

Super Resolution in Spatial
And Wavelet domain



MCS

By

SADAF ADREES

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SUPERVISOR CERTIFICATE

It is to certify that the final copy of the thesis has been evaluated by me, found as per the specified format and error free.

Date:

Col(Retd) Dr. Imran Tauqir

ABSTRACT

Majority of digital imaging applications utilize high-resolution video or images for further processing. The requirement of high resolution video corresponds to two foremost application domains; enhancement of pictorial data for human translation and for programmed machine perception. Imaging acquisition devices generally restrict image resolution. Super-resolution is an idea according to which a high-resolution image or video can be produced by combining low-resolution series of images or videos of a sight. Of late, algorithms for single image super resolutions have been advanced, the most current research dependind single image or video Su R is based on texture hallucination, patch based up sampling and example based Su R, however problem of blur production and over smoothness persists.

In this thesis an algorithm is proposed for SR of videos that utilizes the blend of interpolation alongwith wavelet transform technique. To enhance the efficiency of algorithm guided filters are added to preserve the edges and to retain the maximum information present in the video along the edges . It is notable that in process of generating high resolution output, the blurring effect arises in the section containing details that is mostly near bounderies. The proposed technique attempts to minimize the blur effect across boundaries. Proposed SR process consists of three main phases, Guided filtering for edge preservation, interpolation based magnification process and wavelet based edge boosting.

The research concludes that the combination of these three techniques provides improved results both qualitatively and quantitatively. A comparison of this algorithm with other techniques proposed by other authors is also done to prove the effectiveness of the methods.

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LIST OF ACRONYMS

High resolution	Hi R
Low resolution	Lo R
Wavelet	Wa
Interpolation	Int
Algorithm	ALg
Space frequency localization	SFL
Spatial frequency	SF
High frequency	Hi F
Frequency	f
Mean Square Error	MSE
Continuous Wavelet Transform	CWT
Discrete Wavelet Transform	DWT
Peak Signal to Noise Ratio	PSNR

CHAPTER 1: INTRODUCTION

Hi R videos are necessary in applications for example high quality videoconference, distant survey, HD TV communications or medical solicitations. The potential of Hi R output is lower than requirement Because of limits on camera cost, power, memory size and restricted bandwidth,.

Simplest outcome of Su R algorithm is ability of recreating Hi R video/image from Lo R video/image that appears to be recorded using Hi R equipment. . Hi R indicates the higher number of pixels in a video or image, having ability to provide necessary details about the situation which is most important requirement in many applications.

Best possible solution of this problem is by increasing pixel density in a certain areas; as a result pixel size is reduced. It is possible by changing the manufacturing method of lens. Subsequent to reduced pixel size availability of light will also be reduced, introducing shot noise. This will result in effecting the quality of output .So we can say here is restriction in decreasing pixel size deprived of affecting the quality.

Alternative methodology for improving the spatial size is by upgrading chip size; as a result capacitance will also increase [1]. This method also has its drawback as enormous capacitance makes it challenging to accelerate a charge exchange frequency. Along with that cost of equipment will also be raised which is a limitation for commercial equipment.

One auspicious tactic is use of signal processing methods to get Hi R video/image from detected numerous Lo R videos. Lately, such resolution improvement methodology is considered one of the greatest attractions of researchers calling Su R

Su R are practices that creates Hi R images or video from a number of captured Lo R images or videos, thus enhancing detailed components and eliminating degradations produced due to capturing process of the Lo R camera.

Primary idea after Su R is to collect non-redundant data present in various Lo R frames to recreate a Hi R image or video.

Early Su R algorithms used multiple Lo R videos of same sight and reconstruct single video of Hi R. In topical interval, ALg for real time and single frame Su R are advanced as well as matured.

1.1. Research previously carried out

Various algorithms are developed in recent times that uses texture hallucination, patch based up sampling and example based Su R a[1,2].

In edge-based ALg, certain previous margin knowledge is applied to restructure sharp videos and images however issues in these procedures is yielding ambiguity along with additional evenness over certain sections [3].

Freeman et al. anticipated example-based Su R methodology [4] including patch-based image model depending on available dataset is practiced. Technique provides better outcomes except giving constant consistency and produces some noise too.

1.2. Motivation

Following are the problem in existing methods:

- Spatial domain:
 - Any details of input video is not utilized during up sampling of a video while using Interpolation based methods like pixel replication or bilinear interpolation
 - Above mentioned techniques give fine output in smooth section however boundaries and certain surfaces acquire unclear effect.

- Wavelet domain:
 - Methods dependents on Wa domain have primary difficulty in the assessment of unidentified coefficients of three Hi F sub bands.

1.3. Thesis Statement

Using multiple images/training images in SR produces a high quality HR image but using a single image for the process still needs improvements. When a Lo R image is up sampled or magnified, the loss occurs at the Hi F Components i.e. at the edge of the image which results in the blurring effect in the resultant output.

1.4. Objective

The for most aim of following thesis is development of a system taking a single video and uses both spatial and Wa domain video processing to increase resolution of video at both smoother regions and edges of video.

1.5. Principal approach used

The approach used to solve the above mentioned problem is:

Firstly edges are preserved by using guided filters ,bicubic interpolation is used to up sample the video and lastly Wa analysis is used in order to remove blurring effect , Afterwards up sampling of video because of point spread function (PSF) resulted video appears distorted, in that case Gaussian filter is used and video is down sampled, Error is calculated and back projected to get Hi R video.

1.6. Advantages

The research aims to improve the video quality with the following goals:

- In almost every video solicitation, Hi R images or videos are generally preferred to perform further operations.
- Pictorial statistics can be Improvement to get more understanding
- Automatic machines can get better observation

1.7. Applications

The research will prove to be quite useful in many perspectives, such as:

- High quality Videos required for medical purposes could be regenerated by using video having limited resolution, on these videos Su R techniques are applied and a resultant high quality video can serve the purpose
- If Hi R satellite videos are present it is way easier to separate a specific object from a group of objects.
- If Hi R videos are produced the result of pattern recognition in computer vision can surely be enhanced
- Hi R videos are useful for surveillance applications as well as industrial applications

1.8. Summary of Thesis

Flow of Thesis is shown below:

Chapter 01:

It contains primary overview, problem discussed, scope and objective.

Chapter 02:

It presents an overview of Su R and its several methodologies

Chapter 03:

Chapter 3 gives a brief description of wavelet domain analysis of signals

Chapter 04:

This chapter discusses the ALg in detail

Chapter 05:

This chapter presents different results and simulation.

Chapter 06:

This chapter describes conclusion and future work proposed

CHAPTER 2: LITERATURE REVIEW

2.1 Resolution of an image

Numbers of pixels in an image or video are indicated by word resolution. At times width and height of image or video along with total number of pixels is also called resolution.

- Low-Resolution (Lo R): –Number of pixels within video or image is minor, consequently providing lesser information.
- High-Resolution (Hi R): – Number of pixels within an image or video is greater, thus presenting more particulars.

