IMAGE ENHANCEMENT USING SECOND GENERATION WAVELET TRANSFORM

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Abstract- This paper addresses the problem of recovering a super-resolved image from a set of warped blurred and decimated versions thereof. Due to the factors like processing power limitations and channel capabilities images are often downsampled and transmitted at low bit rates resulting in a low resolution compressed image. In most digital imaging applications, HR images or videos are usually desired for later image processing and analysis. In this paper, we propose lifting schemes for intentionally introducing down sampling of the high resolution image sequence before compression and then utilize super resolution techniques for generating a HR image at the decoder.Extracting more information from multi-source images is an attractive thing in remotely sensed image processing, which is recently called the image fusion. Lifting wavelet transform has its advantages over the ordinary wavelet transform by way of reduction in memory required for its implementation. This is possible because liftingtransform uses in-place computation. The lifting coefficientsreplace the image samples present in the respective memorylocations. In our proposed approach the forward lifting isapplied to the high resolution images which are compressed using Set Partioning in Hierarchical Trees (SPHIT), thecompressed images are transmitted which results in LR images at the encoder, at the decoder superresolution techniques are applied; lifting scheme basedfusion is performed, then decoded using DSPIHT andInverse lifting is applied. Soft thresholding is usedto remove noise and theblur is removed using blind deconvolution, and finally willbe interpolated using our novel interpolation technique.We have performed bothobjective and subjective analysis of the reconstructed image,and the resultant image has better super resolution factor, anda higher ISNR and PSNR.

Keywords- Super-resolution (SR), SPIHT, DSPIHT, Image Registration, Fusion, Interpolation.

I. INTRODUCTION

The super-resolution reconstruction problem is well known and extensively treated in the literature. The main idea is to recover a single high-resolution image from a set of low quality imagesof the same photographed object. Recentwork relates this problem to restoration theory as super-resolutionis a crucial challenge in fields such as astronomy, medical imaging, and microscopy. In electronic imaging, limitations stem from the lens and the size of the sensors, e. g. pixel size.

Since 1970s, charge-coupled device(CCD) and CMOS image sensors have been widely usedto capture digital images. Although these sensors aresuitable for most imaging applications, the currentresolution level and consumer price will not satisfy thefuture demand. Thus, finding a way toincrease the current resolution level is needed. [2]

The most direct solution to increase spatial resolutionis to reduce the pixel size (i.e., increase the no. ofpixels per unit area) by sensor manufacturing techniques.As the pixel size decreases, however, the amount of lightavailable also decreases. It generates shot noise thatdegrades the image quality severely. To reduce the pixelsize without suffering the effects of shot noise, therefore, there exists the limitation of the pixel size reduction, andthe optimally limited pixel size is estimated at about 40µm for a 0.35 µm CMOS process. The current imagesensor technology has almost reached this level. Anotherapproach for enhancing the spatial resolution is toincrease the chip size, which leads to an increase incapacitance. Since large capacitance makes it difficult tospeed up a charge transfer rate, this approach is notconsidered effective. [2]

Terms such as "upscale","upsize", "up-convert" and "uprez" also describe increaseof resolution in either image processing or video editing.Most SR techniques are based on the sameidea: using information from several different images tocreate one upsized image. Algorithms try to extract detailsfrom every image in a sequence to reconstruct other frames. This multiframe approach differssignificantlyfrom sophisticated image (single frame) upsizing methodswhich try to synthesize artificial details.SR works effectively when several LR contain slightly differentperspectives of the same object. Then total informationabout the object exceeds information from any singleframe. If an object doesn't move at all (identical in all frames) no extra information can becollected.Manypractical implementations of super-resolution softwareupscale original material two times. If we need to upsize itfour times, we usually apply SR twice (doneinternally in implementation).[2]

In this paper, the image fusion algorithm based on wavelet transform is proposed to improve the geometric resolution of the images, in which two images to be processed are firstly decomposed into sub-images with different frequency, andthen the information fusion is performed using these images under the certain criterion, and finally these sub-images arereconstructed into the result image with plentiful information. [4]

