Summary

In many applications, it is desirable to enhance an image and/or a video. Enhancement may be due to removal of degradation leading to *image restoration* or generation of a high resolution image leading to image *zooming.* A restored image is void of corrupting noise and blur, resulting in a sharper and better quality image. A high resolution image may have more details than the original low resolution image, which could contribute to a better analysis of the given image. A high resolution video may give a better picture in applications like HDTV. Physical limitations of sensors as well as limitations of the transmission channel affect both the quality and the resolution of image. Better quality of sensors and channels adds to overall cost of the system, making it unaffordable. To overcome the above limitations and to fit into the available bandwidth, the video itself may be compressed before transmission, which necessitates the zooming to be carried out in compressed domain.

Our work addresses the above mentioned areas. We propose a new method for restoration of color image, which is degraded by interchannel blurring. Once images are restored, we move on to enhance image resolution by zooming the images. We propose to increase the high frequency content of image while zooming, to obtain a sharper zoomed image. Still image zooming is further extended to video zooming. The novel feature of video zooming is that the zooming is done by interpolating motion vectors in the compressed domain and not in the spatial domain.

We discuss each of these three applications, namely, robust color image restoration, still image zooming and zooming of compressed video in subsequent parts.

Color Image Restoration: The first problem addressed in this thesis is color image restoration. The aim of image restoration is to recover the original image from an observed degraded image. Degradations may be due to blur and/or corruptive noise. Image restoration - removal of blur and noise - is an *inverse problem.* Most inverse problems are *ill-posed* in nature and are tackled by *regularizing* an energy function. In general, energy functions associated with image restoration problems will be non-convex, and could have

several local minima and a non-unique global minima. These aspects make image processing tasks interesting and challenging. This is more true in the case of color images, as we do not know the exact nature of color processing by the human eye.

Typically, degradation can be modeled by a linear blur. Sources of blur are motion blur, out of focus blur, atmospheric turbulence, and others. Noise may arise from digitization and quantization, transmission and recording medium, thermal noise etc. Classical methods of image restoration assume the blurring operation is exactly known *a priori*. The observed image is then de-convolved using the known blurring function. This approach basically involves solution to ill conditioned equations. This ill-conditioning is overcome by the use of regularization procedures. Regularization imposes some constraints (smoothness, for example), which reduces the solution (search) space. Restoration of monochrome images, when the blurring function is known, is well addressed in literature. Results for color image restoration are not all that satisfactory mainly because, psychology of color image perception in human beings is not fully understood.

We assume color planes interact linearly with each other. For example, blurring in red channel depends not only on the neighboring pixels of the red plane, but also on the pixels in green and blue planes. To account for interchannel blurring, we propose a new model for interchannel interaction, namely, the First Order Interchannel Interaction (FOII) model. Then, a probabilistic approach is used by modeling the color image as a Markov Random Field (MRF). Restoration problem is then cast as a maximum *a posteriori* (MAP) estimation problem. Choice of the energy function in the MRF model takes care of the dependencies between the color coordinates. In general, the energy function will be non-convex with multiple local minima and non-unique global minima. We use simulated annealing (SA) algorithm, which guarantees convergence *in probability*.

We propose two different forms for the energy function. First model assumes that the color planes do not interact with each other, and are mutually independent of each other. Second model assumes First Order Interchannel Interaction (FOII), where we assume a first order model for interchannel interaction. In both the models, we incorporate *line fields* to detect discontinuities and thereby retain sharp edges. We show the FOII model is robust, in the sense that performance is very good even when the amount of interchannel blurring is unknown. Thereby, FOII model can be classified as *partially blind* image restoration model. The performance of FOII remains invariant for the amount of interchannel blur, and hence, FOII can be termed *robust* model.

Still Image Zooming: The second problem addressed in this work is still image zooming. To zoom a given image, we have to *estimate* missing pixels from an observed low-resolution image. We propose to estimate these missing pixels in the wavelet domain.

Present day sensors use Charge Coupled Devices (CCD) that respond to light sources. One needs a high density photo-detectors to have a higher resolution in spatial domain. But the physical limitations allow photo-detectors to be placed at a distance not less than $50\mu m^2$ (approx). This leads to pixelization and the Point Spread Function (PSF) of a point source to be blurred. Image may even get aliased if the sampling rate is low.

Mere re-sizing of the image does not translate into an increased resolution. In fact, re-sizing should be accompanied by approximations for frequencies higher than those representable at the original size and at a higher signal-to-noise ratio. This process of re-sizing is called *re-sampling*. Traditional method of re-sampling is to use interpolating functions wherein the original data is fit with a continuous function and then re-sampled at a finer sampling grid.