2.1.1 Super-resolution

Su R are procedures createing videos having increased size as compared to original video from numerous recorded less-resolution videos, thus enhancing higher f elements besides by withdrawing deterioration produced in capturing the video with the help of equipment having lesser resolution.

Fundamental concept used in Su R is that in process of regenerating high-resolution video information present in numerous low-resolution frames is collected.

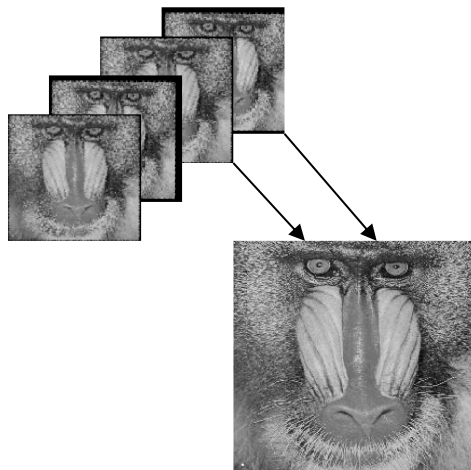


Figure 2.1: Combination of Lo R images to recreate single Hi R image

2.1.2 Requirement of high resolution images:

Necessity for Hi R is common in

- Computer vision applications
- Pattern recognition
- Medical imaging for identification.
- Highlighting explicit region of concern
- Surveillance
- Forensic
- Satellite imaging applications

In process of generating larger sized output single image/video Int based approached can also be used that closely resembles to Su R technique. Conversely due to lack of extra information available, the resultant outcome of the single image/video Int has limited efficiency, and missing details are hard to recover.

In case of Su R, conversely, numerous Lo R interpretations are accessible for renewal process, making the problem easier to solve. The non-redundant data confined in these Lo R videos is normally produced by movement of pixels in different frames. This could be the result of unrestrained movements between capturing devices and surrounding. In process of recording video, camera records a number of lower resolution frames, being down sampled from the Hi R scene due to shifting of pixels in different frames.

The process of Su R can remove the drawback of capturing device by conversing the shifting of pixels and correctly align them for combing to get Hi R output.

Su R as mentioned earlier produces a Hi R outut from multipa or single Lo R inputs.

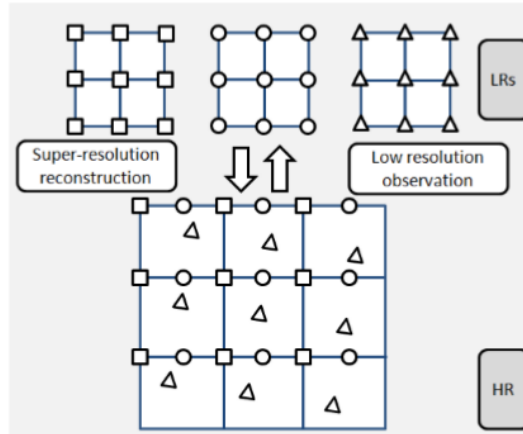


Figure 2.2: Sub pixel shifts

2.2 Super resolution techniques

Su R techniques have following three groups:

- Interpolation based techniques
- Reconstruction based techniques
- Learning based techniques

2.2.1 Interpolation Based Techniques

Int based processes compares Lo R video frames with grid point of its Hi R frame, later innovative pixel values of Hi R videos are projected using a function utilizing content present in existing pixels. Post-processing could be done as well to increase Hi R video clarity.

The most popular techniques in this domain are

- Bilinear Int
- Bicubic Int

Bilinear Int is re-sampling strategy utilizes weighted average value of four adjoining pixel for assessment of newly introduced pixel esteem.

Bicubic Int is comparatively sophisticated and uses 16 pixel values.

Though both these techniques produce good quantitative results but both techniques suffer from undesirable artifacts when assessed using qualitative results.

Much of the research work is done in this area. A Hi R output is created using

alterable Int by pixel-level geometrical shapes that are dependent on preexisting data. It estimate threshold, categorize Int area as a geometrical shapes and allocate appropriate values to pixels how's values are to be allotted whereas luminance variations are preserved along with smoothing [5].

For recreation of Hi R output, firstly a modified system is used introducing the neighborhood pixel esteems in direction where second order image derivative is lesser once introduced values are altered by an iterative refinement lessening contrasts in second order image derivatives, amplifying second order derivative values and smoothing isolate curves[6].

A Hi R image is created by taking in account discontinuities and light changes within the Lo R image and the pixels located closed to boundaries are merged into the edges in a way that aliasing effect is reduced [7]. Spline Int has been used since 1990 to produce a HR image [8]. Edge-guided non-linear Int technique that uses directional filtering (two orthogonal directions) and data fusion [9].

Directional cubic convolution uses edge-directed cubic convolution system that can adjust to altering boundaries structure of images thus producing a sharp Hi R image [10]. A Hi R image is produced in a way that the pixel value of Lo R image is dependent on desired changes for its gradient profile [11].

An image enlargement ALg that is based on merging the traditional method of inserting zeros and Wa transform [12]. An edge-directed image Int method that uses biorthogonal Wa transform [8]. An edge-direct Int ALg that first estimates the local covariance coefficients from a Lo R image and then use these covariance estimates to adjust Int at Hi R image grounded on symmetrical duality between Lo R and Hi R covariance [13].

A Lo R image is first magnified and then divided into patches and then each patch is splited into homogeneous regions using connected-component analysis. After this a spatial-filter is useful to improve the strength variations among adjoining elements [9].

2.2.2 Reconstruction Based Techniques

Pair relationship between Lo R image/video and Hi R image/videos is utilized in this technique. With the help of such association, linear equations could be constructed that correlate the pixel values of Lo and Hi R videos. Hi R videos are created by solving these equations. Some study carried out in this field is described here.

A super-resolution technique that extends the edge-directed Su R technique to add detail from an image/texture example presented by the user [14]. Image enlargement technique using a filtering-based execution scheme and regularization through coupling bilateral filtering [15].

Up-sampling ALg that comprises of a response loop to recreate Hi R frame information present in input Lo R frame [16]. Iterative curvature based Int centered on two step grid filling and an iterative correction of the interpolated pixels [17]. Blurred Lo R images can be believed wavelet alter estimated subbands of Hi R image and this relationship can be used to recover Hi R output [18].

Image up-scaling method that performs constrained smoothing of artifacts and tries to create even restorations of the image's level curves even though preserving image reliability [13].

2.2.3 Learning Based Techniques

It stresses on knowledge regarding construction or detail of videos depending related preexisting information that aids in generating improved outcomes.

Learning based methods slightly reliant on data already existing therefore solitary fits for such videos having prior data existing.

Self-similarity within an image can be used to generate the image database which can be used for filling the missing high-f pixels of Hi R image [19]. Even if image is divided into patches, there exists a difference in the patches.

