution (LR) image and the linear coalition of sparse coefficients from a suitably chosen over-complete dictionary.The study of compressive sensing shows that under vague conditions the sparse representation of a signal can be effectively recovered from the downsampled version of the original signal. By training both LR and HR image patches simultaneously by coupled dictionary learning, we are enforcing the similarity between the sparse representation(SR) of LR and HR image patch pairs with respective to their LR and HR dictionaries. Literature survey suggests that different extracted features are used to compute the coefficients to boost the prediction accuracy of the HR image patch reconstruction. A set of Gabor filters has been employed to extract useful features from the LR dictionary. As the super resolution is an ill posed problem, in this thesis we have considered it as an optimization problem for getting the sparsest representation of image patches using linear regression regularized with L_1 norm, known as a LASSO in statistics.Our method is found to be outperforming the other previous state of art methods in both quantitative and qualitative analysis. The results reveal that proposed method shows promising results in reconstructing the image textures and edges.

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Notations

Notation	Description
LR	Low Resolution image
HR	High Resolution image
SR	Super Resolution image
D_{HR}	High Resolution Dictionary
D_{LR}	Low Resolution Dictionary
l	Low Resolution image patch
h	High Resolution image patch
D	Dictionary for sparsecoding
d	Downsampling operator
α	Sparse Representation
F	Feature Transformation
B	Blurring Filter
$beta$	Matching parameter
$lambda$	Optimization parameter

Chapter 1

Introduction

1.1 Introduction

In most advanced digital imaging applications, high resolution (HR) images or videos are normally coveted for later image handling and examination. The craving for HR images originates from two key application ranges change of pictorial data for human translation; and helping representation for programmed machine discernment. Image resolution portrays the points of interest contained in an image, the higher the resolution, the more the image subtle elements. The resolution of a computerized image can be ordered in various ways pixel resolution, spatial resolution, temporal resolution, spectral resolution, and radiometric resolution. In this connection, we are for the most part keen on spatial resolution.

The spatial resolution of an image is constrained by the image sensors or the image securing devices. The current image securing devices are utilizing charge-coupled device (CCD) or complementary metal oxide semiconductor (CMOS) as dynamic pixel sensor. These sensors are masterminded in two dimensional exhibits to catch two dimensional image signals. The quantity of sensors every unit range or the sensor size decides the quantity of pixels in image. One approach to build the resolution of the imaging device is to expand the sensor thickness by lessening the span of sensors. At the point when the span of sensors is diminished past a cutoff it reasons shot noise in the caught images as lessening the measure of sensor additionally reduce the measure of light occurrence on it. Augmentation in the quantity of sensors in imaging device/system additionally builds the equipment cost. In this manner there is constraint with the equipment that confines the spatial resolution of the image. While spatial resolution is restricted by sensor measure, the image subtle elements (high frequency bands) are likewise restricted by the optics because of lens hazy spots (related with the sensor point spread function (PSF), lens distortion impacts, opening diffraction's and optical blurring because of motion.

Advanced image processing works same as the human vision framework. It includes the procedure of gaining, examining and controlling images utilizing advanced PCs. There are different physical gadgets to catch advanced images like cam, satellite, attractive reverberation imaging machine and magnifying instrument and so forth. The zone of utilization of advanced image handling is extremely immeasurable. The easiest approach to build up the degree of image processing is to order the images as per their source. There are different fields that utilization advanced image processing.

Advanced digital images are pervasively utilized these days, for different purposes. Digital image Handling serves to concentrate pictorial points of interest alongside valuable data from the given Image of lower quality. The essential practical units of image handling are; a. Image securing system, for example, a camcorder, scanner or edge grabber, b. Processing and stockpiling system. In applications like Satellite imaging, medical imaging, microscopy, security systems, prehistoric studies study and so forth it is continuously attractive to have images with point by point data. At the end of the day higher resolution Images are most favored for their definite data likewise, HR images give better edge subtle elements, characterization of locales alongside an additionally satisfying perspective of the Human eye. The resolution of an image is reliant on its sensor resolution, subsequently to obtain higher resolution one will require complex image obtaining gadgets which may be excessive may not be moderate

Developing imaging chips, optical parts to catch HR images is restrictively extravagant and not down to earth in most genuine applications, e.g., broadly utilized observation cams and cams fabricated in mobile phone. In some different situations, for example, satellite imagery, it is hard to utilize HR sensors because of physical requirements. Computerized image handling gives programming level expense amicable methods to develop higher resolution images.

1.2 Application areas of SR Imaging

The requirement for HR is regular in PC vision application for better execution in example acknowledgment and investigation of images. HR is of significance in restorative imaging for analysis. Numerous applications oblige zooming of a particular zone of enthusiasm for the image where in HR is important. SR images are being utilized as a part of numerous zones, for example.

- **Remote sensing** [1] a few images of the same zone are given, and an enhanced resolution image can be looked for.

- **Surveillance videos** [2][3] casing stop and zoom/center area of hobby (region of interest) in videos for human observation (e.g. take a gander at the tag in the image), resolution improvement for programmed target acknowledgment (e.g. attempt to perceive a criminal's face).
- **Video standard change**, e.g. from NTSC video signal to HDTV signal.
- **Medical imaging** (CT, MRI, Ultrasound and so on [4][5] few images restricted in resolution quality can be procured, and SR method can be connected to improve the resolution.

Chapter 2

Theory and background

2.1 SR image reconstruction

It has been well around three decades from since the first endeavors on image processing by PC. The most pivotal motivation to this exertion is that the lion's share of information that individual get is by his perception and image processing strategies are connected in a wide mixed bag of fields, similar to medicinal imaging, observation, mechanical autonomy, modern initiation furthermore, remote sensing[1]. So, in numerous applications the interest for exceedingly itemized images, is steadily expanding. high-resolution(HR) implies that the quantity of pixels inside of a given size of image is large. Therefore a HR image typically offers critical or even discriminating data for different useful applications.

Although charge coupled devises (CCD) and CMOS image sensors have been generally utilized as a part of late decades, however the present resolution level in these sensors does not meet the expanding requests sooner rather than later in light of the fact that as the resolution of a cam sensor expand, it would be more lavish. Along these lines, discovering a viable approach to build image resolution is a matter of significance. One straightforward answer for expansion spatial resolution of low resolution(LR) images is to diminish the pixel estimate by sensor producing strategies. Then again, as the pixel size declines, the force of the light episode to every single photograph locator additionally diminishes that causes corrupting of image quality by lacking sign to commotion proportion so it is difficult to have HR image by diminishing the size of pixels [6].

Another strategy is to enhance the spatial resolution of LR images. Fundamental aim of this methodology is to expand the span of sensor chip that prompts lower charge exchange rate and a more drawn out time of time to catch an image. Along these lines, this strategy is most certainly not satisfactory for financially savvy business applications.With everything taken into account, it is regularly not doable or now and then conceivable to gain such HR images by simply utilizing hardware [7].

In numerous imaging frameworks, nonetheless, the nature of image resolution is constrained by physical limitations. The imaging frameworks yield associated and under examined images if their locator exhibit is not adequately thick. Thus, computerized image handling methodologies have been explored to remake a high- resolution image from various corrupted low- resolution images. Really, by utilizing super resolution calculations, high resolution images can be reconstructed from a progression of low resolution images and the thought behind this idea is to join the data from an arrangement of under sampled(aliased) low resolution images of the same scene and utilization it to develop a high resolution image or image sequence[8]. Numerous recreation techniques have been proposed through the years however, should super resolution recreation techniques utilize taking after steps: image enrollment, interpolation and discretionary reclamation (deblurring, denoising). A few techniques perform these errands independently, while others consolidate two or a greater amount of them. In tailing we would have a recorded change of super resolution procedure.

2.2 Previous works

In tailing we would have a chronicled change of super resolution strategy.

2.2.1 Super resolution in frequency domain

Tsai and Hung were the first to consider the issue accomplishing a HR image from blending an arrangement of LR images. Their information set had been accomplished via Landsat Satellite photos. They displayed the images as associated translationally dislodged variants of a steady scene. They had been utilized from discrete time Fourier change in their system. It can be said that their methodology was taking into account the 3 taking after things:

1. Moving property of the Fourier Transformation.
2. Associating relationship between persistent Fourier change and HR image.
3. Band constrained HR image. Figure (2.1) represent associating relationship between LR image and HR image. In any case, they didn't consider noise and optical obscure in their technique. Ozkan Tekalp furthermore, Sezan by utilizing noise and point spread capacity, broadened Tsai and Haung formulation. Kim, Bose and Valenzuelan likewise utilized the model of Tsai and Haung yet with thought of noise and obscure. The downside with their strategy was that in light of the fact that of vicinity of zeroes in the PSF, this technique was ill- posed. In addition, the notice estimation was not considered in their technique.