Interpolation is the process of determining the values of a function at positions lying between its samples. It achieves this process by fitting a continuous function through the discrete input samples. This permits input values to be evaluated at arbitrary positions in the input, not just those defined at the sample points. While sampling generates an infinite bandwidth signal from one that isband limited, interpolation plays an opposite role: it reduces the bandwidth of a signal by applying a low-pass filter to the discrete signal. That is, interpolation reconstructs the signal lost in the sampling process by smoothing the data samples with an interpolation function. [5]

II. METHODOLOGY

SR techniques works on multiframe approach i.e.
1.Basic premise is the availability of multiple LR imagecaptured form the same scene.
2. These multiple LR images provide different “looks” at the same scene.
3. Each LR is naturally shifted with subpixel precision as well as sub sampled.
4. If LR images are shifted by integer units, then each image contains the same information, SR is not possible.
5. If the LR images have different subpixel shifts from each other and if aliasing is present, however, then each image cannot be obtained from the others. In this case, the new information contained in each LRimage can be exploited to obtain an HR image.

The first step to comprehensively analyze the SR image reconstruction problem is to formulate an observation model that relates the original HR image tothe observed LR images. Several observation models have been proposed in the literature, and they can be broadly divided into the models for still images and for videosequence. To present a basic concept of SR reconstruction techniques, we employ the observation model for still images in this article, since it is rather straight forward to extend the still image model to the video sequence model. The motion that occurs during the image acquisition is represented by warp matrix Mk. It may contain global or local translation, rotation, and so on. Since this information is generally unknown, we need to estimate the scene motion for each frame with reference to one particular frame. The warping process performed on HR image x is actually defined in terms of LR pixel spacing when we estimate it. Thus, this step requires interpolation when the fractional unit of motion is not equal to the HRsensor grid.

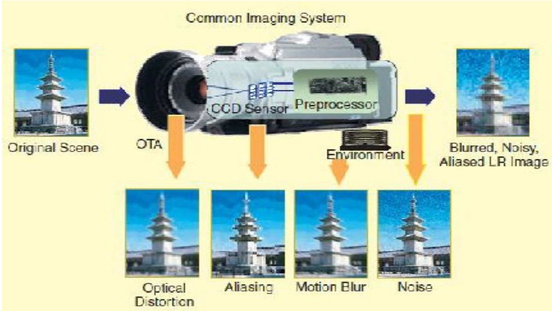


Figure 1: Common imaging system (fig from [2])

Although one could use ideal interpolation theoretically, in practice, simple methods such as zero-order hold or bilinear interpolation methods have been used in many literatures. Blurring may be caused by an optical system (e.g., out of focus, diffraction limit, aberration, etc.) In single image restoration applications, the optical or motion blur is usually considered. In the SR image reconstruction, however, the finiteness of a physical dimension in LR sensors is an important factor of blur. In the use of SR reconstruction methods, the characteristics of the blur are assumed to be known. A slightly different LR image acquisition model can be derived by discretizing a continuous warped, blurred scene. In this case, the observation model must include the fractional pixels at the border of the blur support.

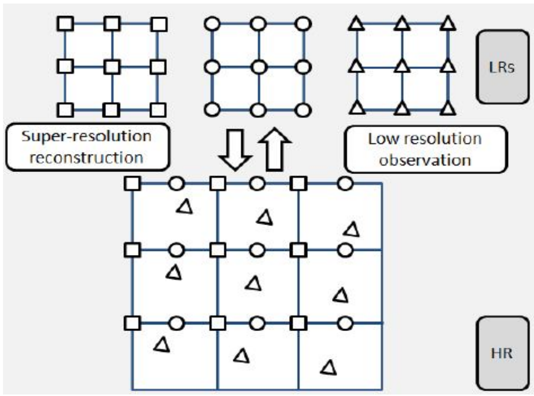


Figure 2:The basic idea for super-resolution reconstruction from multiple low-resolution frames.

Subpixel motion provides the complementary information among the low-resolution frames that makes SR reconstruction possible. (Fig from [9])

❖ Necessity of Interpolation in HR Sensor Grid

An example for global translation is shown in Figure 2. Here, a circle represents the original HR image x, and a triangle and a squareare globally shifted versions of x. If the down-sampling factor is two, a square has (0.5, 0.5) subpixel shift for the horizontal and vertical directions and a triangle has a shift which is less than (0.5, 0.5). As shown in Figure, a square does not need interpolation, but a triangle should be interpolated from x since it is not located on the HR grid.

