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An improved Wavelet Lifting based Image Super Resolution

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***Abstract*- Ever since over three decades, computers have been extensively used for processing and exhibiting images. The capability to process visual information from a super resolution image can improve the information present in the image. The inspiration is from a human eye which takes in raw images (noisy, blurred and translated) and constructs asuper resolution image. In this technique lifting wavelet transform and stationary wavelet transform is used to increase the spatial resolution .The wavelet domain filters support to model the regularity of natural images while the edge details of image get sharper while up sampling. An iterative back projection method is used to reconstruct the high resolution image in an efficient iterative manner.**

***Index Terms*- Super resolution, lifting wavelet transform, stationary wavelet transform.**

I. INTRODUCTION

The low resolution representation resulting from the lowerspatial sampling frequency produces distortion in the image duetheto loss of high frequency components. This causes loss ofimportant information such as edges and textures. Also adegradation occurs due to the sensor point spread function(PSF), and optical blurring due to camera motion or out-offocus. Thus an image captured with a low resolution camerasuffers from aliasing, blurring and presence of noise. Superresolution (SR) refers to the process of producing a high spatialresolution image from several low resolution images, therebyincreasing the maximum spatial frequency and removing thedegradations that arise during the image capturing process usinga low resolution camera. In effect, the super-resolution processextrapolates the high frequency components and minimizesaliasing and blurring. Super Resolution is an emerging technology in signal processing area to get a HighResolution (HR) image. The central aim of Super Resolution (SR) is to enhance thespatial resolution of multiple lower resolution images. HR means pixel density withinthe image is high and indicates more details about original scene. The super resolutiontechnique is an efficient lossy and low cost technology.In this paper we are usingWavelet Transform (WT) technique to get an HR image from Low Resolution (LR)images by involving image registration, blurring, decimation, re-registration, deblurring,denoising and interpolation operation.One way to increase the sampling rate is to reduce the pixel size,thereby increasing the pixel density. But an in crease in pixeldensity causes shot noise and hence the distortion. Also the costof sensor increases with the increase in pixel density. Hence thesensor modification is not always a practical solution forincreasing the resolution. Thus we resort to image processingtechniques to enhance the resolution. The advantage here is thatthere is no additional hardware cost involved and also it offersflexibility such as region of interest super-resolution.

The fundamental idea in the back of this mission is to increase a excessive decision image from aseries of low decision compressed images. Lifting Schemes are proposed on thisstudies for intentionally introducing down sampling of the excessive decision imagesequence before the compression and then utilize the awesome decision techniques forproducing a high-resolutionimage on the decoder. Super Resolution Reconstruction canbe integrated as a feature in video editing software program, mobile networks and video sitesincluding YouTube ought to utilize amazing decision capabilities to enhance the quality ofvideos taken by mobile phones.

II. RELATED WORKS

The methods developed so far can be divided into three differentcategories: (1) frequency domain reconstruction (2) Iterative (3)Bayesian Method. Frequency domain reconstruction methodwas first proposed by Tsai and Huang [2]. In this method, thedata is first transformed to the frequency domain where it is thencombined. This data is then transformed back into the spatialdomain where the new image will have a higher resolution thanthe original frames. A high resolution image can also bereconstructed using a POCS algorithm, where the estimatedreconstruction is successively obtained on different convex sets.The POCS method was originally developed by Tekalp, Ozkan,and Sezan [3]. The method proposed by Michal Irani andSchmuelPeleg [4] falls into the class of iterative algorithms.The main feature of the Irani and Peleg method is that ititeratively uses the current best guess for the SR image to createLR images and then compare the simulated LR images to theoriginal LR images. These difference images (found bysubtracting real LR - simulated LR) are then used to improve theinitial guess by" back projecting" each value in the differenceimage onto the SR image. The Bayesian method was developedby Cheeseman [9] at NASA for SR reconstruction of planetaryimages. The name comes from Bayes theory, this method relieslargely on the statistical knowledge that pixel to pixeldifferences are very small, and can be modeled with aprobability distribution function. The Bayesian method seeks tofind the solution possessing the maximum probability (i.e. themost likely surface given the observed values and theobservation conditions).The major challenges for super resolution are image registration, computationefficiency, robustness aspects, and speed issue (fast algorithm implementation).