2.2.2 Super resolution in spatial domain

Really, a large portion of exploration that has been done in super resolution field is in this class of remaking systems and the explanation behind that is firstly, the requirements are much simpler to form and besides, this method incorporate an incredible adaptability in the movement model, movement obscure, optical obscure and the examining procedure

2.2.3 Projection and interpolation

In the event that perfect inspecting is viewed as, then our issue decreases basically to projection a HR images matrix and inserting of non-uniformly separated examples. Examination between distinctive insertion techniques with HR reproduction results can be found in [4] and [9].

2.2.4 Probabilistic strategies

Demonstrating of images as likelihood appropriation is by all accounts adequate in light of the fact that super resolution has been handing-off on the estimate of parameters and information that are obscure.Debin and Richard [10] utilized Huber Markov arbitrary fields as a part of Bayesian structure to clear up irregularity protecting earlier image thickness capacity. MAP estimation that relate on to autonomous movement is finished by angle projection calculation is considered. Movement estimation blunder is additionally considered as likelihood thickness capacity. Hardie, Barnard and Armstrong additionally took after the Debin and Richard in any case; they had any kind of effect by assessing the HR image and movement parameters at the same time. Actually, their work had the upside of not evaluating movement straight forwardly from LR images. Additionally, Tom and Brian [7] rather than MAP methodology they utilized ML system to decrease obscure and noise. By using special case amplification method they get enrollment and rebuilding simultaneously.

2.2.5 Iterative techniques

The iterative techniques are the most vital strategy in spatial space strategies. the advantages of this system is the likelihood of managing unlimited scope of data(images)sequence, simple incorporation of spatial area and the ability of this method to using changing corruption. Really, by the cycle system above all else we make a harsh speculation and afterward attempt to accomplish effectively more created estimation. Truly, there are such a variety of iterative systems to unravel super resolution reproduction systems. Feuer and Elad use diverse rough guess to the Kalman channel and appraisal its execution by Recursive Least Square (RLS), Least Mean Square (LMS) and Steeped Descent (SD). Irani and Peleg presented the Iterative Back Projection (IBP) calculation situated from PC supported tomography (CAT). To reduction the ill posedness and noise stack et.al. connected an arrangement of theoretic calculation projection on to arched sets(POCS). Peleg and Irani adjust their system to manage more mind boggling movement sorts like neighborhood movement halfway impediment and straightforwardness. Furthermore, Shah, Zakhor likewise took after the Peleg and Irani proposed a novel methodology for movement estimation.

2.2.6 Projection on to convex sets (POCS)

This strategy is an option iterative system to have a highlight in view of former knowledge about conceivable arrangement into the recreation process. Really this methodology approximates the super resolution image in light of discovering answer for the issue of introduction and reclamation. This strategy was initially presented by Oskoui and Stark [11].They utilized from convexity also, closeness of the requirement sets to guarantee union of iteratively anticipating the images on to the sets; yet their answer has a few downsides. Case in point, it was reliance of starting conjecture and it was non-novel. At that point utilized from Oskoui and Stark plan and make that stronger by considering the perception commotion and the movement blur [12].

In light of the POCS strategy joining from the earlier learning into the arrangement can be spoken to as a breaking point to answer for be an individual from a shut arched set Ci which can be communicated as an arrangement of vectors that fulfill a particular property. On the off chance that the restricting sets have a non-exhaust crossing point, then an answer that has a place with the convergence set Cs can be found by projections onto those raised sets. The upside of POCS system is that it utilizes from solid spatial area perception model. Also, its straightforwardness and adaptability ought not to be overlooked. Furthermore, a few issues with this procedure is having a high computational expense, moderate union also, non-uniqueness. Peleg and Irani alter their strategy to manage more perplexing movement sorts like nearby movement fractional impediment and straightforwardness. Shah and Zakhor additionally took after the Peleg and Irani and proposed a novel methodology for movement estimation.

2.2.7 Edge-safeguarding strategies

Goldstein et.al [13] proposed utilizing the L1 standard as a part of the super resolution both for information combination also, for the image enlistment. L_1 standard has the ability of uprooting exception proficiently. In addition, it performs spatially well in confronting with non-Gaussian commotion. Furthermore, the outcomes that accomplished by L_1 standard methodology are less touchy to the exception in the super resolution images

2.3 Single frame SR techniques

Traditional ways to deal with producing a super-resolution (SR) image oblige numerous LR images of the same scene, which are adjusted to sub-pixel exactness. The SR assignment is give a role as the converse issue of recuperating the first HR image by melding the LR images, on the premise of sensible suspicions or former learning about the perception or era model from the HR image to the LR images. The essential recreation imperative for SR is that applying the image era model to the recouped image ought to create the same LR images as watched. Then again, the SR image reproduction methodology is for the most part a seriously badly postured issue due to the insufficient number of LR images, badly molded enlistment, and obscure obscuring administrators, and in light of the fact that the arrangement from the recreation imperative is not special.

Different regularization techniques were proposed to further settle the reversal of such a badly postured issue, for example, [14][15]. Furthermore, the execution of these recreation based super-resolution calculations debases quickly when the fancied magnification variable is expansive or the accessible data images are restricted. However, the outcomes may be excessively smooth, lacking imperative high-frequency subtle elements [16]. Another class of super resolution methodology is taking into account interjection [17] [18]. While straightforward introduction systems, for example, bilinear or bicubic insertion have a tendency to produce excessively smooth images with ringing and rugged ancient rarities, insertion by misusing the normal image priors will by and large deliver more ideal results. Dai.et.al. [19] spoke to the nearby image patches utilizing the foundation/closer view of descriptors and reproduced the sharp irregularity between the two. Sun.et. al. [20] investigated the inclination profile earlier for nearby image structures and connected it to super-resolution. Such methodologies are effective in protecting the edges in the upscaled image. On the other hand, they are restricted in demonstrating the visual intricacy of the genuine images. For common images with tune compositions or smooth shading, these methodologies have a tendency to produce watercolor-like antiques. Another class of super resolution methodology is in light of machine learning systems, which endeavor to catch the co-event former between LR and HR image patches. Marshall F. et al. [21] proposed an illustration based learning technique that applies to bland images where the LR to high- resolution expectation is found out through a Markov irregular field (MRF) unraveled by conviction engendering. Fan et al. [21] develops this methodology by utilizing the primal portrayal priors to upgrade obscured edges, edges, and corners. By the by, the above systems regularly require huge databases of a great many HR and LR patch sets to make the databases sufficiently expressive, and are, along these lines, computationally escalated. Yeung et al. [22] embrace the reasoning of

LLE [23] from complex learning, accepting comparability between the two manifolds in the HR patch space and the LR patch space.

The calculation in [24] maps the nearby geometry of the LR patch space to the high-resolution patch space, creating HR fix as a straight mix of neighbors. Utilizing this method, more fix examples can be spoken to utilizing a littler processing database. Be that as it may, utilizing an altered number of K neighbors for recreation frequently brings about obscuring impacts, because of over or under fitting. While the methodologies specified above were proposed for non-specific image super- resolution, particular image priors can be joined when tailed to SR applications for particular areas, for example, human countenances. Pastry specialist and Heung-Yeung Shum liu2001two began the spearheading take a shot at face pipedream. Then again, the inclination pyramid-based forecast does not show the face former, and the pixels are anticipated independently, bringing on brokenness and curios. Yang et al. [25] proposed a two-stage factual methodology incorporating the worldwide PCA model and a neighborhood patch model. Despite the fact that the calculation yields great results, it utilizes the all-encompassing PCA model, which has a tendency to render results like the mean face, and the probabilistic nearby fix model is likewise convoluted and computationally requesting. Zhuang et al. [26] proposed another methodology with respective to raw patchs. While this calculation adds more subtle elements to the face, it additionally presents more artifacts

2.4 SR technique based on sparse

This proposed work concentrates on the issue of recuperating the super resolution adaptation of a given LR image. Additionally to the previously stated learning-based strategies, we will depend on patches from the data image. In any case, as opposed to working straightforwardly with the image patch sets examined from HR and LR images [26], we take in a minimal representation of these patch sets to catch the co-event former, significantly enhancing the pace of the calculation. Our methodology is persuaded by late results in sparse sign representation, which recommend that the direct connections among HR signals can be precisely recouped from their low-dimensional projections [27] [28]. In spite of the fact that the super-resolution issue is badly postured, making exact recuperation inconceivable, the image patch sparse representation shows both effectiveness and heartiness in regularizing the converse issue To be more exact, let D be an over-complete word reference of K bases and assume a signal $x \in R^n$ can be written as a sparse straight mix as for D. That is, the signal x can be composed as $x = D\alpha_0$ where $\alpha_0 \in R^K$ is a vector with not very many $(<< K)$ nonzero sections. By and by, we may just watch a little arrangement of estimations y of x