III. OBSERVATION MODEL

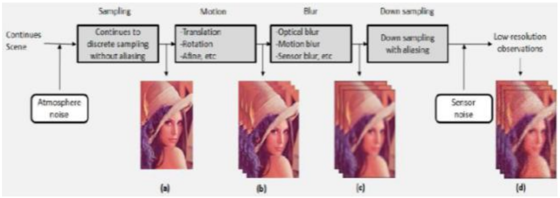


Figure3:The observation model of a real imaging system relating a high resolution image to the low resolution observation frames with motion between the scene and the camera.

The digital imaging system is not perfect due to hardware limitations, acquiring images with various kinds of degradations. For example, the finite aperture size causes optical blur, modeled by Point Spread Function (PSF). The finite aperture time results in motion blur, which is very common in videos. The finite sensor size leads to sensor blur; the image pixel is generated by integration over the sensor area instead of impulse sampling. The limited sensor density leads to aliasing effects, limiting the spatial resolution of the achieved image. Thesedegradations are modeled fully or partially in different SR techniques.

IV. WAVELET TRANSFORM

The lifting-based wavelet transform can be seen as a succession of three operations: split, predict and update. In the first operation, data is the split into even and odds parts (known also as the lazy wavelet transform). Then, differences or details are calculated through the usage of a predictor. Finally, to compute the average, the even part is updated using the details previously calculated.

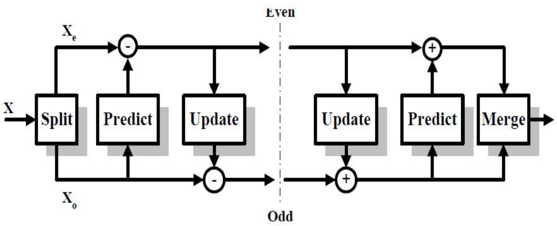


Figure 4: lifting-based wavelet transform. (Fig from [3])

- Split - Divides data into even half and odd half
- Predict –the predict step uses a function that approximates the data set. The difference between the approximation and the actual data replaces the odd elements of the data set. The even elements are left unchanged and become the input for the next step in the transform. In this step odd values are “predicted” from the even value is described by the equation. The inverse predicts transform adds the prediction value to the odd element. In the inverse transform the predict step is followed by a merge step which interleaves the odd and even elements back into a single data stream.
- Update – the update follows the predict phase the original value of the odd elements as been overwritten by the difference between odd and even “predictor”. Does normalization and performs scaling function this smooth’s the data.

❖ Image Compression

The discrete wavelet transform, whichreplaces the DCT, is applied first to the source image. The transformed coefficients are then quantized. Finally, the output coefficients from the quantizer are encoded (using eitherHuffman coding or arithmetic coding techniques) to generate the compressed image. To recover the original image the inverse process is applied.

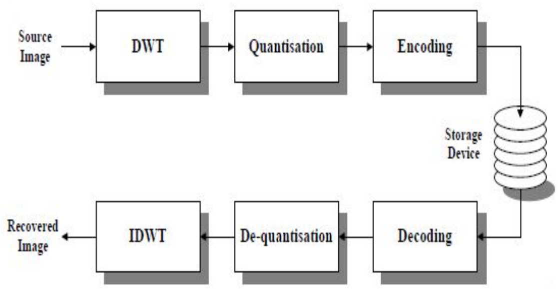


Figure 5: Wavelet based encoding scheme (fig from [3])

❖ Lifting scheme forward Wavelet Transform

- Set Partitioning in Hierarchical Trees (SPIHT) is an image compression algorithm that exploits the inherent similarities across the sub bands in a wavelet decomposition of an image. The algorithm codes the most important wavelet transform coefficients first, and transmits the bits so that an increasingly refinedcopy of the original image can be obtained progressively.
- SPIHT consists of two passes, the ordering pass andthe refinement pass. SPIHT maintains three lists of coordinates ofcoefficients in the decomposition. These are the Listof Insignificant Pixels (LIP), the List of SignificantPixels (LSP) and the List of Insignificant Sets (LIS).
- To decide if a coefficient is significant or not SPIHTuses the following definition. A coefficient is deemedsignificant at a certain threshold if its magnitude islarger than or equal to the threshold.

