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Enhancing the resolution and perceptual quality of web video and images by super-resolution

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Abstract*— In this paper, we present a robust single-image super-resolution (SR) method in the compression scenario, which is competent for simultaneously increasing the resolution and perceptual quality of web image/video with different content and degradation levels. Super resolution terms such as "upscale", "upsize", "up-convert" and "uprez" also describe increase of resolution in either image processing and for video we used certain interframe interaction and simple spatio-temporal coherency optimization. First, we propose to analyse the image energy change characteristics during the iterative regularization process, i.e., the energy change ratio between primitive and non-primitive fields. Based on the revealed convergence property of the energy change ratio, appropriate regularization strength can then be determined to well balance compression artefacts removal and primitive components preservation. Second, we verify that this adaptive regularization can steadily and greatly improve the pair matching accuracy in learning-based super-resolution. Consequently, their combination effectively eliminates the quantization noise and meanwhile faithfully compensates the missing high-frequency details, yielding powerful super-resolution performance in the compression scenario. The algorithm attempts to recognize local features in the low resolution images and then enhances their resolution in an appropriate manner. Enhancements treated here include improvement of image resolution, perceptual quality of objects.

Keywords*— artefacts removal, compression, energy change ratio, learning-based super-resolution (SR), Primitive & non-primitive field,** **partial differential equation** ***(PDE), regularization, spatio-temporal coherency optimizatio.

I. INTRODUCTION

In most digital imaging applications, high resolution images or videos are usually desired for later image processing and analysis. The desire for high image resolution stems from two principal application areas: improvement of pictorial information for human interpretation; and helping representation for automatic machine perception. Image resolution describes the details contained in an image, the higher the resolution, and the more image details. The resolution of a digital image can be classified in many different ways: pixel resolution, spatial resolution, , temporal resolution, and radiometric resolution. Previous work on single-image SR can be roughly divided into four categories: interpolation-based [1]–[4], reconstruction- based [5], [6], classification-based [7] and learning-based [8]. Despite great diversity in implementation, these methods have a common premise that the LR image is only degraded by down sampling. This is not always true in the web environment, where compression is widely adopted. For image search engines, compression helps reduce the thumbnail size by up to 50% without obvious perceptual quality loss when presented in the LR form.

Video super-resolution is a technique to increase the resolution of a movie by exploiting the redundancy between frames. It’s easiest to understand the technique by first thinking of the corresponding technology in images. It’s possible to increase the effective resolution of an image by taking multiple pictures, each offset by a fraction of a pixel, and subsequently joining them. Some early digital photo cameras had this pixel-shifting technology built-in; the CCD was physically displaced (or maybe it was a lens) by half a pixel horizontally and two images would be stitched together. Video super-resolution uses the same basic premise. Subsequent frames in a video are only slightly different from each other - this is what makes video highly compressible. You can model the change from one frame to the next as a non-rigid transformation. Once optic flow has been estimated images can be aligned by undoing the warping created by optic flow. Then subsequent video frames can be stitched together as in image pixel-shifting to form a super-resolution video.

There is a large demand for improving the perceptual quality of web image/video, between which the resolution enhancement, also known as super-resolution (SR), is an especially important issue and attracts a lot of attention. SR refers to the techniques achieving high-resolution (HR) enlargements of pixel based low-resolution (LR) image/video. Basically, there are two kinds of SR, according to the amount of LR images utilized: multi-image

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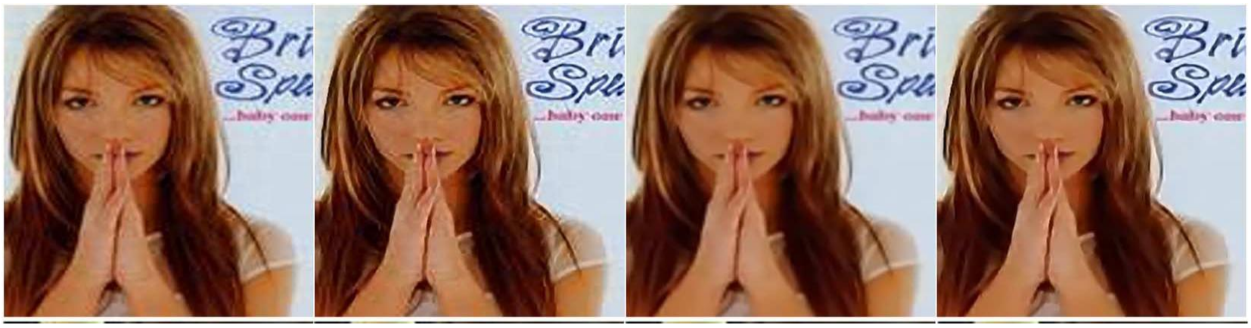
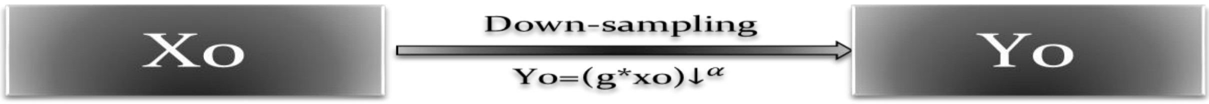
SR, which requires several LR images of the same scene to be aligned in sub pixel accuracy, and single-image SR, which generates a HR image from a unique source.