To overcome this image is divided into patches based on structure feature and then these patches are matched against the pre-defined image dictionaries [20]. A learning-based ALg that learns the gradient field and combine the horizontal gradient map with vertical gradient map to produce HR video [21].

Super-resolution ALg uses the combination of two approaches: multi-image super-resolution and example based Su R technique [22].

Using single image for the purpose of Su R without using any prior knowledge (whether in the form of multiple images or predefined image database) still has a space for improvements.

2.3 Undesirable Artifacts in Images

Various undesirable artifacts that affect the quality of videos are described below:

2.3.1 Blocking effect: In this effect the video seems like divided into small blocks as shown in Figure 2.3(a)

2.3.2 Ringing effect:

Due to presence of unwanted flowing kind of effect near boundaries due to missing of details information in an video is called ringing effect as shown in Figure 2.3(b)

2.3.3 Aliasing effect: An unwanted effect that results in “jaggies” as shown in Figure 2.3(c)

2.3.4 Blurring effect: This effect occurs when the edges of video lose their values and the difference across the edges is reduced. This is shown in Figure 2.3(d)



(a)



(b)



(c)



(d)

Figure 2.3: Undesirable artifacts (a) Blocking Effect (b) Ringing Effect (c) Aliasing effect (d) Blurring Effect

CHAPTER 3: WAVELET ANALYSIS

3.1 Introduction

From the latest couple of decades, another methodology, as substitution to sinusoidal transformation systems for instance discrete Fourier change and discrete cosine change has touched base to execute on lower bit rates. The changed framework another thought of wavelet premise has displayed. Wa are of constrained timespan and has rotating f . With the goal of reviewing the SF information of recordings on a few sizes, previously mentioned little wa can be scaled or migrated. We can say Wa can consider recordings at modified goals and work as striking assets in Multi-goals Examination (MRA).

Besides, Wa investigation can be considered as a procedure looking at event part of video alongside factor three-dimensional areas additionally called SFL. Working of this strategy could be explained by following representation as suppose we are attempting to discover and assessing the points of interest of a video at explicit unique area with the assistance of an amplifying glass. We can focus on a specific indicate alongside that by gradually moving the enhancing glass parallel to video seeing at assorted regions. SFL quality needs in prior sinusoidal upheaval techniques..

A video is simply association of moving pixels esteems stored two dimensionally; to get any SF data from such game plan is absurd. Generally by utilizing sinusoidal change of recordings, SF proof is achieved anyway area of substance is difficult to assessed. Wa Change outfits for the response to the two defects hence conveys genuine gainful MRA and coding capacity.

Wa change is incredible wellspring of sign articulation. A sinusoidal sign is used to express a sign in normal Fourier. spectral subtleties are available however fleeting data is absent.

On the other hand, in some of solicitations like structure alongside frequencies time data is required to take into elucidation that implies bargain among Ghostly and time based data is required.

Wavelets are utilized to symbolize a particular sign in wave change. Wavelets have limited time term having zero normal esteem [23, 24]. Some of well-known wavelets are presented in fig. 3.1.

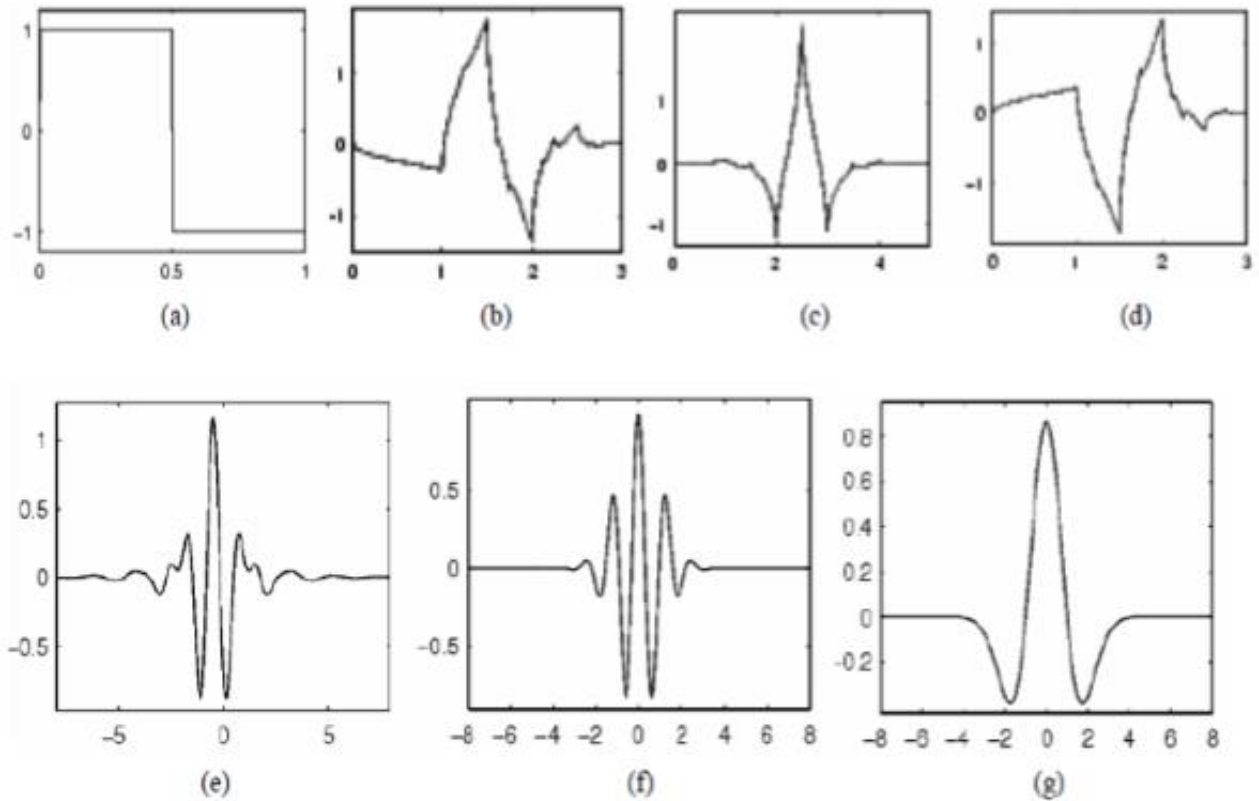


Figure 3.1 Wavelet Families (a) Haar (b) Daubechies (c) Coiflet1 (d) Symlet2 (e) Meyer (f) Morlet (g) Mexican Hat

It is well known that any capacity connected to video is essentially connected on matrix, and human sight is less fragile to Greeting F components in a video.

By keeping these certainties into consideration we can pack the Hi F components alongside compacted video yield is realistic.

3.2 Background

Each picture is measurably a 2 D course of action of pixels likewise called shading intensity esteems between "0" to "255". A picture incorporates both huge and little articles. Hi R is required to watch minor size substances and then again Lo R to see enormous size substances. The idea provides some insight for commitment of MR

handling.