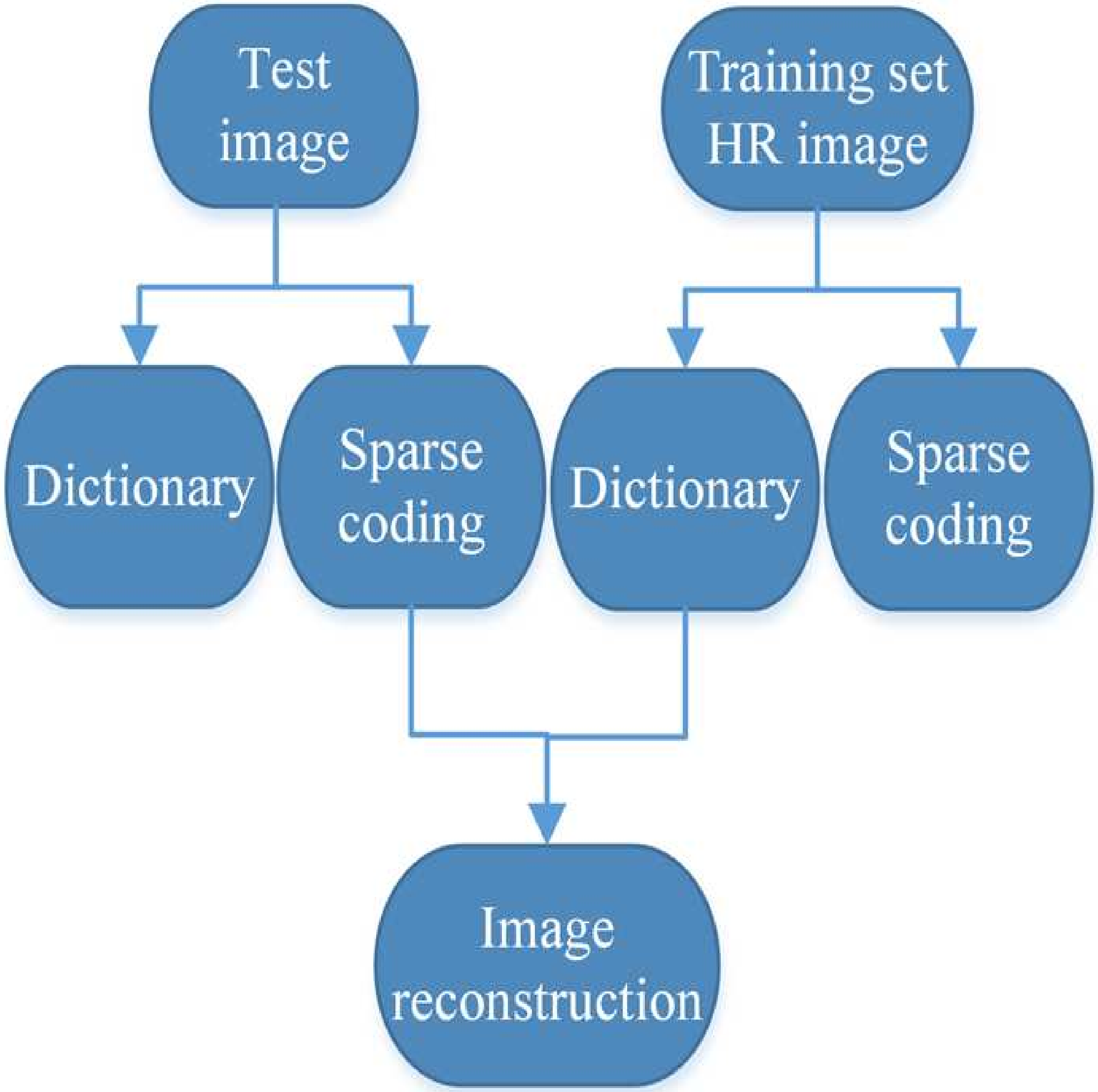


Figure 2.1: Block diagram of image reconstruction by sparse representation

2.1 shows the basic model for image reconstruction by using sparse representation. In the event that the word reference D is overcomplete, the comparison $x = D\alpha$ is underdetermined for the obscure coeffcients . The mathematical statement $y = LD\alpha$ is considerably all the more significantly under-determined. By the by, under mellow conditions, the sparsest arrangement to this mathematical statement will be novel. Besides, if D fulfills a suitable close isometry condition, then for a wide mixture of grids L, any adequately sparse direct representation of a HR image patch x regarding the D can be recuperated splendidly from the LR image patch [29][30]. Figure 1.1 demonstrates a sample that shows the abilities of our strategy got from this rule.

The image of the cat like face is obscured and downsampled to a large portion of the first size. And afterward we zoom the image to the first size utilizing our technique. Notwithstanding for such a confounded composition, sparse representation recoups an outwardly engaging recreation of the first signal. Recently, sparse representation has been effectively connected to numerous other related reverse issues in image processing, for example, denoising [30] and restoration [31] regularly enhancing the cutting edge. For instance, the creators utilize the K-SVD calculation [31] to take in an overcomplete word reference from regular image fixes and effectively apply it to the image denoising issue. In our setting, we don't specifically process the sparse representation of the HR patch. Rather, we will work with two coupled word references,D_{HR} for HR patches, and $D_{LR}$for LR patches. The sparse representation of a LR fix regarding D_l will be specifically used to recuperate the comparing HR patch from D_h. We acquire a mainly reliable arrangement by permitting patches to cover and requesting that the recreated HR patches concede to the covered zones. Dissimilar to the K-SVD calculation, we attempt to take in the two overcomplete word references in a probabilistic model like [35]. To authorize that the image patch sets have the same inadequate representations concerning D and D', we take in the two word references all the while by linking them with standardization.

The educated smaller word references will be connected to both nonexclusive image super-resolution and face fantasy to exhibit its viability. Contrasted with the previously stated patch-based techniques, our calculation requires just two reduced scholarly word references, rather than a vast processing patch database. The processing, mostly taking into account direct programming or arched enhancement, is substantially more efficient and versatile, contrasted and [22] [25].

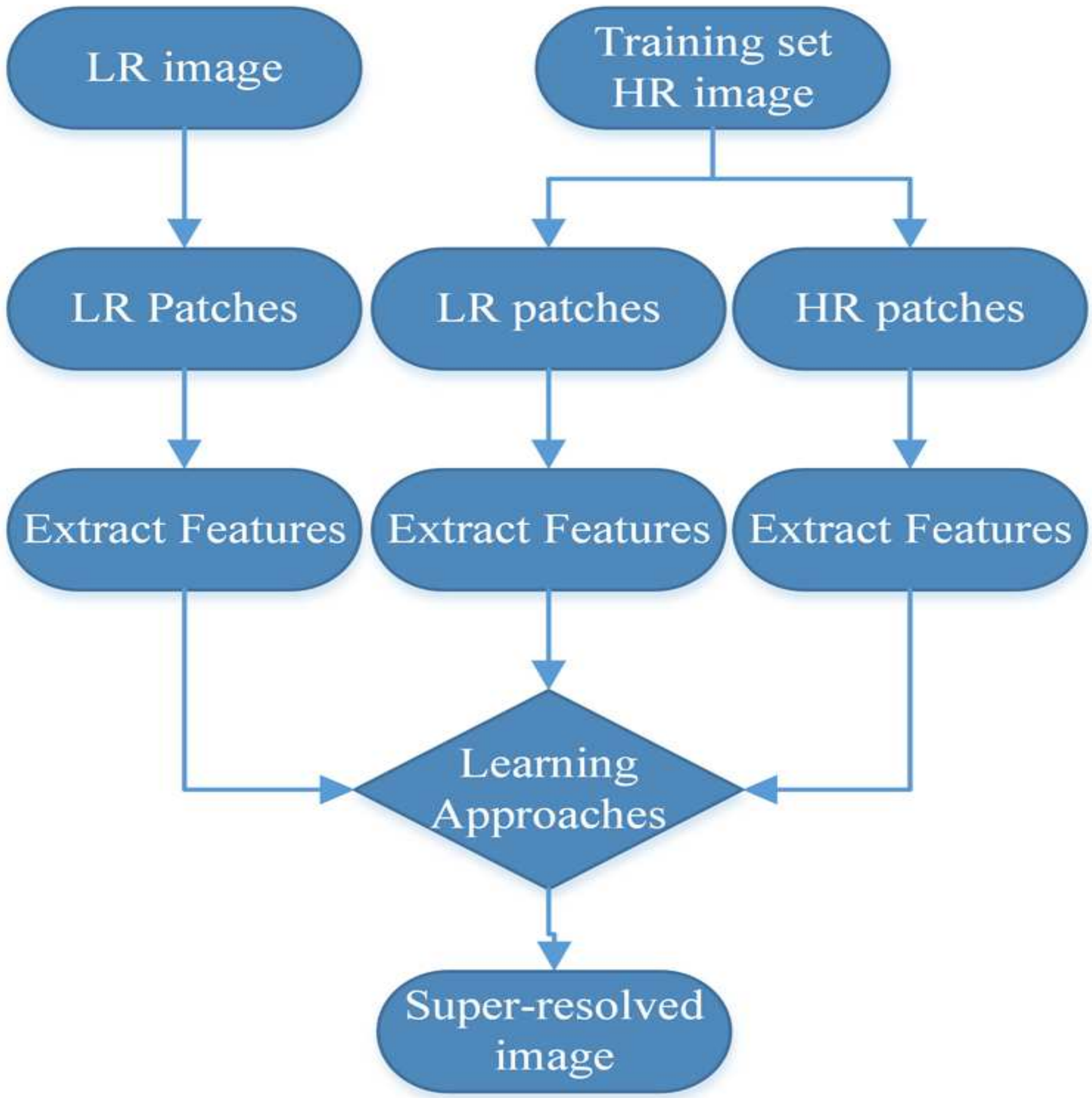


Figure 2.2: Block diagram of super resolved image

2.2 is the representation of super resolved image reconstruction.The online recuperation of the sparse representation utilizes the LR Dictionary, and the HR dictionary is utilized just to figure the final HR image. [22] [25].