Zooming involves filling intermediate pixel values. Most commonly used methods involve placing zeros in the intermediate samples and then passing through a filter. Different methods are attributed to different types of filters. Classical methods include linear interpolation and pixel replication. Linear interpolation tries to fit a straight line between two points, That is, the missing pixel is the average of adjacent two pixels. Averaging is first carried out on rows to estimate missing column elements, and, then followed by averaging along columns. Due to averaging, this leads to blurred images. Second popular method is pixel replication. This method copies neighboring pixel to the empty location. Again, the operations are carried out along rows first, followed by columns. (Operation on rows and columns are interchangeable). Due to copying of adjacent pixel element, this technique tends to generate a *blocky* image. Approaches like spline and sinc interpolation are proposed to reduce these two extremities. Spline is inherently a smoothing operation, giving a smooth image. Sinc assumes the signal under consideration is band limited and thus zooming can be carried out by zero extension of the Fourier Transform (FT). Because of zero-padding in the frequency domain, this leads to ripples at the edge of the image in spatial domain. These approaches do not attempt to remove blurring present in the observation due to low resolution sampling. In fact, most of them are low-pass kind of filters, and, introduce blurring. In order to increase the sampling rate, high frequency components should be added to the image.

In this work, we propose a Multiresolution analysis (MRA) based approach for estimating the wavelet coefficients at higher (finer) scales. Using wavelet coefficients available at coarser levels, we *estimate* finer level coefficients required for synthesizing the high resolution signal. Having estimated the coefficients, rest is a standard wavelet synthesis filter.

We make use of zerotree property to estimate coefficients at a finer level.

Zero tree concept has the following properties:

- If a wavelet coefficient at a coarser scale is insignificant with respect to a given threshold θ, then all wavelet coefficients of the same orientation in the same spatial location at finer scales are likely to be insignificant with respect to that θ.
- In a multiresolution system, every coefficient at a given scale can be related to a set of coefficients at the next coarser scale of similar orientation.

Wavelets also gives rise to multiresolution analysis (MRA). The MRA has the following useful properties: Let A_2^j be the operator which approximates a signal at a resolution 2^j. Then:

- The approximation signal at a resolution 2^{j+1} contains all the necessary information to compute the same signal at a lower resolution 2^j. This is the causality property.
- The approximation operation is similar at all resolutions. The spaces of approximated functions should thus be derived from one another by scaling each approximated function by the ratio of their resolution values.

Using the above properties, we estimate wavelet coefficients at a finer scale, and then synthesize a high resolution image. Ratio of coefficients across coarse scale are used to estimate the coefficients at a finer scale. The coefficients are up-sampled and passed through the synthesis filter to obtain a zoomed image.

Compressed Video Zooming: The third problem addressed here is video zooming. Novelty of the approach is that zooming is done in the compressed domain, by interpolating the *motion vectors.*

Video zooming problem can be looked as falling in to two classes: temporal to interpolate missing frame in a video sequence and zooming - where a given video is zoomed to get a high resolution video. Temporal zooming is a classical method and, is well addressed in literature. Of late, motion zooming in compressed domain is drawing attention among researchers.

Due to limitations in the channel capacity, we might be transmitting a low resolution version of a given video. At the receiver, we need to extract a high resolution version of the transmitted video. Moreover, video may not be transmitted directly, but, a compressed version may be transmitted. Typically motion information from the adjacent frames, which exploits temporal redundancy, is coded and quantized for video compression. Conventional method which is to decompress the video and then apply interpolation technique is not only computationally high, but may also result in a poor video quality. On the other hand, if we can interpolate the data in the compressed domain, unnecessary coding-decoding can be avoided. Moreover, while doing so, we will have a scheme that is independent of compression standards. Motion vectors are the ones which are independent of compression standards. Thus, if we can interpolate motion vectors at the receiver, we can reconstruct higher resolution video stream at the receiver.

In this work, we develop a motion vector interpolation scheme in the Multiresolution Motion Estimation (MRME) framework. Motivation for doing estimation and compensation in wavelet domain is to avoid the computation of inverse wavelet transform so as to make the overall video encoder/decoder fast. It is observed that traditional block based motion estimation and compensation methods in spatial domain works well with hybrid video coders which incorporates block transforms, unlike the wavelet transform which is global in nature. To remove blocking artifacts caused by motion compensation in spatial domain, overlapping block motion compensation is suggested. This method gives better results when used along with wavelet transform, but with an increased computational cost, due to the need to compute inverse discrete wavelet transform. In the basic MRME scheme motion vectors at finer levels of the wavelet transform are the refinements of the motion vectors at coarser level. It is assumed that the motion vectors at different levels are highly correlated, and this assumption is the basis for our proposed video zooming.