In wavelet change a thought of mother wavelet $W(t)$ is used connected toward signifying any state of waveform by deciphering or dimensional difference in mother wavelet $W(2^k t - m)$. here

$W(t)$ = wave from time $t = 0$ to $t = T$,

k = scaling factor

m = translating or shifting factor.

Therefore $W(2^k t - m)$ is $W(t)$ existing from $t = m$ to $t = m + T$ besides shrink by 2^k .

Fig. 3.2 showcases mother wavelet to diverse estimations of k and could be seen in assume that as the value of scaling factor is improved mother wavelet becomes more slender.

Broadened wavelets are undifferentiated from sinusoids of decreased f , though compacted mother wavelet looks like to sinusoids of unrivalled f . A symmetrical wavelet is one having internal product equivalent to 0.

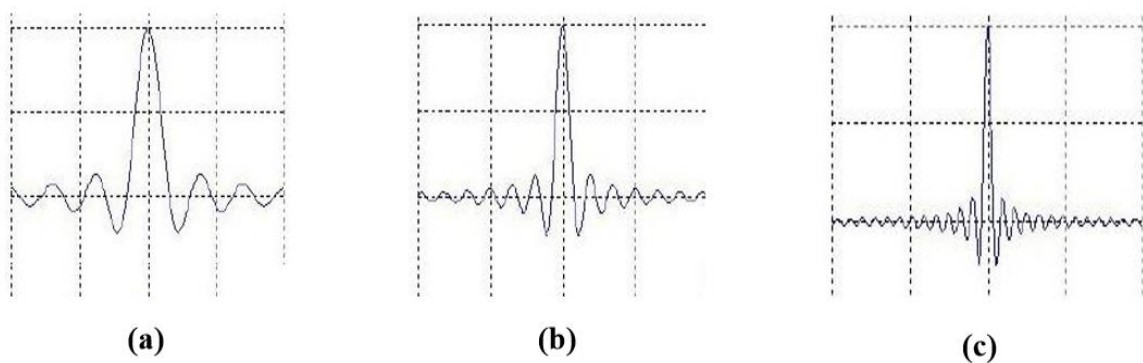


Figure 3.2 Scaling Wavelet (a) $k=1$ (b) $k=2$ (c) $k=3$

3.3 Need for Multi-Resolution Analysis

It is seen that at various areas of a video distinctive detail levels are available

more important data is available at higher detail level position and the other way around. To get data from higher subtleties areas, Hi R is important.

To get this sort of data multi R examination is required; by utilizing this procedure favored data could be gained for extra working. MRA have a dynamic position in removing auto relationship of video through R. Wa investigation most famous Methodologies for Multi-goals examination as of late.

3.4 Why wa analysis is required?

Wa investigation gets need in various sales like OPTics, picture compression, unsteadiness etc. Compression of information is indispensable zone where Wa investigation applies on the information (picture or video) at differing R scales accordingly it parts information in different sub groups dependent to their f as in [25], [26] and [14].

The best critical components of Wa changes is execution of neighborhood breakdown of greater sign and with the assistance of Wa coefficient exact areas of the time space intrusions could be assign.

Preferences of Wa change are plainly a lot higher than Fourier change. Premise work in FT extends from negative to positive unendingness. While in Wa change mother Wa includes endless time interim. Likelihood is additionally an issues in Fourier change as sinusoids are smooth, then again in Wa change Wa are sporadic.

So Wa change has clear advantage to speak to the sign having sharp changes as contrast with Fourier where the outcome is difficult to acquire.



Figure 3.3 Comparison (a) sine wave (b) wavelet

3.5 Wavelet Analysis

We can reason that Fourier change convey us with best goals in f space. Alongside in time area best outcome is given by haar wavelt (motivation work).

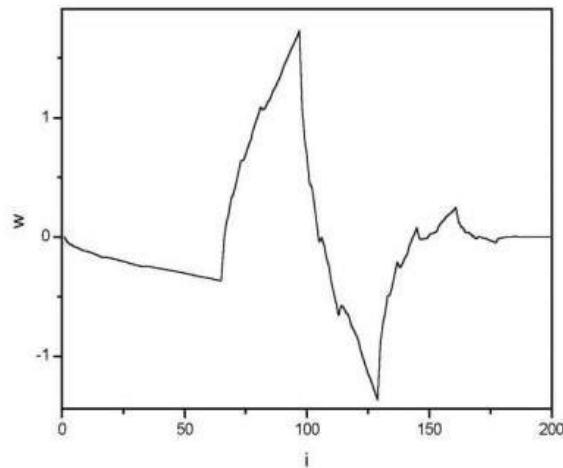


Figure 3.4 Compactly supported Daubechies wavelet

Daubechies displayed in 1988, new formed W_a otherwise called Daubechies W_a appeared in fig 3.4. This is obvious from assume that this W_a is proficiently supported W_a .

A windowing impression is utilized in W_a investigation. A window is variable estimated square shape as in [1]. Altered Interim sizes are utilized in W_a investigation. Four distinct methodologies are given relying on the extent of the window.

Shannon: Time space estimate having just Hi R of time scale is essential, windows are acclimated uniquely for time axis are likewise called Shannon given in Fig. 3.5 (a).

Fourier: f space estimate having just Hi R of f scale is compulsory and windows are adapted solitary for f axis are called Fourier transform as showed in Fig. 3.5 (b).

STFT: STFT represents Brief time Fourier Change. For such situation a

immovable windows estimate issued to depict a signal, for example it is a compromise among Shannon and Fourier pictured in Fig. 3.5 (c).

Wavelet: Having flexible magnitude box is utilized to symbolize image. Fig 3.5(d)