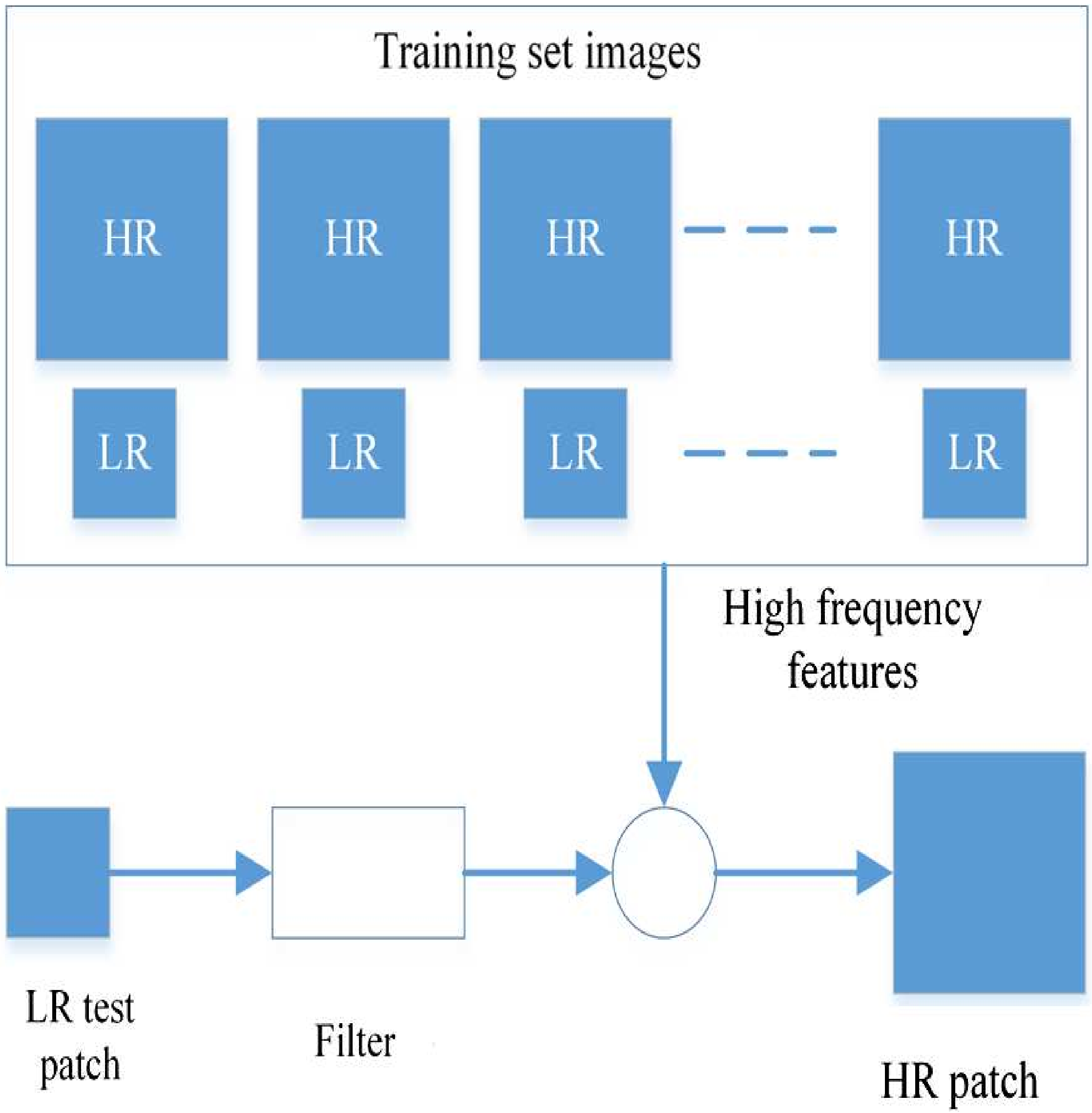


Figure 2.3: Block diagram for generating HR patch

2.3 which shows the generation of HR patch from the training set images and the LR image.The figured sparse representation adaptability chooses the most pertinent patch bases in the dictionary to best speak to every patch of the given LR image. This prompts unrivaled execution, both subjectively and quantitatively, and produces more honed edges and clearer compositions, contrasted with routines [25] that utilization a settled number of closest neighbors. Furthermore, the sparse representation is vigorous to noise as proposed in [30]; and, in this manner, our calculation is more hearty to commotion in the test image, while different techniques can't perform denoising and super-resolution at the same

2.5 Organization of This Thesis

The rest of this postulation is sorted out as follows. In Chapter 3, details about the proposed method and solution for the image super-resolution issue in view of sparse representation is described. In particular, the focus is on the best way to apply sparse representation for both nonspecific image super-resolution. In Chapter 4, we examine how to use two dictionaries for the HR and LR image patches for dictionary training. Different experimental results are presented in Chapter 5 which exhibit the viability of sparsity as a former for regularizing image super-resolution. Chapter 6 discusses the conclusions and future work.

Chapter 3

SR based on sparse representation

3.1 Super-resolution Constraints

The single-image super-resolution issue demands: Given a low-resolution image L, recuperate a higher-resolution image H of the same scene. Two imperatives are demonstrated in this work to unravel this not well posed issue: 1) reconstuction imperative, which obliges that the recuperated H ought to be predictable with the info L with admiration to the image perception model; and 2)sparsity prior, which expect that the high resolution patches can be deficiently represented by an appropriately picked overcomplete reference dictionary, and that their sparse representations can be recovered from the low resolution recognition.

3.1.1 Constraint for Reconstruction

The watched low-resolution image L is an obscured and downsampled adaptation of the high-resolution image H:

$$\text{Ł} = dBH \tag{3.1}$$

Here, 'B' speaks to an obscuring channel, and 'd' speaks to the downsampling operator. Super-resolution remains greatly poorly postured, subsequent to for a given low-resolution data L, endlessly some high-resolution images H fulfill the above remaking imperative. We further regularize the issue by means of the accompanying former on little patches l of H.

3.1.2 Constraint for sparse recovery

The patches h of the high-resolution image H can be spoken to as an inadequate direct blend in a dictionary D_{HR} prepared from high-resolution patches inspected from preparing images

$$l \approx D_{HR}\alpha \tag{3.2}$$

The lacking representation α will be remade by addressing fixes l of the data picture L, concerning a low-determination word reference D_{LR} co-arranged with D_{HR}. The system for dictionary arrangement is examined in Chapter 4. We apply our strategy to manage both textured pictures and face pictures. For insipid picture super-resolution, we seclude the issue into two stages. At first, as suggested by the sparsity prior Eq. (3.2), we find the inadequate representation for each area patch, in regards to spatial similitude between neighbors. Next, using the result from this adjacent scanty representation, we further regularize and refine the entire picture using the revamping basic Eq. (3.1). In this technique, an area model from the sparsity prior is used to recover lost high-frequency for adjacent inconspicuous components. The overall model from the changing basic is then joined with oust possible ancient pieces from the first step and make the picture all the more enduring and standard. The face pictures contrast from the nonexclusive pictures in that the face pictures have more reliable structure and in this way entertainment prerequisites in the face subspace can be more reasonable. For face picture super-determination, we modify the more than two stages to enhance use of the overall face structure as a regularize. We first find a suitable subspace for human faces, and apply the propagation necessities to recover a medium-determination picture. We then recover the area unpretentious components using the sparsity prior for picture pathes.