II. IMAGE SUPER-RESOLUTION

A. DOWN SAMPLING

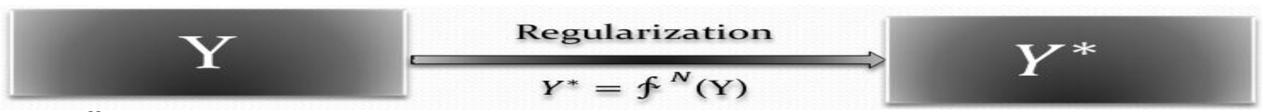


X_0=Original HR image and Y0=(g*X_0)$\downarrow^{\alpha}$ Add noise in HR image X_0 i.e Gaussian noise & uniform noise$\downarrow^{\alpha}$ is decimation operator with scaling factor α.In signal processing, down-sampling (or "subsampling") is the process of reducing the sampling rate of a signal. This is usually done to reduce the data rate or the size of the data.

B. COMPRESSION

Y=Y0+EQ where Y0=Combination of HR image with Gaussian noise EQ=Quantization noise Here we get actual input to our Project which is noisy image at the time of Down-sampling & Compression Image compression: is minimizing the size in bytes of a graphics file without degrading the quality of the image to an unacceptable level.

C. REGULARIZATION



$Y^* = f^N$(Y)

where f(.)=Denotes the PDE regularization function N=Superscript N represents total number regularization Now we perform UP-Sample on data that is Y to Y^* using regularization & biqubic interpolation Regularization is mathematical & statistical term Its mostly used in learning & inverse the problem

PDE Regularization (Partial Differential Equation) Here we check SNR signal to noise ratio
Noise =noise data-original
If ver.noise==0
S=99.99% INF.Clean image
Else

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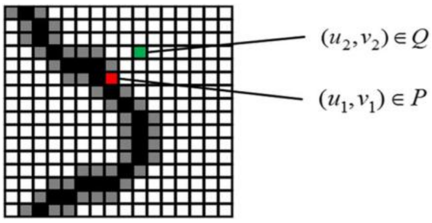
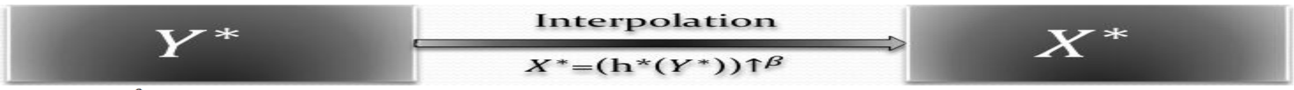
S=10*log10(var original/var noise)
end

Iteration number N.Most of the time the image obtained at $n \rightarrow \infty$ is constant So here compression artifacts are effectively eliminated while primitive components well preserved

Adaptive Regularization:



D. INTERPOLATION



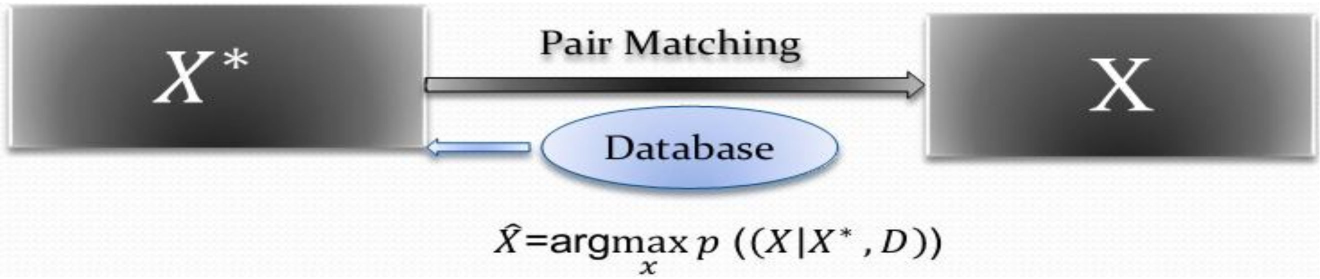
$X^*=(h^*(Y^*))\uparrow^{\beta}$

where h= bicubic interpolation filter, Y^* =up-sample image ,B=Scelling Factor. Here we find edge & non edge portion (PF & NPF form). Interpolation produces a function that matches the given data exactly. The function then can be utilized to approximate the data values at intermediate points. Interpolation may also be used to produce a smooth graph of a function for which values are known only at discrete points, either from measurements or calculations.