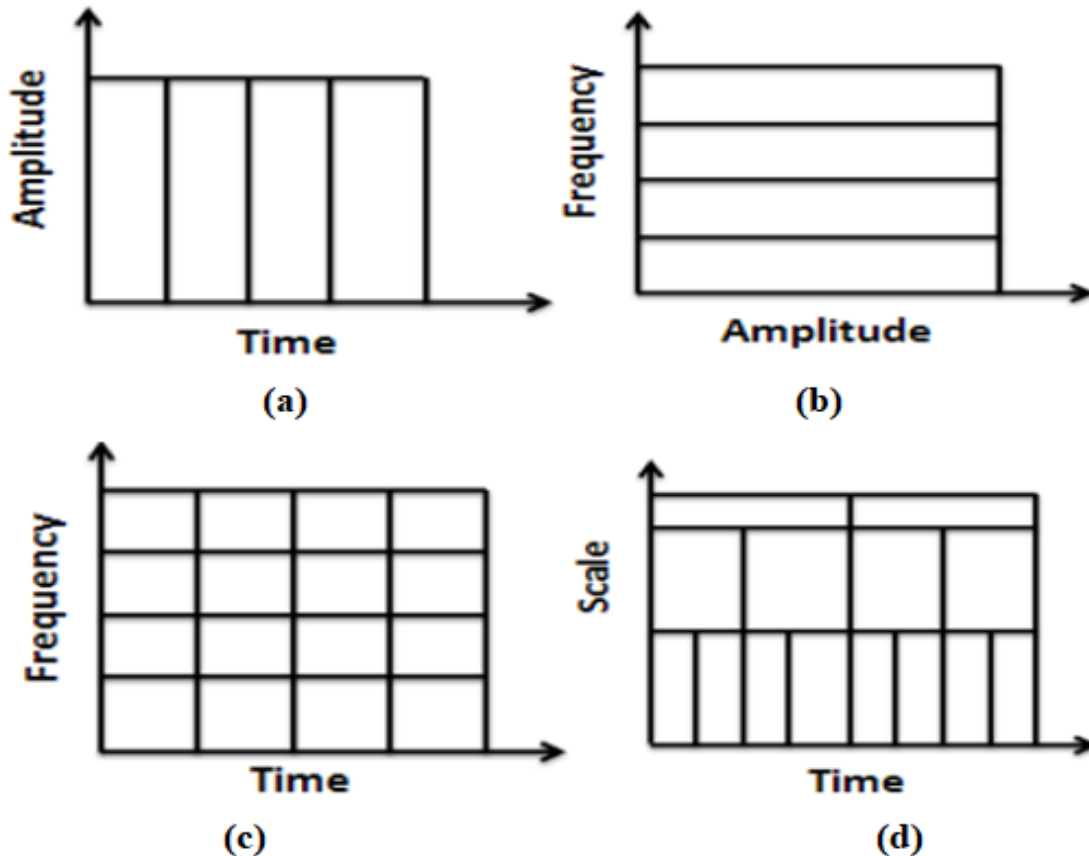


Figure 3.5 Different views of a signal (a) Time-domain (Shannon), (b) frequency-domain (Fourier), (c) STFT based (Gabor) (d) wavelet base

3.6 Perfect Reconstruction Filter Bank

So as to reproduce a sign a stream or stream of channels is utilized referred as reproduction channel bank. At the point when an information picture or video move along this channel bank it is similarly isolated into double band restricted groups or segments called sub-groups.. Sub-band coding is comparable to the Multi-Goals Examination (MRA).

It is essential to spare the last yield from any extra blunder so for this reason manufactured channels are connected at end of the framework to protect the yield signal from undesired mistakes.. Fig. 3.6 speaks to double channel immaculate recreation channel bank.

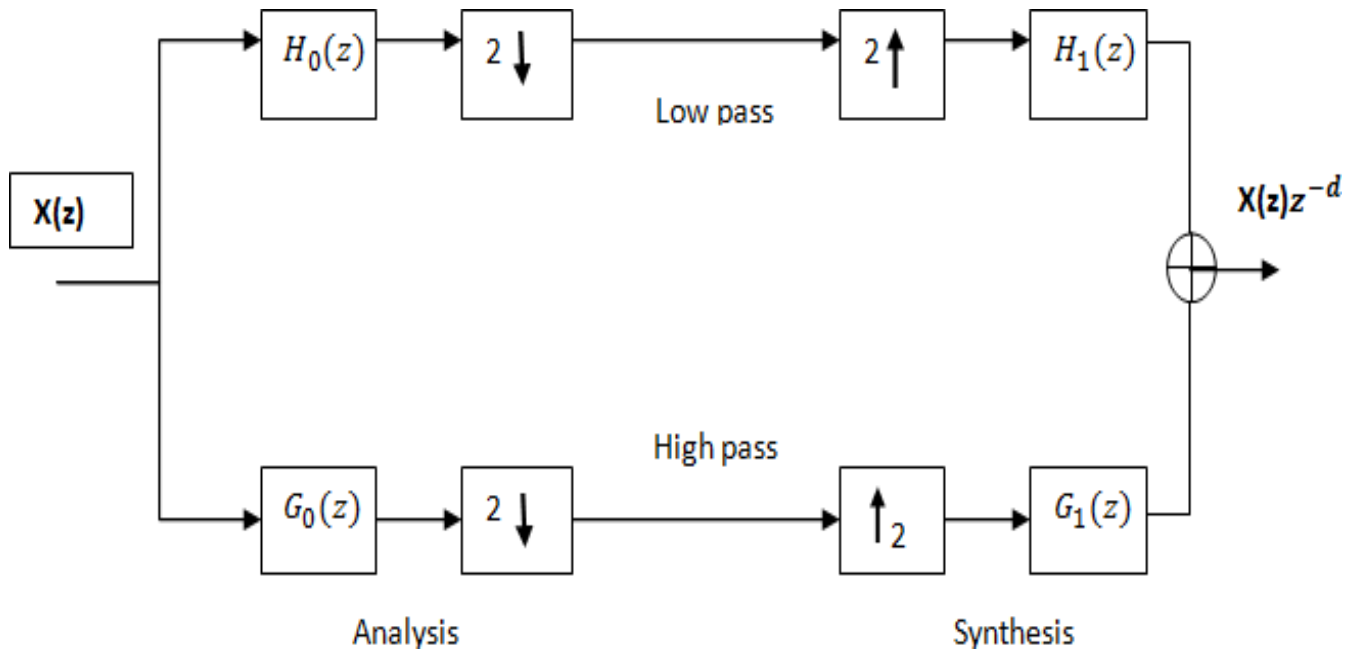


Figure 3.6 One dimensional, one level perfect reconstruction filter bank

Where

- $X(z)$ = transmitted signal
- $H_0(z)$ = low-pass analysis filter
- $G_0(z)$ = high-pass analysis filter

Whereas

- $H_1(z)$ = low-pass synthesis filter
- $G_1(z)$ = high-pass synthesis filter

Here it could be watched $X(z)$ is contribution to examination channel and $H_0(z)$ and $G_0(z)$ are its resultant sub groups high pass and low pass separately having littler transfer speed than in unique information signal.

The procedure of investigation is finished by down inspecting these sub groups which are gained in the wake of going of unique sign through examination channel bank the subsequent stage is reproduction. In this progression down examined sub groups moves toward becoming contribution of engineered channel indicated by $H_1(z)$ and $G_1(z)$ referred to low pass manufactured channel and high pass engineered channel. Yield signals at this stage converged to get unique sign which is impeccably reproduced

In the accompanying arrangement of conditions z^{-1} specifies the conceding element uniting both sub-groups. So to protect examining rate an associating impact is presented since it's anything but a perfect model. Some stage and greatness deterioration is additionally included examination step

Primary target of blend channels is to effectively lessen these changes. Following conditions show connection among investigation and engineered channel

$$\begin{aligned} G_0(z)H_0(z) + G_1(z)H_1(z) &= 2 & 3.1 \\ G_0(z)H_0(-z) + G_1(z)H_1(-z) &= 0 \end{aligned}$$

3.7 Classes of Wavelets

Due to alteration of relation between analysis and synthesis filters W_a is distributed into following two groups .