3.2 Image Super-resolution from Sparse representation

3.2.1 Neighborhood model for sparse representation

Hence to the patch-based systems said as of now, our figuring tries to understand the high-resolution image patch for each low-resolution image patch from the information. For this adjacent model, we have two word references D_{HR} and D_{LR}, which are arranged to have the same insufficient representations for each high-resolution and low-resolution image patch pair. We subtract the mean pixel regard for each patch, so that the dictionary identifies with picture surfaces rather than aggregate intensities. In the recovery set up, the mean quality for each high-determination picture patch is then expected by its low-determination adjustment. For each data low-determination patch y, we find a pitiful representation with respect to D_{LR}. The relating high-determination patch bases D_{HR} will be merged as shown by these coefficients to make the yield high-determination patch h. The issue of discovering the sparsest representation of l can be characterized as

$$\min \|\alpha\|_0 s.t \, \|FD_{LR}\alpha - Fl\|_2^2 \leq \varepsilon \tag{3.3}$$

where F is a (linear) feature extraction operator. The primary part of F in Eq. (3.3) is to give a perceptually important constraint on how nearly the coefficients α must estimated l. We will talk about the decision of F in Section 4.3. In spite of the fact that the advancement issue Eq. (3.3) is NP-hard in general, later results [24, 25] recommend that the length of the sought cofficients α are sufficiently sparse, they can be efficiently recuperated by rather minimizing the $l1 - norm$ as follows:

$$\min \|\alpha\|_1 s.t \, \|FD_{LR}\alpha - Fl\|_2^2 \leq \varepsilon \tag{3.4}$$

Lagrange multipliers offer a comparable definition,

$$\min_{\alpha} \|FD_{LR}\alpha - Fl\|_2^2 + \lambda\|\alpha\|_1 \tag{3.5}$$

where the parameter λ counterbalances sparsity of the game plan and consistency of the nearby estimation to l. Notice that this is fundamentally an immediate backslide regularized with L_1-standard on the coefficients, alluded to in authentic written work as the Lasso [28]. Handling Eq. (3.5) freely for each adjacent fix does not guarantee the comparability between abutting patches. We maintain closeness between adjoining patches using an one-pass computation like that of [29].4 The patches are taken care of in raster-breadth organize in the picture, from left to right and through and through. We change Eq. (3.4) so that the super-resolution redoing D_{HR} of patch l is constrained to almost agree with the officially figured neighboring high-resolution patches. The resulting improvement issue is

$$\begin{aligned} &\min \|\alpha\|_1 s.t \, \|FD_{LR}\alpha - Fl\|_2^2 \leq \varepsilon_1 \\ &\|PD_{HR}\alpha - w\|_2^2 \leq \varepsilon_2 \end{aligned} \tag{3.6}$$

where the framework P separates the district of cover between the present target patch and beforehand remade high-resolution image, and w contains the estimations of the already reproduced high-resolution image on the cover. The compelled streamlining Eq. (3.6) can be likewise reformulated as

$$\min_{\alpha} \left\| \overset{\cap}{D}\alpha - \overset{\cap}{l} \right\|_2^2 + \lambda\|\alpha\|_1 \tag{3.7}$$

where $\overset{\cap}{D} = \begin{bmatrix} FD_{LR} \\ \beta PD_{HR} \end{bmatrix}$ and $\overset{\cap}{l} = \begin{bmatrix} Fl \\ \beta w \end{bmatrix}$ The parameter β controls the tradeoff between coordinating the low-resolution info and discovering a high-resolution fix that is perfect with its neighbors. Given the ideal arrangement α^* to Eq. (3.7), the high-resolution patch can be reconstructed as $h = D_{HR}\alpha^*$

3.2.2 Enforcing global model

The HR image generated from local model based patch-wise sparse recovery may not satisfy the reconstruction constraint absolutely. This is because of Eq.(3.4) and Eq.(3.6) dont claim the exact equality between the LR patch and the reconstructed . Hence, to efficiently satisfy the reconstruction constraint the solution from local model is passed through the global model. In many of the SRR methods via sparse the global reconstruction model uses gradient descent method for obtaining the HR image that satisfies the reconstruction constraint. By using the iterative method, the ringing and zipper artifacts dominants along the strong edge area of the reconstructed HR image and the quality severely degrades with increase in the magnification factor. In order to suppress the effect of artifacts and to well preserve the high frequency components of the HR image a weighted high frequency mask is added in each and every iterative step. The global reconstruction model produces the HR image by solving Eq.(3.9)

$$H^* = \arg\min_{H} \|dBH - L\|_2^2 + c.(mask(H, H_0)) \tag{3.8}$$

$mask(H, H_0) = H - H_0$ $c = \left(\frac{c_{\max} - c_{\min}}{c_{\max} + c_{\min}}\right) * \max\_itr$ where $c_{\max}$ and $c_{\min}$ are initial and final weights and $iter_m ax$ is the maximum number of iterations and $iter$ is the current iteration number.

The mask used is a simple sharpening operator which enhances edges along with other high frequency components in the reconstructed image through a procedure which subtracts a smoothed version of the up-sampled (B-spline) input LR image. From the original image, the result from the above optimization process after a predefined number of iteration is our final reconstructed HR image. However, the proposed sparse representation based SRR process is summarized in Algorithm 1.

Algorithm 1 *(Patch wise sparse representation based SRR with the learnt coupled dictionary)*:

1. **Input**:D_{LR},D_{HR} and H,$H0$
2. **Initialize** H=0
3. for each 5x5 patch l of l'
4. Compute mean pixel value $M = mean(l)$
5. Perform to deal with image texture $t = \|l - M\|_2$.
6. Get the feature vector F of l' using Eq. 10

$\min_{\alpha} \|FD_{LR}\alpha - Fl\|_2^2 + \lambda\|\alpha\|_1$

10. Generate the HR patch $h = D_{HR}\alpha^*$.
11. Set patch $h = h + M$
12. Put the HR patch h into the desired HR image H
13. **end for**
14. Perform the global reconstruction given in Eq.(3.9) to find the closest image to H.

15. **Output**: Get the reconstructed SR image.

3.3 Linear Regression Optimization

In the run of the mill univariate straight relapse situation, the data is n occurrences of a procedure portrayed by $p+1$ variables,and we try to locate a direct blend of a chose p variables (the components) that best predicts the staying variable (the objective). We ordinarily characterize the outline framework X as a network having n columns and p sections, speaking to the p variables for n occurrences. So also, we characterize the objective vector y as a segment vector of length n containing the relating estimations of the objective variable. The issue can then be planned as discovering a "decent" esteem for the length p coefficient vector w and the scalar inclination term w_0 in the accompanying model (assumed control i from 1 to n):

$$y_i = w_0 + \sum_{j=1}^{p} x_{ij} w_j + \in_i \tag{3.9}$$

$\in_i$ means the clamor (or mistake) term for example i, and it is regularly expected that the estimations of $\in_i$ have zero mean, and are both autonomously and indistinguishably circulated. Consequently, we normally don't demonstrate $\in$ straightforwardly. On the other hand, we can't understand for w and w_0 straightforwardly given just X and y, in light of the fact that $\in$ is obscure. Moreover, the clamor term may bring about the same or comparable estimations of x_i to yield distinctive qualities. We accordingly characterize a loss function that surveys how well a given arrangement of parameters w predicts y from X.

3.4 Feature Extraction:

The feature extraction operator F guarantee about the best fit for the computed sparse coefficients along the most relevant part of the input LR image patch to boost up the prediction accuracy. In literature the typical choice for the F is of high-pass filter (HPF) to extract the high frequency components. The commonly used HPF is first and second order filter gradients applied on the up-sampled version of the input LR image using Bi-cubic interpolation. The interpolation technique fails to capture the fast evolving statistics of the high frequency components of the image as a result sharp edges get blurred. Moreover, as the magnification factor goes on increasing the interpolation process produces severely over smoothed image which lacks important high frequency information. Hence, the traditional feature extraction techniques applied on the up-sampled image are not much competent to extract the dominant features.

In order to overcome this limitation, Gabor filter is used as an alternate linear feature extraction operator to be applied on each LR patch. During patch wise sparse recovery the mean pixel value for each patch is subtracted every time so as to present image texture rather than absolute intensity. The basic advantage of using Gabor filter is its efficiency to provide the multi-resolution features for images with fine textures as well as smooth shading. However, the Gabor filtering operation is constructed via filter banks tuned to different frequencies f_m and orientation θ_n to provide several multi-resolution features. The basic 2D Gabor filter function [10] in the spatial domain is given in Eq.(3.12)

$$\psi(x,y) = \frac{f^2}{\pi\gamma\eta} e^{-(\frac{f^2}{\gamma^2}x'^2 + \frac{f^2}{\eta^2}y'^2)} e^{j2\pi f x'} \tag{3.10}$$

$$\left.\begin{aligned} x' &= \quad x\cos\theta + y\sin\theta \\ y' &= -x\sin\theta + y\cos\theta \end{aligned}\right\} \tag{3.11}$$

Gabor filter in Eq. (3.12) can be described as a complex plane wave i.e., a 2D Fourier basis function multiplied by an origin-centered Gaussian. Here is the central frequency and is the rotational angle of the filter bank. and denotes the bandwidth of the filter bank along the Gaussian major and minor axis respectively.