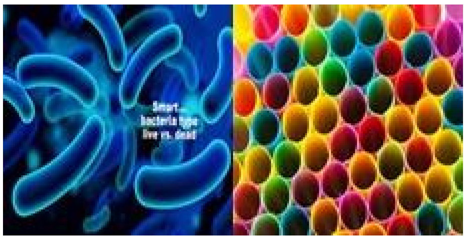
V. ALGORITHM

I. Five input low resolution blurred, noisy, under sampled, rotated, shifted and compressedimages are considered.
II. The images are first preprocessed, i.e.registered using FFT based algorithm.
III. The registered low resolution images aredecomposed using lifting schemes to a specifiednumber of levels. 3. At each level we will haveone approximation i.e., A subband and 3 detailsubbands, i.e. H, V, D coefficients.

IV. Each low resolution image is encoded usingSPHIT. The decomposed images are fused using the fusion rule, detail coefficients are fused separately.
V. Inverse lifting scheme is applied to obtain the fused image.
VI. The fused image is decoded using DSPHIT.
VII. Restoration is performed in order to remove the blur and noise present in the image.
VIII. Most of the additive noise will be eliminated during the fusion process, to achieve further noise reduction soft thresolding is applied, whereas the image is deblurred using Iterative Blind Deconvolution Algorithm (IBD).
IX. Finally a super resolution image is obtained by wavelet based Interpolation.

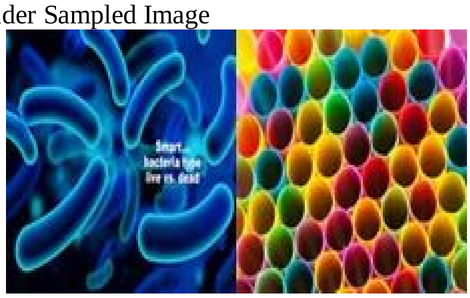
VI. RESULTS

1. Blurred Image

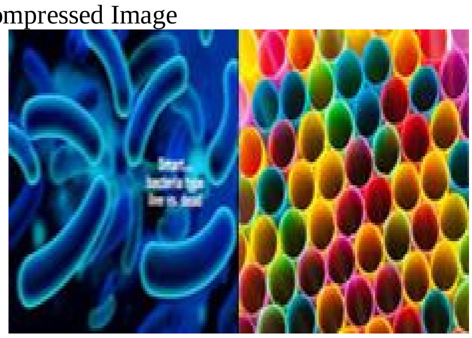


2. Noisy Image

3. Under Sampled Image



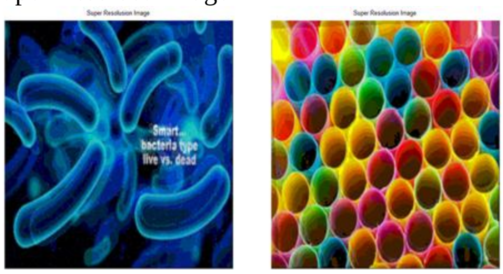
4. Compressed Image



5. Rotated Image

6. Fused Image

7. Super Resolved Image



CONCLUSION

Here different types of down sampled images are obtained from the single image by adding different distortion like blur, rotation, noise and compression to down sample images. Then these images are fused for further processing super resolution techniques have proved to be useful in many different applications in terms of quality and computational complexity. A hardware and software implementation of SRR is possible. SRR can be incorporated as a feature in video editing software, cellular networks and video sites such as you tube could utilize super resolution capabilities to improve the quality of video clips taken by cellphones. The advantage of the proposed method is that lifting schemes is used for there construction of a high resolution image.

Wavelet lifting schemes are faster, easier to implant the inverse transform requires less memory and can be used on arbitrary geometrics.

In the proposed approach, we are using FFT based image registration to register the rotated, shifted images and we are using SPIHT algorithm for encoded and DSPIHT algorithm for decoding and finally we are performing iterative blind deconvolution to deblur the image. The super-resolution techniques for image can be extended to a video sequence by simply shifting along the temporal line.

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