Bicubic Interpolation: For bicubic interpolation, the block uses the weighted average of four translated pixel values for each output pixel value. For example, suppose this matrix, represents your input image. You want to translate this image 0.5 pixel in the positive horizontal direction using bicubic interpolation. The Translate block's bicubic interpolation algorithm is illustrated Zero pad the input matrix and translate it by 0.5 pixel to the right

Principal component analysis(PCA): Principal component analysis (PCA) is a mathematical procedure that uses orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal Components.Commonly used to find form factor Linear projection method is used to reduce number of parameter. ransfer the set of correlated variable to new uncorrelated variable**.** Map data in to a space of lower dimensionality and we form eigenvalue and eigenvector. Eigen vector shows the direction of axis and the eigenvalue shows the significant of corresponding axis

E. PAIR MATCHING



$\hat{X}=\arg\max_{x} p\ ((X|X^*, D))$

where X is obtained after learning base pair matching from X*, D= Database, MAP= Maximum Posterior Probability.perform on Learning base Pair Matching Its Perform on 3 different categor

1-Without compression P0, 2-With compression but not regularization P1, 3- With compression and regularization P2For pair Matching we used.

ROC(Receiver operating character curve): Which shows the tradeoff between match error & hit rate

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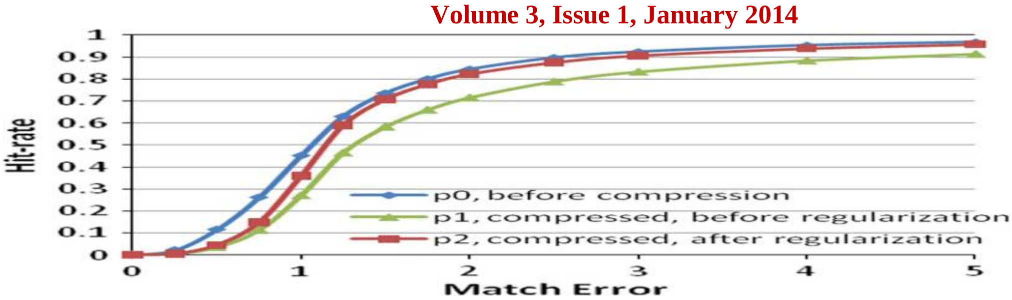
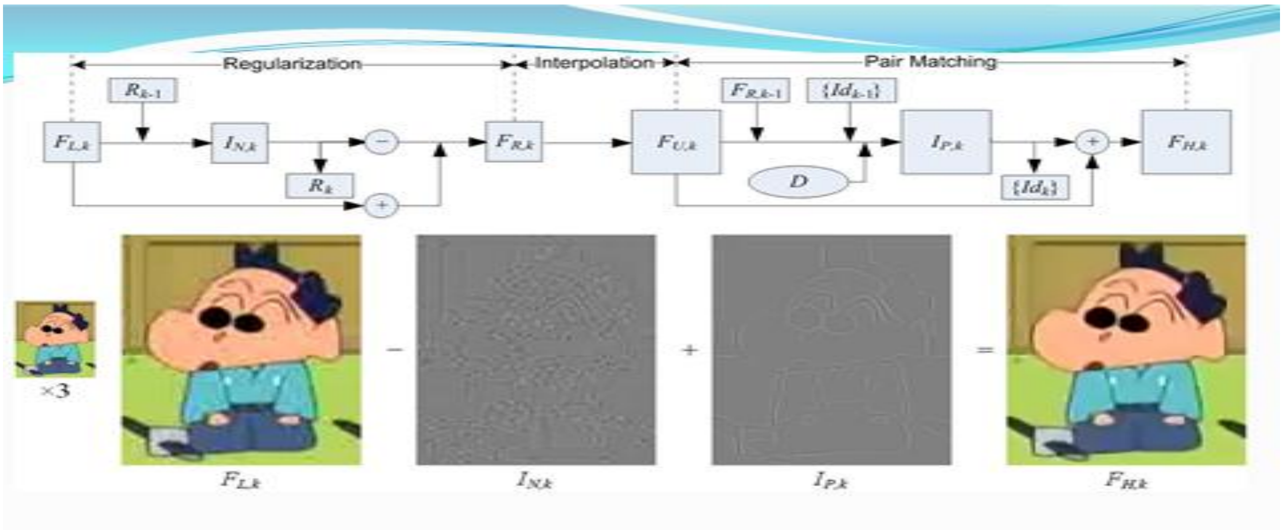


ROC curves of pair matching accuracy. 50,000 primitive patches are tested over 100,000 trained examples.