$$f_m = k^{-m} f_{\max}; m = \{0, 1, 2.....M-1\} \tag{3.12}$$

$$\theta_n = \frac{n2\pi}{N}; n = \{0, 1, 2.....N-1\} \tag{3.13}$$

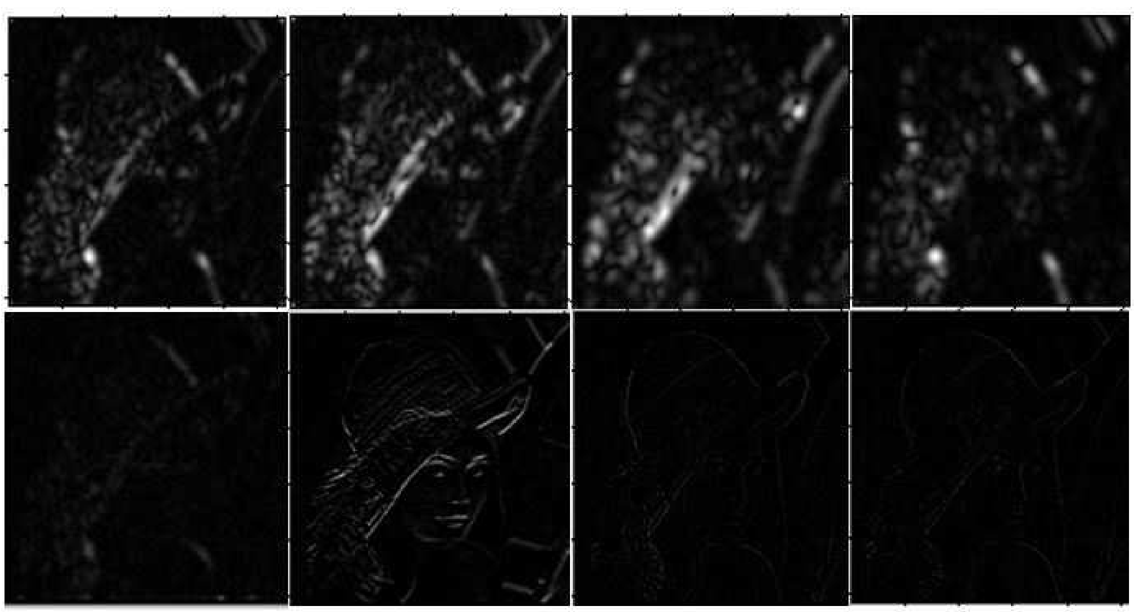


Figure 3.1: feature extraction process,First row using Gabor filter and second row using first and second order gradients

Where k is called frequency scaling factor and usually chosen as $k > 1.f_m$ is the m^{th} frequency and $f_{\max}$ is the highest frequency desired.N is the total number of orientation. In the present work F denotes the feature vector containing features extracted from four filter banks at four orientations. The parameters f_m= 0.25 ,$\gamma = \eta = \sqrt{2}$ are chosen. Fig.3.1 shows the how the Gabor filter is extracting multiresolution features and hence provides the better prediction accuracy of the HR image than that of first and second order filter gradients.

Chapter 4

Dictionary learning for sparse representation

4.1 Introduction

To capture the significant properties of the signals requires good data representations which will commonly do by signal processing and pattern recognition techniques. For compression data should be represented such that most important content of the signal with a few coefficients only exists. In the recent days representations with orthogonal and bi orthogonal dictionaries are mostly used for their mathematical simplicity and computational efficiency. These dictionaries have the flexibility to represent wider range of signals in the compression of the signals. In the past section, we talked about regularizing the super-resolution problem utilizing the sparse prior that every pair of HR and LR image patches has the same sparse representations concerning the two dictionaries Dh and Dl. A direct approach to get two such lexicons is to test image patch combines straightforwardly, which safeguards the correspondence between the HR and LR image patch things [15]. moreover, such a technique will bring about vast word references and, henceforth, costly reckoning. This part will concentrate on taking in a more conservative dictionary pair for accelerating the calculation.

4.2 Sparse coding by single dictionary training

The target of sparse coding is to speak to an information signal $x \in R^K$ generally as a weighted straight blend of a few essential signs called reason iotas, routinely searched an over-complete dictionary $D \in R^{d \times K}$ $(d < K)$. Sparse coding is the framework to thus discover such an average game plan of reason atoms.The issue of taking in a dictionary for sparse coding, in its most noticeable structure, is disentangled by minimizing the essentialness work that joins squared propagation slips and the $L1$-sparsity disciplines on the representations.In this thesis,we mostly concern on the accompanying definition

$$D = \arg\min_{D,Z} \|X - DZ\|_2^2 + \lambda \|Z\|_1 s.t \, \|D_i\|_2^2 \leqslant 1, i = 1, 2....K \tag{4.1}$$

The optimization performs in an alternative manner over Z and D

1. Initialize D with a Gaussian random matrix,with each colum unit normalized

2. Fix D,update Z by

$$Z = \arg\min_{Z} \|X - DZ\|_2^2 + \lambda \|Z\|_1 \tag{4.2}$$

which can be solved efficiently through linear programming.

3. Fix Z,update D by

$$D = \arg\min_{D} \|X - DZ\|_2^2 \, s.t \, \|D_i\|_2^2 \leq 1, i = 1, 2....K \tag{4.3}$$

which is a quadratically constrained quadratic programming that is ready to be solved in many optimization packages.

4. Iterate between 2)and 3)until they converge.In our implementation,we used a matlab package.

4.3 Sparse coding by joint dictionary training

Dissimilar to the standard sparse coding, joint sparse coding considers the issue of taking in two dictionaries D_{HR} and D_{LR} for coupled highlight spaces, H and L respectively. Given the training sampled image patches $p = \{X^{HR}, Y^{LR}\}$, where $X^{HR} = \{x_1, x_2....x_n\}$ and $Y^{LR} = \{y_1, y_2....y_n\}$. The individual sparse coding problems in the HR and LR patch spaces are

$$D_{HR} = \arg \min_{\{D_H RZ\}} \left\|X^{HR} - D_{HR}Z\right\|_2^2 + \lambda \|Z\|_1 \tag{4.4}$$

$$D_{LR} = \arg \min_{\{D_L RZ\}} \left\|Y^{HR} - D_{LR}Z\right\|_2^2 + \lambda \|Z\|_1 \tag{4.5}$$

We combine these two HR and LR representations to use same codes as

$$\min_{\{D_{HR}D_{LR}Z\}} \frac{1}{N} \left\|X^{HR} - D_{HR}Z\right\|_2^2 + \frac{1}{M} \left\|Y^{LR} - D_{LR}Z\right\|_2^2 + \lambda(\frac{1}{N} + \frac{1}{M})\|Z\|_1 \tag{4.6}$$

where N and M are the dimentions of HR and LR image patches.eq(4.6) can be rewritten as

$$\min_{\{D_{HR}D_{LR}Z\}} \|X_c - D_cZ\|_2^2 + \lambda(\frac{1}{N} + \frac{1}{M})\|Z\|_1 \tag{4.7}$$

or

$$\min_{\{D_{HR}D_{LR}Z\}} \|X_c - D_cZ\|_2^2 + \hat{\lambda}\|Z\|_1 \tag{4.8}$$

where

$$D_c = \begin{bmatrix} \frac{1}{\sqrt{N}} D_{HR} \\ \frac{1}{\sqrt{M}} D_{LR} \end{bmatrix}, X_c = \begin{bmatrix} \frac{1}{\sqrt{N}} X^{HR} \\ \frac{1}{\sqrt{M}} Y^{LR} \end{bmatrix} \tag{4.9}$$

4.4 Sparse coding by coupled dictionary training

Instead of particularly using raw pixel values, we remove fundamental components from HR and LR fixes independently concerning the signs in their coupled spaces. The DC part is at first ousted from each HR and LR patch subsequent to the mean estimation of a patch is continually shielded well through the mapping from HR space to LR space. Similarly, we isolate slant highlights from LR picture settle as in Yang et al. [25], since the center recurrence band in LR patch is acknowledged to be more huge to the missing high repeat information. Finally, all the HR and LR patch signs (isolated highlights) are institutionalized to unit length with the objective that we don't need to push over the shrinkage effect of $L1$ standard minimization on the scanty representations. As can be seen, the resultant HR or LR picture patch (highlight) sets are tied by a mapping limit essentially more complex than the immediate structure considered in most routine converse issues, for instance, compressive sensing.Algorithm 4 condenses the complete strategies for our coupled lexicon learning.

Algorithm 4 *Coupled Dictionary Training*

1. Input:train patch pairs $\{(HR_i, LR_i)\}_{i=1}^{N}$ and dictionary size K
   2. Initialize $D_{HR}^{(0)}$ and $D_{LR}^{(0)}$, $\eta = 0$,$t = 1$
   3. Repeat for $i = 1, 2, ...N$
   4. Compute gradient $a = dL(D_{HR}^{(n)}, D_{LR}^{(n)}, HR_i, LR_i)/dD_{LR}$
   5. Update $D_{LR}^{(n)} = D_L R^{(n)} - \eta(t)$
   6. Project the columns of $D_{HR}^{(n)}$ 7. $t = t + 1$
   8. end for
   9. Update $D_{LR}^{(n+1)} = D_{LR}^{(n)}$
   10. Update $D_{HR}^{(n+1)} = D_{HR}^{(n)}$
   11. $n = n + 1$
   12. Until converge.