If we want to manipulate video in compressed domain, we have to manipulate motion vectors; namely, we should *interpolate* motion vectors to zoom a compressed video. Using the assumption that motion vectors at different levels to be highly correlated, we estimate motion vectors for the finer resolution. In a conventional coder/decoder, each frame in spatial domain is broken in to sub-blocks of size 8×8 or 16×16, and motion information between two adjacent frames is estimated for each of the sub-blocks. Motion vectors thus estimated are coded directly and motion compensation information is coded in a transform domain, usually the Discrete Cosine Transform (DCT) domain or it could be Discrete Wavelet Domain (DWT) domain. (We use DxT to denote either of the schemes). Decoding operation is the reverse of the coding operation.

Conventional decoders use motion vectors and error components to decompress the given video stream and generate a video of original size. Our algorithm will be a part of the decoder. Once motion vectors are obtained from the conventional video decoder, we interpolate these motion vectors to generate a video of twice the size.

Specific contributions of this dissertation are now summarized below:

- *Color Image Restoration:* A robust color image restoration scheme is proposed, wherein we consider interchannel degradations into account. We assume the blurring on a color plane is dependent on other color planes, and the dependencies on the other color planes is unknown. That is, degradations in red color plane is dependent not only on the neighboring pixels in red plane, but also on the pixels in green and blue plane. Dependencies on the green and blue plane is unknown, but, blur within the red plane is assumed known. A similar assumption is valid for green and blue color planes. We propose a First Order Interchannel Interaction (FOII) model to restore such degraded images.

  We show the utility of proposed model by considering degradations in other color planes as well. We degrade the image in another color plane and apply the FOII model for restoration. We see that the proposed model can restore the images very well even in such applications. Compared to the model that does not consider interchannel interactions, performance of FOII is better, and, the restored images looks better. Thus, the proposed model works very well and is fairly independent of degradations across color planes. We can term FOII as partially blind restoration. Also, performance remains invariant with the amount of interchannel blur, making the FOII model a robust one.

- *Still Image Zooming:* Here we propose to zoom the given image in wavelet domain. We use the properties of zerotree and MRA, to estimate wavelet coefficients at a finer scale. Our new scheme is consistent with the property which states that at sharp edges wavelet coefficients decay exponentially. We take this as a cue to estimate wavelet coefficients at a finer scale. Specifically we use ratio of wavelet coefficients at coarser scales to estimate coefficient at a finer scale. Note that the ratio corresponds to an exponential decay. Proposed method is fast and gives good results. Images have sharp edges, void of blurring. Sharp edges may be attributed to addition of high frequency components. The proposed method performs better, both visually and numerically (SNR) compared to conventional methods.

  The scheme is extended to color images also, and we see that the results are encouraging. Scheme also works well for the principle component of color images.

- *Compressed Video Zooming:* We propose to zoom the given video in compressed domain. This is done by interpolating motion vectors. First we show that we can zoom a given video, frame by frame, by interpolating motion vectors. For this purpose, we evaluate the motion vectors (between frames) of the given video clip. We skip the coding/decoding and quantization/dequatization steps. Motion vectors obtained are directly interpolated to obtain a zoomed video frame. We consider DCT and DWT domain and show that both the domains give similar and acceptable results, with the DWT performing better than the DCT method.

Once we show that motion vector interpolation can give a zoomed video frame, we proceed to zoom an *actual* compressed video stream. We use the MRME based compression scheme. MRME considers motion vector at different levels for coding and quantization, and, is ideal for our requirements. Our algorithm is included during decoding/decompressing. Using motion vectors at different levels we estimate motion vector at finer levels to obtain a zoomed video frame.

We extend the same principle to frame interpolation applications. Frame interpolation is estimating missing frames in a given video. We estimate motion vectors between two frames, and use this information to estimate a location of the block in the missing frame. Effectively, this estimates a frame in a given video. Performance is comparable to the linear interpolation (in spatial domain) method.

The results validate the proposed motion vector based interpolation schemes. The proposed scheme works for different applications and in different domains.

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DEDICATED

To My Father

ನನ್ನೀ ಜೀವನ ಸಮುದ್ರ ಯಾನಕೆ
ಚಿರ ಧ್ರುವ ತಾರೆಯು ನೀನು

मेरे जीवन का समुद्र यान को
चिर ध्रुव तारा हो तुम

For the voyage of my life,
you are the pole star

my Mother

ಮನೆಯೆ ಮೊದಲ ಪಾಠಶಾಲೆ
ಜನನಿ ತಾನೆ ಮೊದಲ ಗುರುವು

घर हि पेहला पाठशाला जननि ही पेहला गुरू

Home is the first school,
mother is the First teacher