Image Registration: For a successful multi-frame SR reconstruction, image registration is critical as theuseful high resolution image spatial samplings are fused together. Image Registration isa simple problem in image processing whereas in SRIR, this becomes more complicatedsince the reference images used here are low resolution images with high aliasingartifacts. As the resolution of an image decreases, resulting decrement in theperformance of the image registration algorithms, yielding more errors. Theseregistration errors can give birth to the artifacts which are more annoying visually than ablurred image. Robinson and Milanfar (2004) proposed that registration performance isbounded even in global translation. Low resolution image registration and highresolution image estimation are in some way dependent on each other. High resolutionimage estimation gets its advantage from accurate sub pixel motion estimation which ispossible because of high quality image. Hence low resolution image registration andhigh resolution image estimation can together lead to joint ML or MAP framework. Theinterdependency between LR image registration and HR image estimation is recordedby these joint estimation algorithms and the improvements in performance are alsoconsidered.

Computation Efficiency: Expensive matrix manipulations due to large number of unknowns results inferiorcomputation efficiency. In the practical scenario, high efficiency of SR reconstruction isrequired due to its real time applications such as surveillance video. For tuningparameters in loop, the SR systems efficiency is also desired. Hardie (2007) proposed analgorithm with good computation efficiency compared to previous algorithms in realtime with global translation model. As the non-translational errors occur, thecomputation goes up and this condition gets better by massive parallel computing. Inturn parallel computing like graphics processing unitand hardware implementationsaffect the future applications of SR techniques.

Robustness Aspects: Traditional Super Resolution techniques are not able to withstand the outlier's such asmotion errors, inaccurate blur models, moving objects, motion blur,noise etc.Robustness of SR technique is of high attention because of inadequacy in the perfectestimation of the image degradation model parameters and the low ability to withstandthe outliers. Chiang and Boulte (2000) combined the up-sampled images to handle withoutliers from non-stationary noise using median estimation. Zomet et al. (2001) gave adifferent way of handling the problem by using the robust median based gradient for theoptimization to avoid the influence of outliers. M.V.W.Zibetti and J.Mayer. (2006)proposed a Huber norm simultaneous super resolution as the prior for robustregularization. Phamet al. (2006) proposed a robust certainty to each neighboringsample for interpolating unknown data, with the same photometric based weightingscheme used in bilateral filtering. Probabilistic motion model (2009) also makes use ofsimilar uncertainty scheme to handle optical flow motion estimation errors based onblock matching. Most of the algorithms discussed above have shown goodimprovements in case of outliers.

Performance Limits: Fundamental understanding of the performance limits of SR reconstruction algorithmsis very much important. As performance limits may help in understanding the SRcamera design, in analysis of model errors, number of frames, zooming factors etc. Thestudy of the performance limits of all SR techniques is quite difficult. Many componentsdependent on each other which are existing in SR reconstruction makes it a complextask. In case of example based approaches, the most informative part for a given SRreconstruction task is still unknown. Other than a simple Mean Square Error (MSE), agood measure is required for performance evaluation. An estimation with higher MSEdoes not have a pleasing view. Bi-cubic interpolation is successful in achieving smaller MSE when compared to some example based approaches.

III. PROPOSEDWORK

The low resolution image IL can be obtained by multiplyingwith a scaling factor S,which work as top left quadrant (LL) offinal high resolution image. Thus obtained input lowresolution image is decomposed into different frequency subbands by lifting wavelet transform using Haar as lift wave.Four frequency sub bands are generated by LWT, out of whichthree are high-frequency and one is low-frequency sub band.The high frequeny sub bands contain detail coefficients whichare essential in the reconstruction of the final high resolutionimage.

The stationary wavelet transform which generates variousfrequency sub bands ,high-frequency sub bands containhorizontal, vertical and diagonal detail coefficients of inputimage.The sub bands generated by SWT has the size same asthat of the input image.Initial interpolation of high-frequencysub bands generated using LWT is required because LWTuses sampling that generates frequency sub bands half of thesize of input image. So high-frequency sub bands generated byLWT are initially interpolated with factor of 2 . Theseinterpolated high frequency sub bands are adjusted by addinghigh-frequency sub bands generated using SWT. We combinethe high wavelet sub bands (LH,HL and HH) achieved by bothLWT and SWT with the low wavelet band (LL) used in LWT.This combination result in initialization of detailed highfrequency sub bands which is essential for iterative backprojection.

Based on this pre-process, we are able to refine the waveletcoefficients in different sub bands in the later iterations. Thesub bands are combined using inverse lifting wavelettransform. After up-sampling the image IH(t) can be blurredlittle bit, by using a Gaussian filter which merely work assmoothing kernel. As the blurred effect is very low orignorable Gaussian filter is applied only once.Fig.1 is the block level representation of the proposed algorithm and the following introduces the details in each step. The first step is down sampling to get low-resolution image. The low-resolution image can be created by taking the high-resolution and down sampling by a factor of 4.The high resolution image is first divided into 2x2 blocks and the new pixel value of down sampled image IL is obtained by taking the mean value of each block.