The proposed coupled learning calculation is nonexclusive, and subsequently can be conceivably connected to numerous sign recuperation and PC vision assignments, e.g., picture pressure, surface exchange, and super-resolution. In the accompanying, we will concentrate on its application to fix based single picture super-resolution.

Chapter 5

Results and Analysis

This section illustrates the effectiveness of the proposed sparse representation based SRR method applied to color image. Color images Lena, Parrot and peppers are used in the present work to test the robustness of the proposed method.

The proposed SRR method is effectively used for various magnification factors such as 2, 4, and 6. Due to shortage of length of the paper, the results for magnification of by a factor of 4 are presented here. The observed LR image is generated from as given in Eq.(3.1). In training of dictionaries, 5x5 LR image patches with single pixel overlapping between adjacent patches and 9x9 HR images patches with 3 pixel overlapping are used respectively. To check robustness of the algorithm to noise, we have added different levels of blur and noise to the observed LR image. Different blurring kernels of size 3x3, 5x5 and standard deviation of the Gaussian noise ranges from 2-20 are used. Algorithm 1 is processed successfully to get the optimal SR image.

Figure 5.1 5.2 5.5 **??** **??** shows the reconstructed HR image from the proposed method compared with other state-of-art techniques such as Bi-cubic interpolation method, Neighbor embedding (NE) [32], Sparse based SR reconstruction proposed by Yang et al. [26] with magnification factor of 2.

(a) HR image

(b) zoomed LR image

(c) bicubic method

(d) NE method

(e) Yang.et.al. method

(f) Proposed method

Figure 5.1: SRR results of butterfly image based on different methods with magnification factor 2

(a) HR image

(b) zoomed LR image

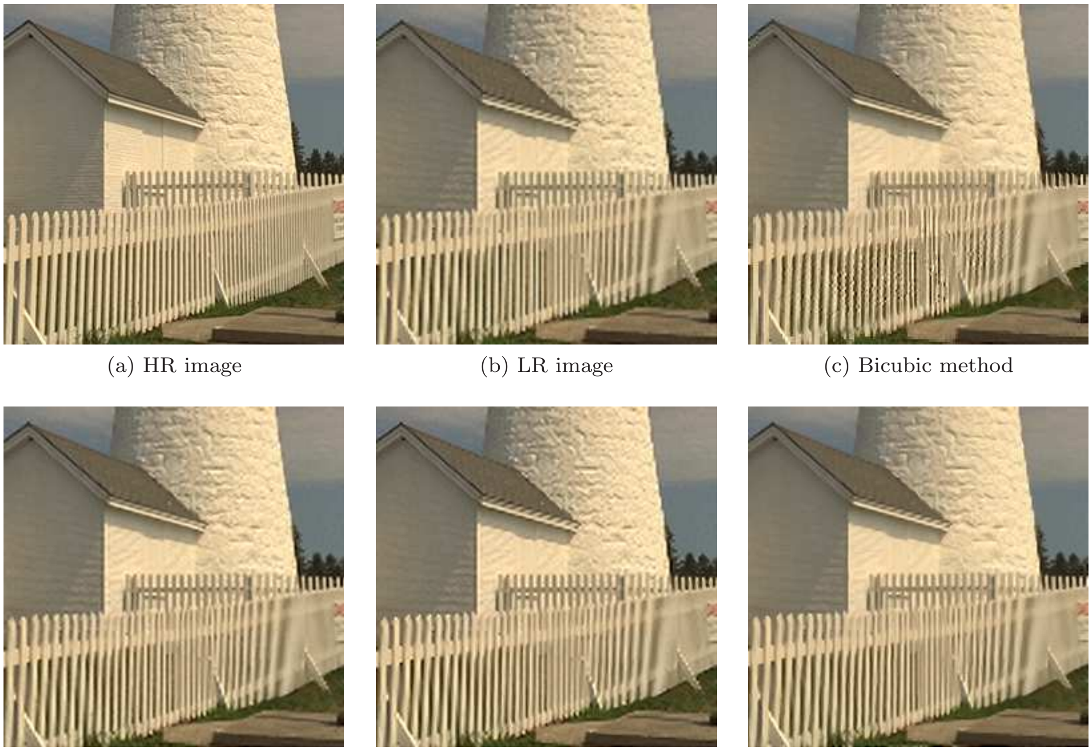
(c) Bicubic method

(d) NE method

(e) Yang.et.al method

(f) Proposed method

Figure 5.2: SRR results of starfish image based on different methods for magnification factor 2

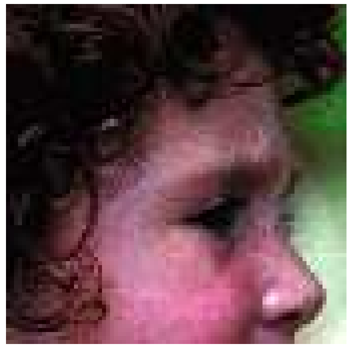


(a) HR image   (b) LR image   (c) Bicubic method

(d) NE method   (e) Yang.et.al method   (f) Proposed method

Figure 5.3: SRR results of fence image based on different methods for magnification factor 2

(a) HR image



(b) LR image

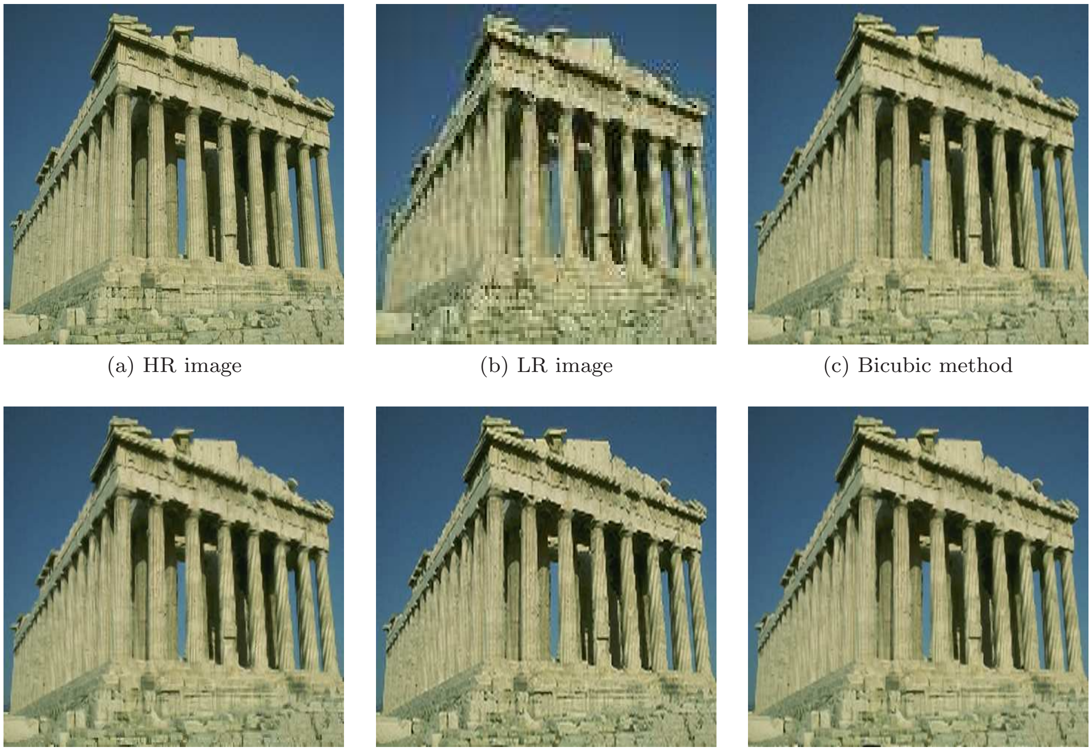
(c) Bicubic method

(d) NE method

(e) Yang.et.al method

(f) Proposed method

Figure 5.4: SRR results of girl image based on different methods for magnification factor 2