III. VIDEO SUPER-RESOLUTION



our scheme is competent for the SR task of web videos with dynamic content and different degradation levels.First, a K th frame $F_{l,k}$ from an LR video is divided into PF and NPF. Iterative PDE regularization is performed on $F_{l,k}$ during which the energy change velocities in both PF and NPF are recorded.When the ratio of these two velocities converges regularization stops and the accumulated noise image $I_{n,k}$ is subtracted from $F_{l,k}$. resulting in an artifacts-relieved frame $F_{R,k}$. Then $F_{R,k}$ is upsampled to the desired resolution through bicubic interpolation.Last, the primitive components in the interpolated frame $F_{U,k}$ are enhanced with learning-based pair matching. Meanwhile, the temporal consistency is enforced by referring to the previous interpolated frame $F_{U,k-1}$ and its pair matching indices $I_{d,k-1}$.Adding the primitive enhancing image $I_{p,k}$ back to $F_{U,k}$, the final HR frame F_{Hk} is generated.

IV ALGORITHM IMPLEMENTATION

Algorithm: The algorithm for compressed image SR is as follows:
Input: Compressed Low resolution image Y
Output: Enhanced high resolution image X (i.e. SR)
START
1. Perform up sampling Y to X_o* using Bicubic interpolation

2. Find the Edges (primitive field) and non-edge portion (Non primitive fields) partitioned (P,Q) of X_o* through the orientation energy edge detection.
2.1 perform PCA based training

3. Perform iterative PDE regularization on Y:
3.1 After each iteration, up sample the regularized image Y_n* to X_n*, where n=1,2,…….through Bicubic interpolation;
3.2 Calculate the image energy change based on the PF/NPF partition
3.3 Calculate the energy change ratio between PF and NPF

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3.4 Find the maximum value of ratio
3.5 mention a condition to stop regularization

4. Extract LR primitive patches from and find corresponding HR primitive patches from a prepared database through pair matching speeded up by the approximate nearest neighbour (ANN) tree searching.

5. Add the HR primitive patches back to X_N* to form the final HR image X, where the compatibility of neighbouring HR primitive patches is enforced by averaging the pixel values in overlapped regions.

V. RESULTS ACCOMPLISHED

Legend used for the tables

A. MAP estimation of PSNR
B. MSE estimation of PSNR
C. Using Uniform Gaussian Type
D. Using Non-Uniform Gaussian Type
E. Using AR
F. Using AR_Areg
G. Using AR_Areg_PM
H. Using Dataset-1
I. Using Dataset-2