- (i) Orthogonal W_a bases
- (ii) Bi-orthogonal W_a bases

3.7.1 Orthogonal Wavelet Bases

The coefficients of orthogonal filters comprise of real numbers these coefficients depicts same length without any symmetry. Between these analysis and synthetic filters an association is present which is reversed in time.

$$\begin{aligned} H_1(z) &= H_0(z^{-1}) \\ G_1(z) &= G_0(z^{-1}) \end{aligned} \quad 3.2$$

If 'N' symbolizes the interval of the filter then following equation is satisfied

$$G_0(z) = -z^{-N}H_0(-z^{-1}) \quad 3.3$$

Presently we can signify entire filter bank as solitary filter that is LP analysis filter.

Occupation of orthogonal filters is much easier since we can represent when complete filter bank with single low pass analysis filter.

3.7.2 Bi-Orthogonal Bases

Integers or the real values represent coefficients of bi-orthogonal filters typically. in this case following relationship is satisfied

$$\begin{aligned} G_0(z) &= H_1(-z) \\ G_1(z) &= -H_0(z^{-1}) \end{aligned} \quad 3.4$$

It is apparent from previously mentioned relations that bi-symmetrical channel bank could be collected otherwise executed by lone two channels, that are Lo P examination besides union channel. Bi-symmetrical Wa bases can be accomplished with channels having direct stage reaction. These low and high pass channels have various lengths. symmetric qualities are seen in low pass case while in high pass the outcomes are switched.

3.8 Wavelet Transform

Following are two major categories of Wa transform since sine and cosine basis are used to observe spectral components of signals.

3.8.1 Continuous Wavelet Transform (CWT)

CWT could be represented as ,

$$C(\text{Scale}, \text{position}) = \int_{-\infty}^{\infty} f(t)\psi(\text{Scale}, \text{position}, t) dt \quad 3.5$$

For reason for computing CWT result of sign is taken with mother Wa. Signal is altered as scaled and deciphered type of having mother Wa $\psi(t)$ brief term called minimized help mother Wa. Its premise are:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left[\frac{t-b}{a}\right]; a, b \in \mathbb{R}^1 \text{ and } a > 0 \quad 3.6$$

‘x’ means scaling coefficient , ‘y’ presents the translating coefficient

The CWT is presented by

$$W_f(a, b) = \int_{-\infty}^{\infty} x(t) \psi_{a,b}(t) dt \quad 3.7$$

3.8.2 Discrete Wavelet Transform (DWT)

For distinct time signals Discrete Wavelet Transform (DWT) could be used. Picture is a 2D type of any 1D signal. To investigate components of a picture or video two one dimensional wavelet change can be utilized in progression. Info data of edge is given to one dimensional stage in line. Aftereffect of earlier stage is given to the one dimensional stage in segment. The fig appeared underneath presents 2D DWT and IDWT in impeccable reproduction channel bank.

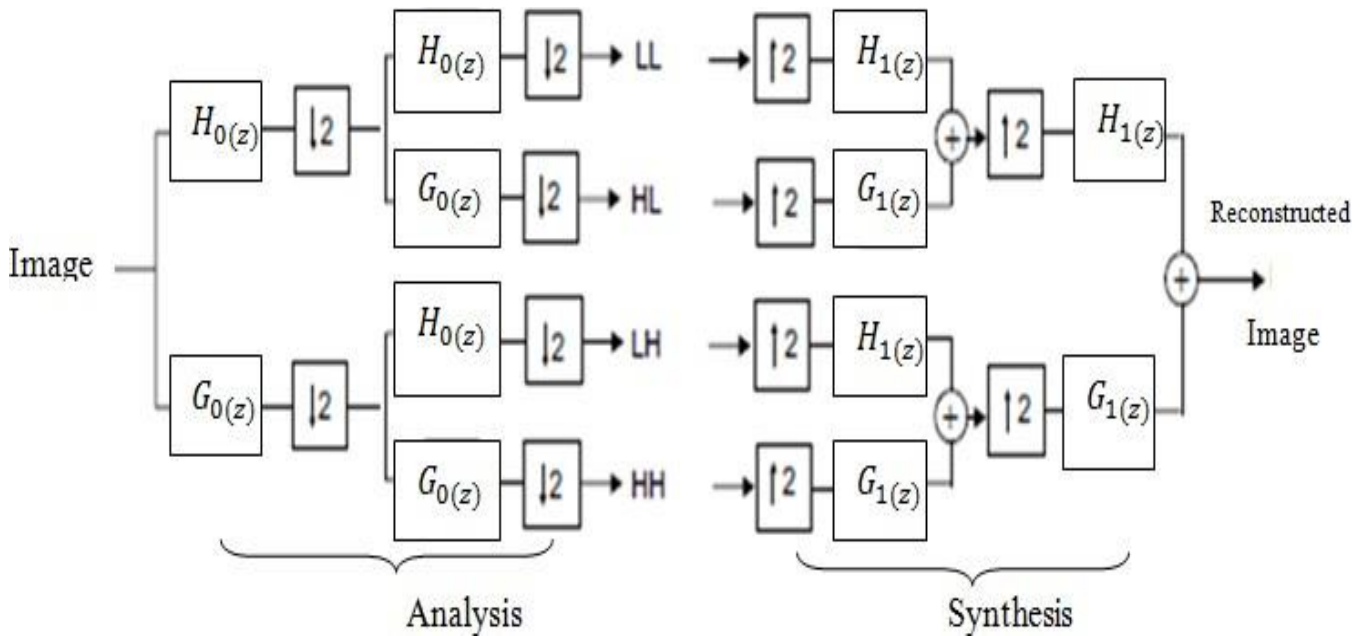


Figure 3-7 Reconstruction filter bank for 2D DWT and IDWT

Last outcome is achieved as far as modified coefficients; following conditions are fulfilled when video is exposed to premise work

Scaling function of video is denoted by $\phi(u, v)$ here, and wavelet functions are $\psi_1(u, v)$, $\psi_2(u, v)$ and $\psi_3(u, v)$

$$\begin{aligned} \phi(u, v) &= \phi(u) \phi(v) \\ \psi_1(u, v) &= \psi(u) \phi(v) \\ \psi_2(u, v) &= \phi(u) \psi(v) \\ \psi_3(u, v) &= \psi(u) \psi(v) \end{aligned} \quad 3.8$$

A splited frame is acquired As a result which has four sub bands as LL, LH. HL, HH containing approximation, vertical details, horizontal details, diagonal details respectively

CHAPTER 4: DESIGN AND IMPLEMENTATION OF ALGORITHM

4.1. Introduction

The following chapter describes the strategy of the suggested Su R ALg and then gives details of the ALg.

The algorithm proposed for Su R utilizes blend of wa transform and Int based technique. During the process of getting Hi R video from Lo R video normally blurring effect appears along the boundries of the frames having details content of video. The proposed process attempts to minimize blurring effect along boundries.

Proposed Su R process consists of three main phases, Guided filtering for edge preservation, interpolation based magnification process and wavelet based edge boosting. The details of these phases are discussed in the following sections.