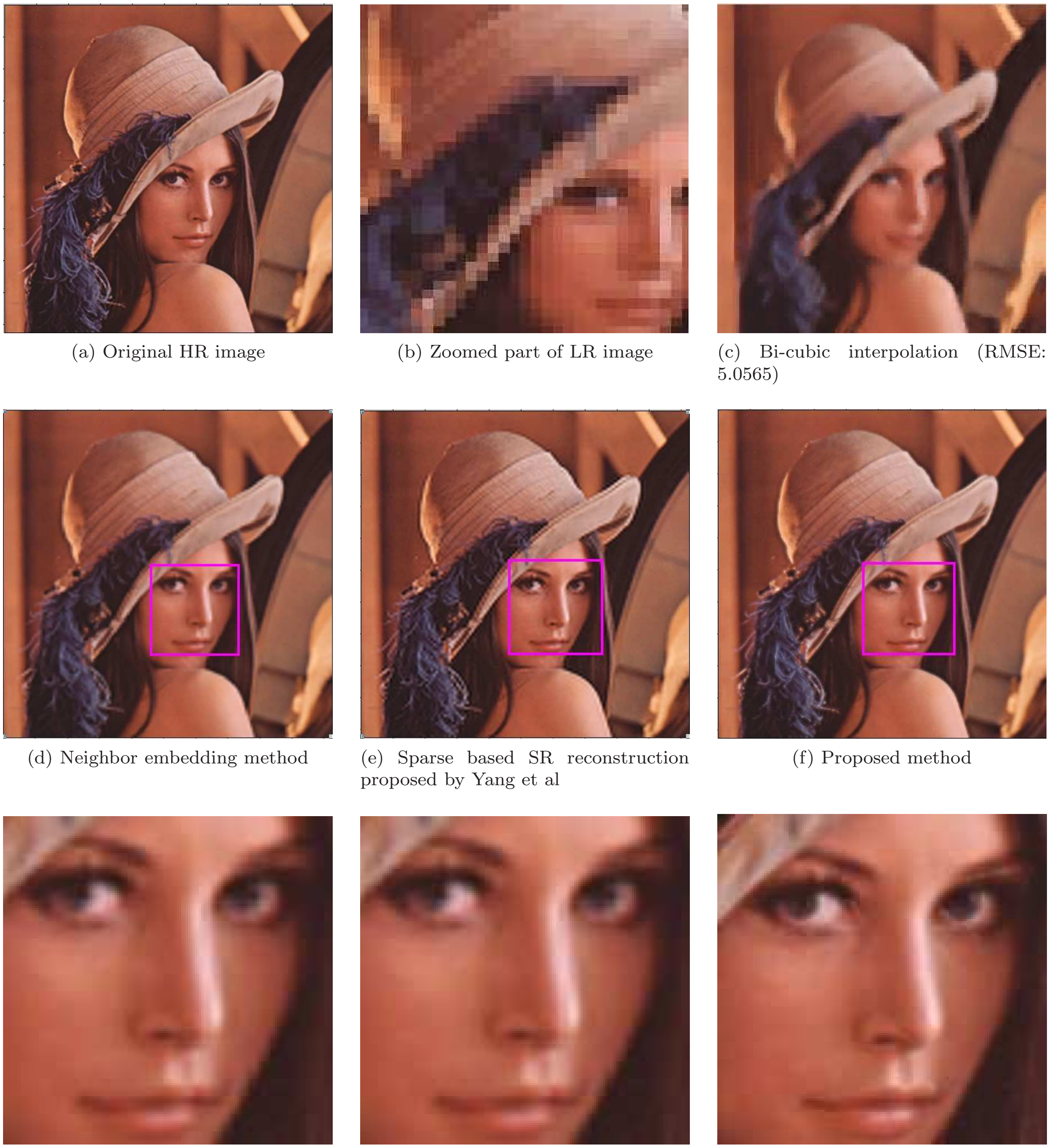


(a) HR image (b) LR image (c) Bicubic method

(d) NE method (e) Yang.et.al method (f) Proposed method

Figure 5.5: SRR results of Parthenon image based on different methods for magnification factor 2

From the visual perception in Fig 5.6 it is observed that Bi-cubic interpolation method does not show proper reconstruction result as this interpolation technique lacks preserving the high frequency details and hence produces an overly smoothed output HR image. The results from NE generates sharper edges bur blurs the texture content. However, the reconstruction method in [26] is one of the widely used reconstruction technique. But as the magnification factor increases the quality of the output degrades. This is due to the fixed choice of sparse regularization parameter and universal matching constraint. The use of traditional feature extraction technique fails to track the varying features of the image. Whereas, the gradient descent method used for global reconstruction introduces ringing and jagged artifacts in the strong edge areas.



(a) Original HR image

(b) Zoomed part of LR image

(c) Bi-cubic interpolation (RMSE: 5.0565)

(d) Neighbor embedding method

(e) Sparse based SR reconstruction proposed by Yang et al

(f) Proposed method

(g) Zoomed part of Neighbor embedding method result

(h) Zoomed part of Sparse based SRR method proposed by Yang et al.

(i) Zoomed part of proposed method result

Figure 5.6: SRR results of Lena image based on different methods for magnification factor 4

However, the reconstructed images from the proposed work provide a high quality and sharpened observation. The dynamic choice of similarity parameter enhances the better tradeoff between matching of the LR input image patches to find a HR patch compatible with its neighbors. Whereas, the better feature extraction techniques as well as optimal penalty parameter improves the sparsity of the solution. Finally the ringing artifacts are reduced as the high frequency details of the image are well preserved by the use of sharpening mask.

Images	Quality Measures	Bi-cubic	NE	Yang et al.[3]	proposed
Lena	PSNR(dB)	34.053	34.683	35.290	36.883
	SSIM	0.9148	0.9201	0.9286	0.9677
	FSIM	0.9135	0.9569	0.9647	0.9784
	Time	0.6532	125.34	382.65	395.54
butterfly	PSNR(dB)	20.856	20.932	21.650	26.160
	SSIM	0.9252	0.9295	0.9375	0.9729
	FSIM	0.7963	0.8013	0.8214	0.9157
	Time	0.8312	132.24	233.56	242.89
fence	PSNR(dB)	36.481	36.894	35.290	39.883
	SSIM	0.9252	0.9268	0.9286	0.9677
	FSIM	0.9592	0.9593	0.9601	0.9831
	Time	0.5678	142.23	245.78	267.08

Table 5.1: Quantitative analysis of different images

Table 5.1 provides the details of the objective quality measures such as: PSNR, SSIM [33], FSIM [34] and the computational time in seconds. SSIM index between the original and reconstructed images are calculated by comparing the local configurations of pixel intensities. Whereas, FSIM index considers the low level features of the original and reconstructed image to calculate the feature similarity between the images. The higher the SSIM and FSIM value, the more similar the considered images.Fig **??**discusses proposed method time complexity, compared with the other state of art methods.

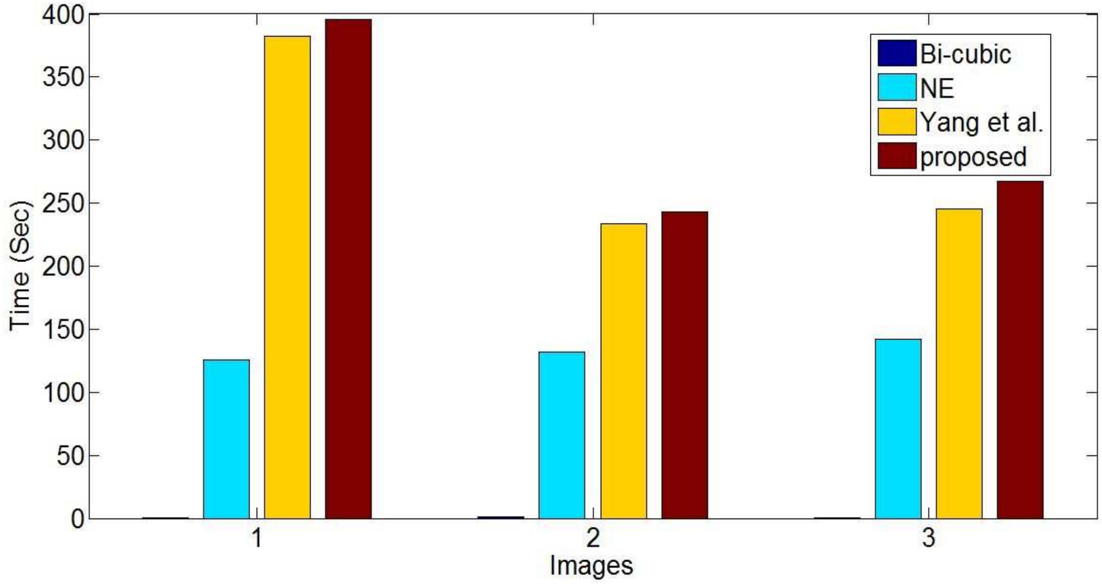


Figure 5.7: comparison of time complexity between different methods.

Chapter 6

Conclusions and future work

This thesis presents an efficient single image super resolution image reconstruction based on patch wise sparse representation. The coupled dictionary training is employed to learn the low and high resolution dictionaries. Sparse prior from the LR patches are used to reconstruct the HR patches which are obtained by norm optimization process. In the optimization process, Gabor filter is used as to well track the feature at different frequencies and orientations. Normalized Cross Correlation is used as a better matching constraint to maintain a proper compatibility between the LR and recovered HR patches. Based on the amount of blur and level of noise present in the input image adaptive selection of sparsity penalty parameter is done using the PSO optimization technique. A small penalty parameter is used for high noisy image whereas the larger value is used for noise less or low noisy images. The optimal sparsity penalty parameter makes the proposed sparse model robust to noise and maintains a proper balance between the sparsity of the solution and the fidelity of the approximation. Experimental results demonstrate the effectiveness of the proposed SRR method as compared to the other existing state of art methods at a cost of high computational complexity. The future investigation aims to use an optimal dictionary which will minimize the time complexity in SRR method

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