ALGORITHM IN TEST: AR

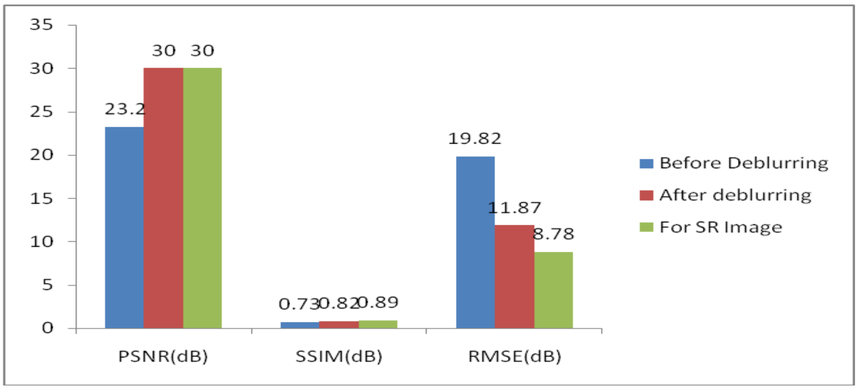

Fig.1 Combination for Test A-C-E-H in AR Algorithm

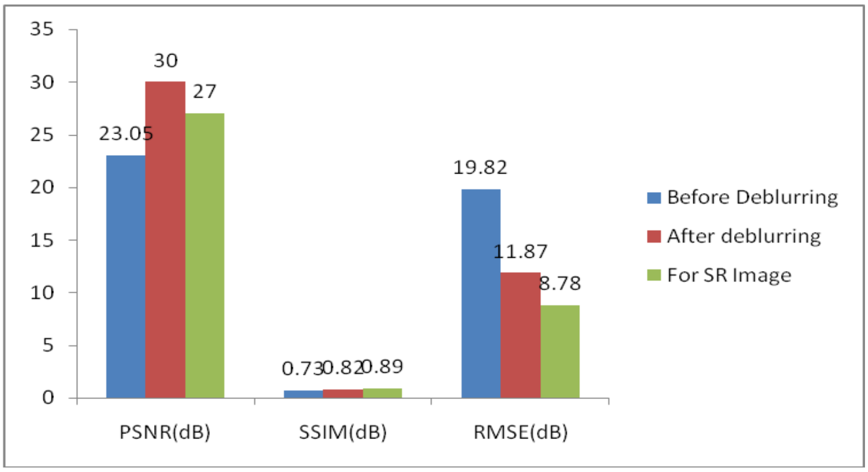

Fig.2 Combination for Test B-C-E-H in AR Algorithm

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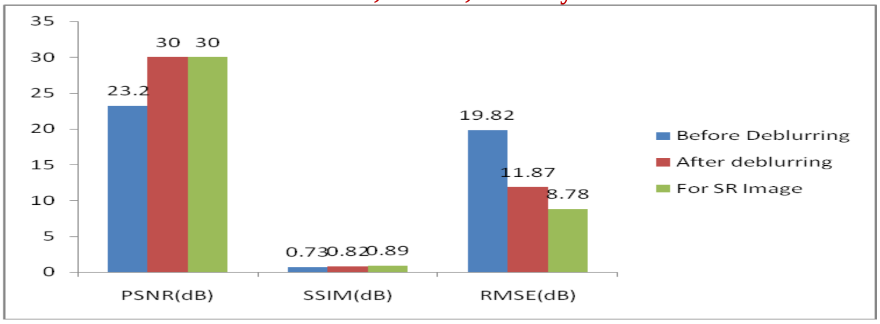