4.2. Design of Algorithm

The proposed algorithm involves three basic steps: Guided filtering for edge preservation, interpolation based video magnification and wavelet based edge boosting. As mentioned earlier, the magnification causes blurring. So to avoid this after magnification the input video edges are boosted in the wavelet transform

In the first step guided filters are used to preserve the edges followed by bicubic interpolation method used for magnification and the resulting blurring effect at the edges is mitigated with the help of wavelet transform processing. To limit the noise factor Gaussian filter is applied and output is compared with original image to calculate the error. This error is back projected to get the final magnified output with minimum loss at the edges.

The details of the algorithm are discussed in later sections

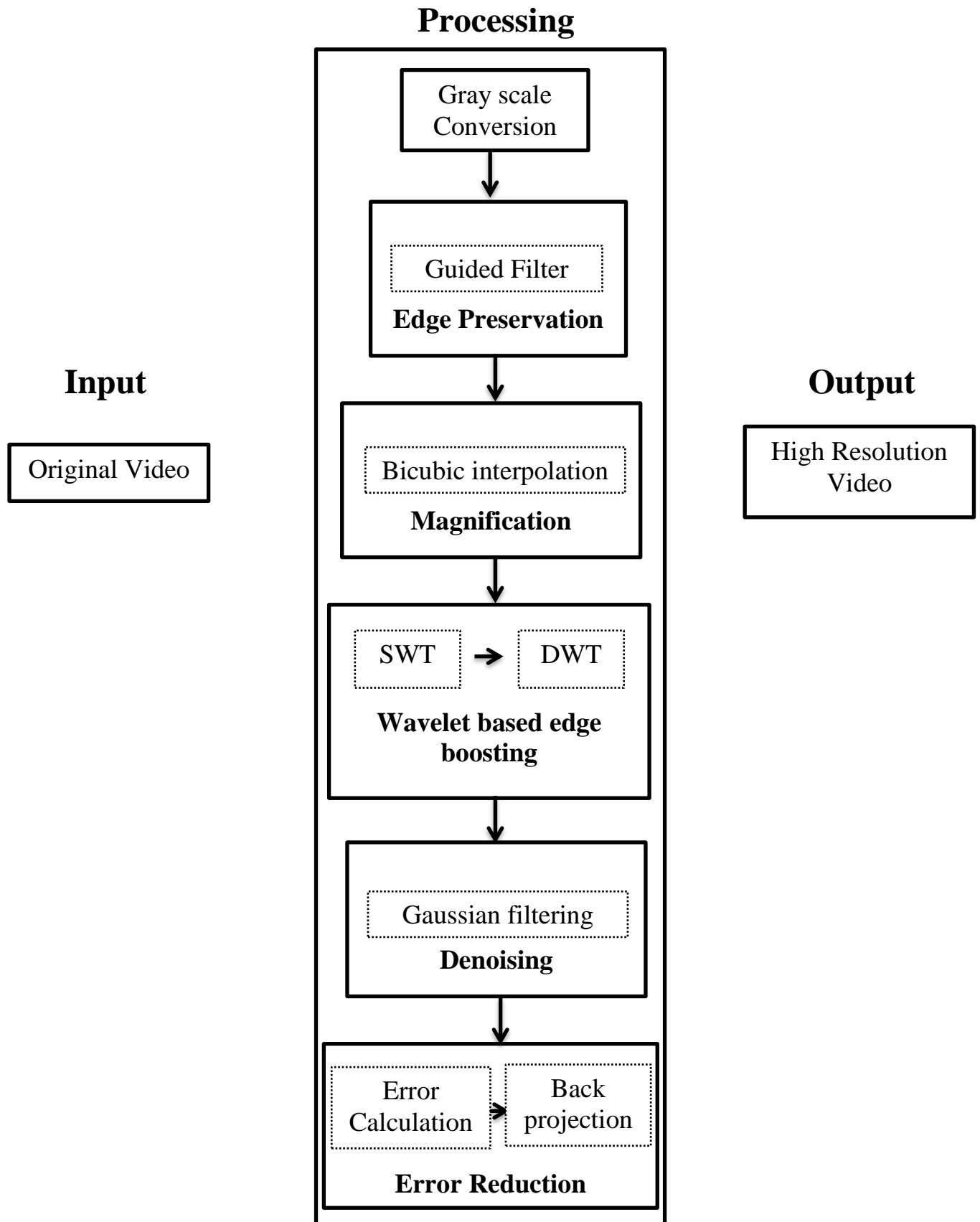


Figure 4.1: Block Diagram

In the sections 4.4 and onwards, the algorithm steps mentioned in section 4.2 are discussed in detail.

4.3. An overview

In the proposed method firstly coloured video is transformed in gray scale for further processing. Then edges are preserved by using guided filters before magnification, in the next step for magnification process bicubic interpolation method is used which gives an enlarged video output at the cost of little blur at edges to overcome this blurring effect stationary wavelet transform and discrete wavelet transform are applied respectively, output video contains noise due to point spread function, this issue is resolved by using Gaussian filter, now the output is down samples so that it could be compared with the original sized input video to calculate the error. Lastly error matrix produced is up sampled and added with high-resolution video recreated with bicubic interpolation.

Now each step is explained in detail in following sections

4.4. Gray scale conversion

Conversion of RGB frame to gray scale is a very complicated process. Due to conversion, frame may lose its sharpness, contrast and structure. Nature of video/image relies on number of bits used to store a video/image frame. True coloured frame requires 8 bits for each R, G and B colour band, thus needs 24 bits altogether for representation of 16, 777, 216 different colours. However luminance of gray scale frame uses only 8 bits representing 256 different intensities (0-255).

Coloured frames are good for visualization but computation of luminance and chrominance need additional computation, to avoid this proposed technique utilizes information contained only in luminance grayscale frame. Initially the low bit depth true colored video frames are converted to grayscale frame. There are two methods used for RGB to grayscale conversion i.e average method and luminosity method. Since R, G and B contain unlike wavelengths and involvement in image formulation, brightness technique

is superior to get desirable outcome.

Let $I_t(p,q,\alpha)$ be the intensity of color input video frame at point $p = 0,1,\dots,P$ along with $q = 0,1,\dots,Q$ and at time t , α signifies red, green, blue colour groups i.e. $\alpha \in \{R,G,B\}$. The gray scale image $G_t(p,q)$ [30] is shown in equation 4.1.

$$G_t(p,q) = 0.2989 \times I_t(p,q,R) + 0.5870 \times I_t(p,q,G) + 0.1140 \times I_t(p,q,B) \quad (4.1)$$

According to above equation, Red has 29%, Green has 58% and Blue has 11% contribution in image. RGB coloured frames can be easily reconstructed from gray scale. This conversion produces a high quality gray scale Image/video.