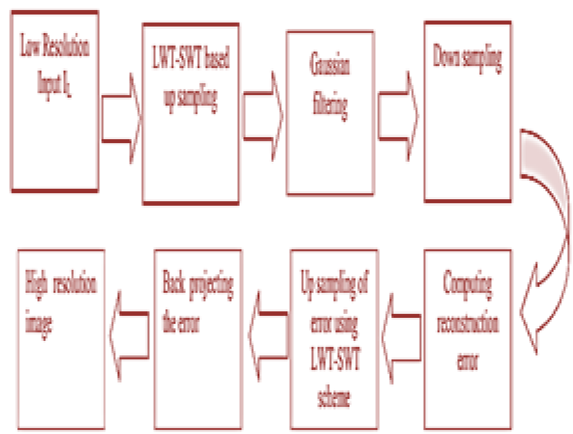

Fig1. Block level representation of the algorithm

Next we have to up sample the image which is the secondstep of the algorithm. The initial high-resolution image IH(0) isachieved by the synthesis of wavelet coefficients from highresolution image nterpolated by using LWT and SWT. Themother wavelet used is HAAR because it is computationallyfast. There are several other wavelets such as sym; db4 etc. butthe computation time required is more. The proposed upsampling scheme is shown in fig 2.The analysis filter bank which consist of low pass and highpass filters at each decomposition stage can be used for signaldecomposition and split signal into two bands. The coarseinformation is fetched by the low pass filter (equivalent to anaveraging operation) whereas the high pass filter fetch detailinformation (equivalent to a differencing operation) of theimage.

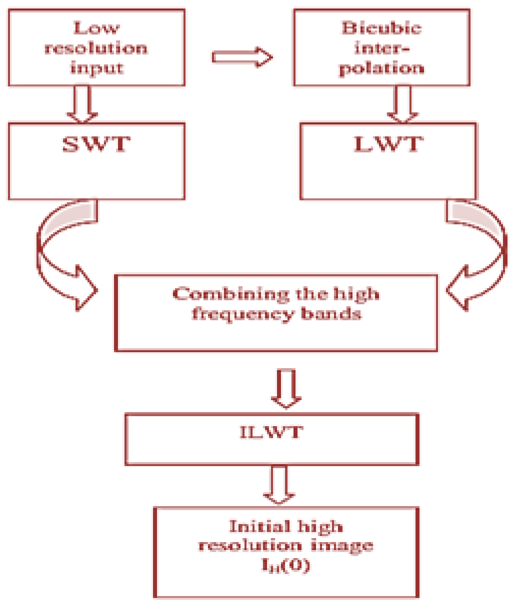

Fig 2. Proposed Up-sampling Scheme

For 2-D transform, filtering of the image is done along thex-dimension using low pass and high pass analysis filters anddecimated by a factor two, followed by filtering of the subimage along the y-dimension and decimated by two. After onelevel of decomposition the resultant image has been split intofour bands LL, HL, LH, and HH,. The LL band is againsubject to decomposition. This process is called pyramidaldecomposition of the image. Reversing the above procedureresults in the reconstruction of the image.Finally all four-sub bands are interpolated by a factor K/2and inverse LWT is taken to get the up sampled image withsize km x kn .

The third step is Gaussian filtering. After the up samplingprocess the image may look little bit blurred. So Gaussianfilter can be used to reduce rise and fall time of the stepfunction of the input. Since Gaussian filter is a smoothingkernel, it is applied once in the first stage of iteration .Thefiltered image IhG , is then down-sampled. It is same as that ofstep 1 ie, down-sampled by averaging every 4pixels, formingIId(t),where t means the tth iteration.Reconstruction is the most important part of thealgorithm.In this stage of algorithm error is calculated betweenoriginal low-resolution image IL and down sampled image IhGand is termed as reconstruction error E(t).The error that wefind in this stage is used as the correction parameter forrefining coefficients of sub bands. After three iterations errorbecomes so small that it can be neglected.

IV. CONCLUSION

Super resolution techniques have verified to be useful in manydissimilar applications in terms of quality and computationalcomplexity. Utmost of the existing super resolution methodstry to increase the resolving power by means of bilinearinterpolation, which only adds pixels but does not progress theresolving power. The lifting scheme forms a newwavelet, with amended properties, by adding a new basisfunction and does not necessitate auxiliary memory. The LWT hasbenefit over DWT such as the transform can be modifiedlocally while preserving invertibility.

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