Fig.3 Combination for Test A-D-E-H in AR Algorithm

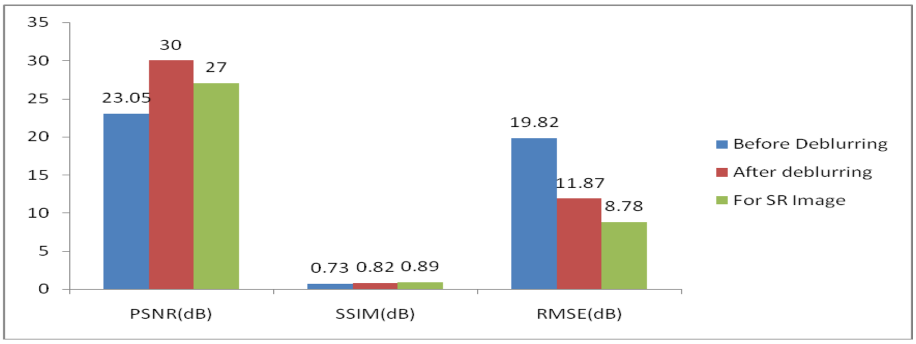

Fig.4 Combination for Test B-D-E-H in AR Algorithm

ALGORITHM IN TEST: AR_Areg

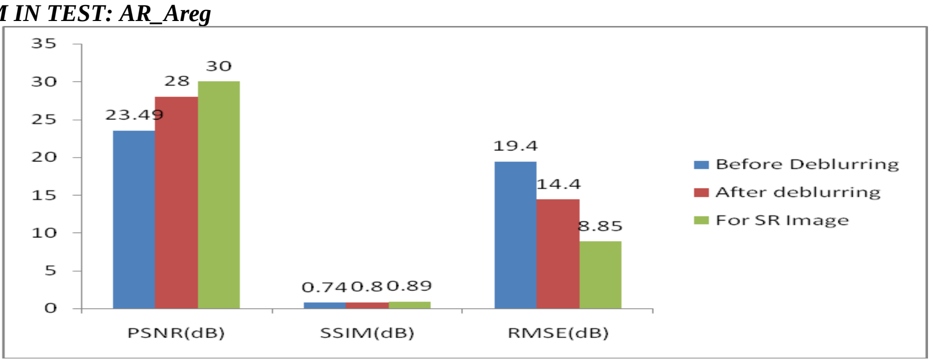

Fig 5 Combination for Test A-C-F-H in AR_AReg Algorithm

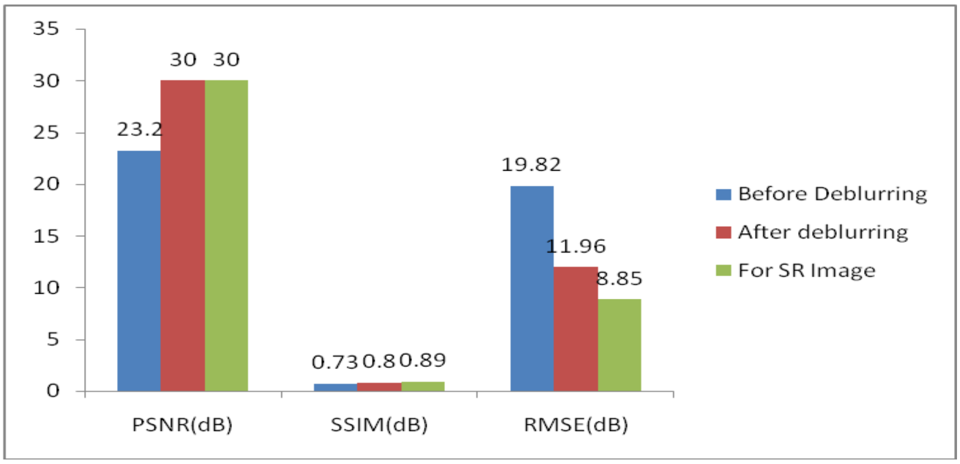

Fig 6. Combination for Test B-C-F-H in AR_AReg Algorithm

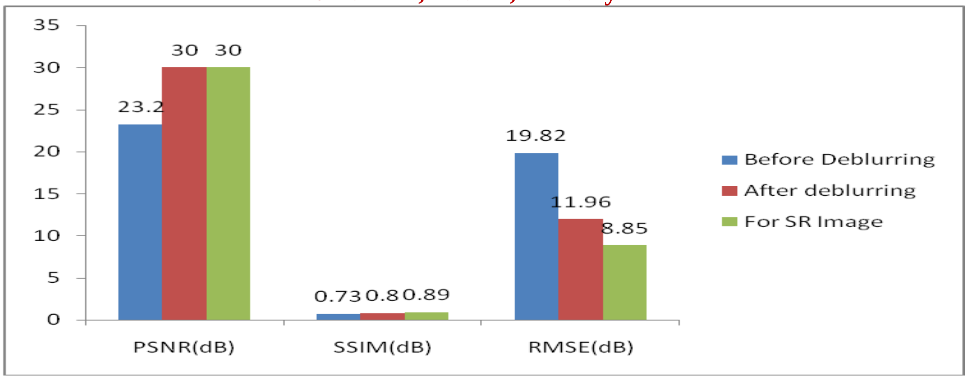

Fig 7. Combination for Test A-D-F-H in AR_AReg Algorithm

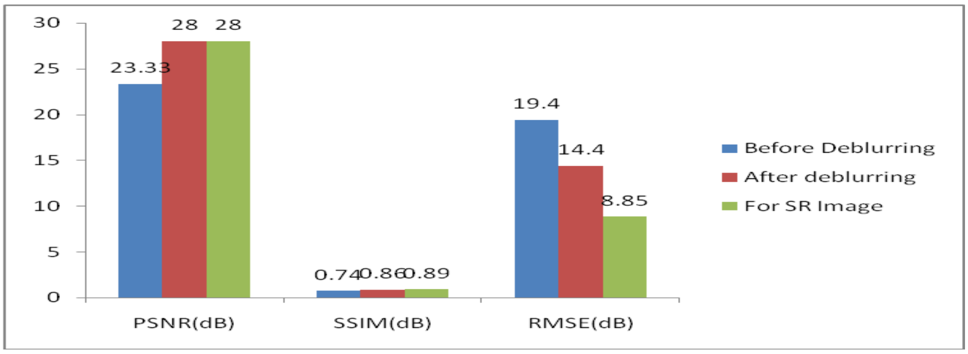

Fig 8. Combination for Test B-D-F-H in AR_AReg Algorithm

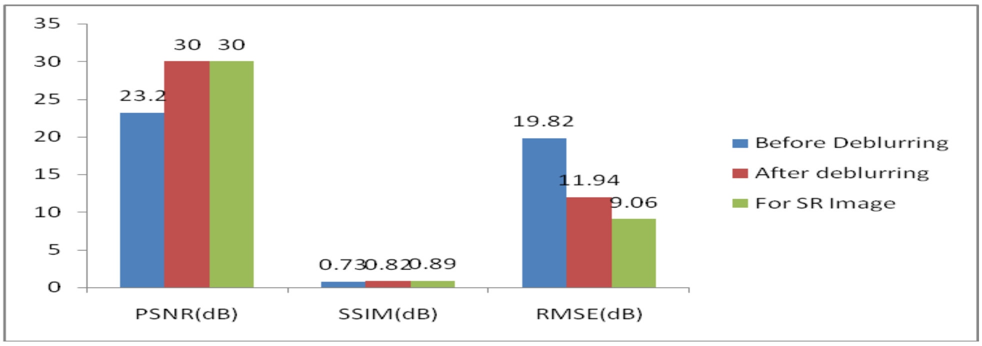

Fig 9. Combination for Test A-C-G-H in AR_AReg_PM Algorithm

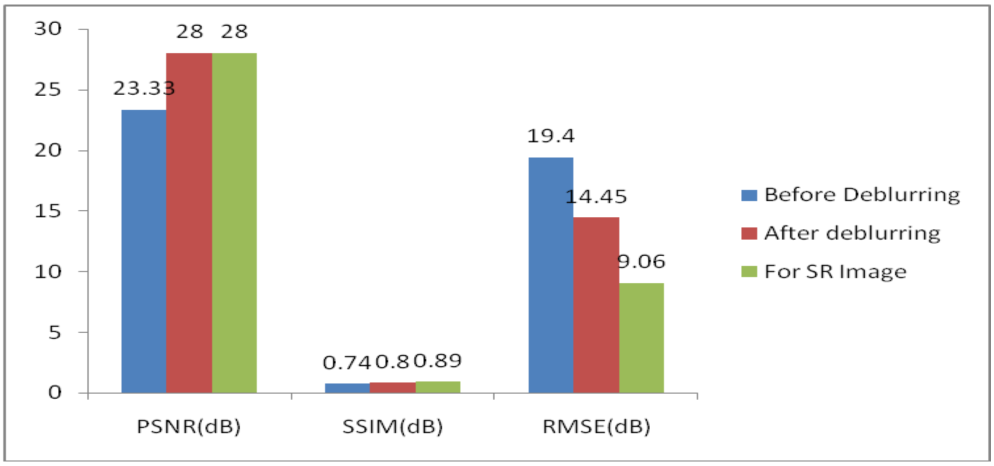

Fig 10. Combination for Test B-C-G-H in AR_AReg_PM Algorithm

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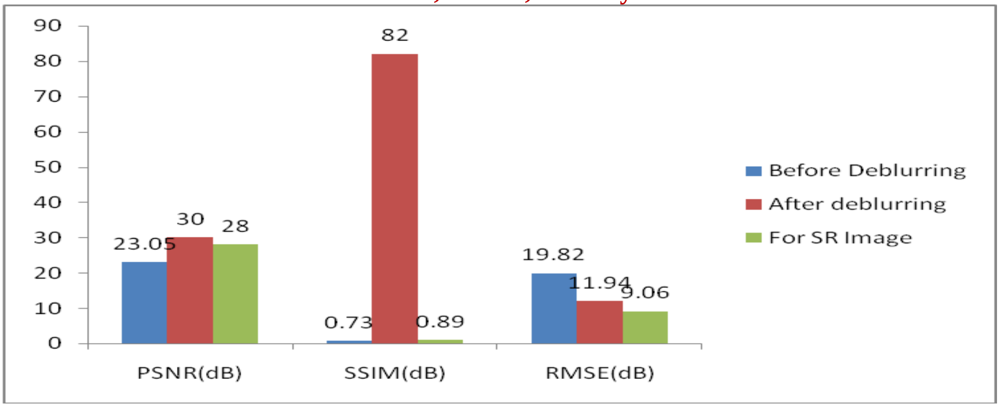


Fig 11. Combination for Test A-D-G-H in AR_AReg_PM Algorithm

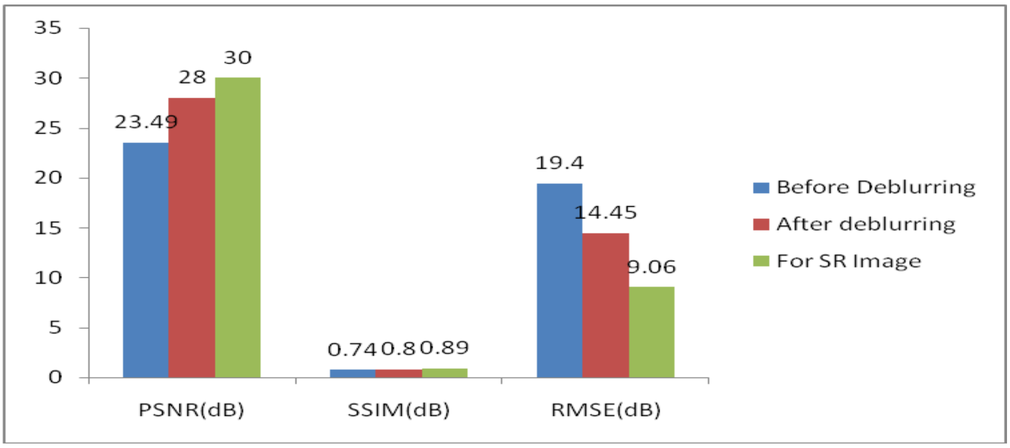


Fig 12 Combination for Test A-D-G-H in AR_AReg_PM Algorithm

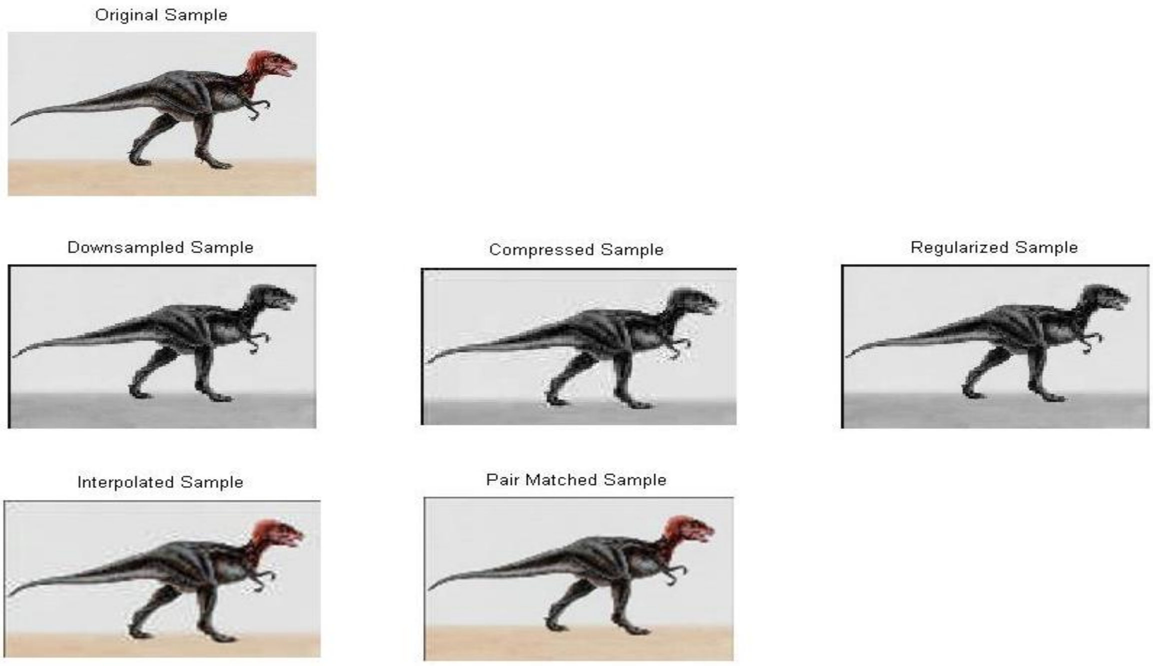
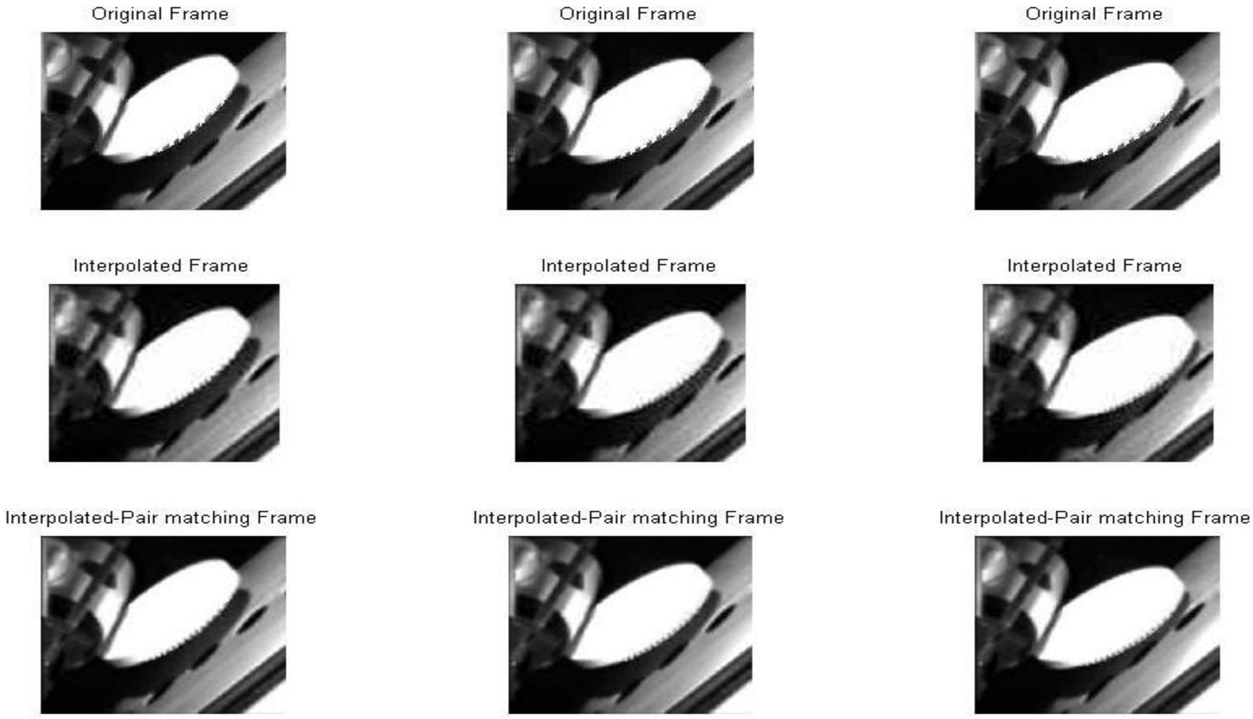


Image Output



Video Output

VI. CONCLUSION

Its increasing the resolution & perceptual quality of web image/video . Proposed an efficient way to combine PDE regularization & learning based SR.We extended this method for video with certain interface interaction and simple spatio-temporal coherency optimization.This method is works on both offline & online tests to validate the effectiveness. Due to robust performance & low complexity its provide practical enlarge -preview tool for thumbnail web image.

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