Figure 4.2: (a)Original frame (b) Grey scale converted frame

4.5. Edge Preservation (Guided Filter)

Guided filters are important in many computer hallucination and computer visuals applications in order to extract the content in images and videos. These filters are also known as edge preserving filters like bilateral filters but have better result near the edges. The output of this filter is a linearly transformed result of the guidance input video. Guided filtering is also a more common concept beyond smoothing i.e. it transfers the guidance input properties to the filtered output.

These are used in applications like haze removal and feathering. The guided images or videos has many other applications like enhancement, HDR compression, matting etc and performs much faster than the other filters.

The important postulation of the Gu F is a local linear model among the guidance I and the filter output q . We adopt that q is a linear transform of I in a space ω_k centered at the pixel k

$$\mathbf{q}_i = \mathbf{a}_k \mathbf{I}_i + \mathbf{b}_k \quad (4.2)$$

where (a_k, b_k) are linear coefficients and i belongs to ω_k supposed to be continual in ω_k . This local linear model ensures that q has an edge only if I has an edge, because $\nabla q = a \nabla I$. In super-resolution techniques this equation has proven useful.

In our proposed algorithm Gu F is applied on input video after gray scale conversion to preserve the edges, here guided filter is applied as self-guidance which means input is itself used as guided video there for no already existing data set is required making it practical in single image super resolution techniques, qualitative as well as

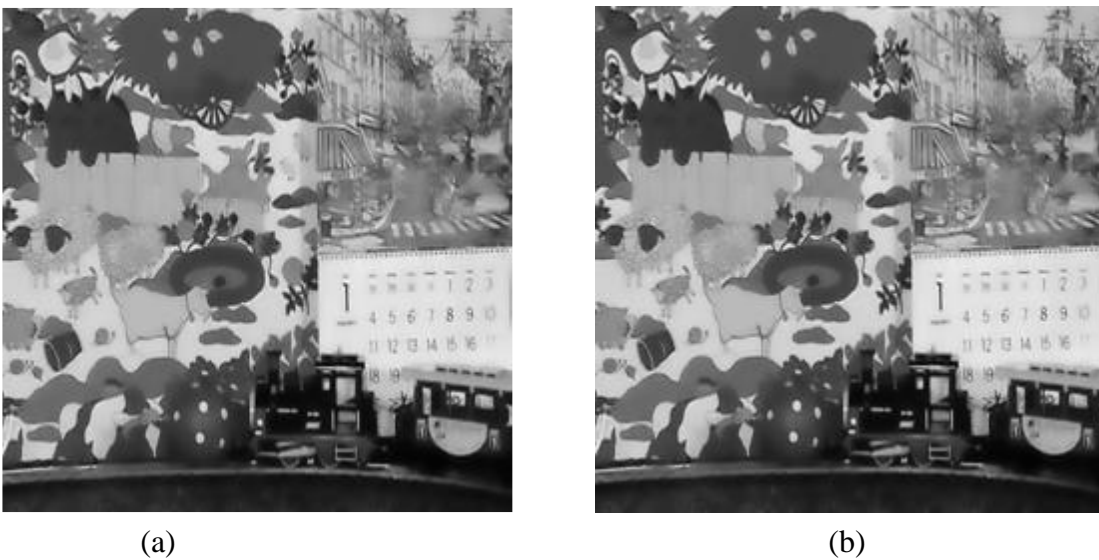


Figure 4.3:(a) Grey scale converted frame (b) Guided filter result

quantitative result shows that proposed method gives much better output in presence of guided filter which is shown in next chapter.

4.6. Magnification(Bilinear interpolation)

Bicubic interpolation method is utilized for getting Hi R in suggested system. Interpolation is a strategy wherein we evaluate estimated continuous value of a system. Huge numbers of interpolation methods like nearest neighbor, bicubic, bilinear are existing. Numerous solicitations of interpolation includes video resizing, video enlargement, video improvement, video reduction, sub pixel picture cataloguing, image breakdown, precise spatial misrepresentations etc

In figure 4.2 we have presented the fundamental idea of how we can increase size using interpolation. Interpolation is method of shifting video from one R to alternative deprived of losing picture quality. Below figure shows the effect of interpolation on an image

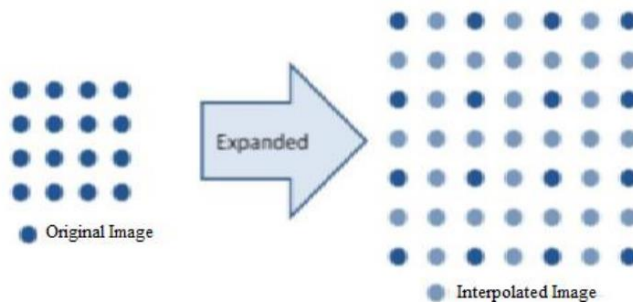


Fig 4.2: Basic principal of interpolation

Non-versatile interpolation procedures depends on straight influence on pixels as an alternative to bearing in mind any feature or data of video. These methods pursue a similar example for each picture element having less computation complexity and easy to accomplish. Different non-versatile procedures includes closest neighbor, bilinear and bicubic.

Nearest Neighbor interpolation: In this strategy the introduced pixel is supplanted

by the closest pixel

Bilinear interpolation: Bilinear interpolation takes a weighted normal of the 4 adjacent pixels to ascertain unknown value.

Bicubic interpolation: Bicubic interpolation is finest amongst all non-adaptive procedures. Bicubic interpolation uses a weighted normal of the 16 pixels to ascertain its last added esteem. These pixels are at different separations from obscure pixel. Closer pixels get higher weight in the count. Bicubic generates sharper output than past two strategies. Mentioned strategy provides enhanced outcome however computational time is higher. At the point where time isn't a requirement this strategy offers finest outcome against all nonadaptive methods. The interpolation kernel for bicubic interpolation is :



(a)



(b)

Figure 4.3: (a) Guided filter Frame (b) Magnified frame

$$\begin{aligned}
u(x) = & \begin{cases} 3/2|x|^3 - 5/2|x|^2 + 1 & 0 \leq |x| < 1 \\ -1/2|x|^3 + 5/2|x|^2 - 4|x| + 2 & 1 \leq |x| < 2 \end{cases} \quad (4.3)
\end{aligned}$$

x denotes distance between interpolated point and grid point.[33]

4.7. Wavelet based edge boosting(SWT and DWT)

Wavelet transform breakdowns the frame in four sub-bands, low-low (LL), low-high (LH), high-low (HL) and high-high (HH). Discrete Wavelet Transform (DWT) and Stationary Wavelet Transform (SWT) are two forms of wavelet transform.

SWT is identical to DWT though SWT produces each sub-band of dimension of frame whereas in DWT all sub-bands have dimension divided by two of frame. Fig 4.5. The three sub-bands (LL, HL and HH), signifies the frame boundaries consequently improved by multiplying with suitable threshold "Th".

Scheme suggested in [9] is proposed for up-sampling. Denoising process will be implemented on HH band, HAAR wavelet is selected for this process, in place of Cohen-Daubechies-Feauveau (CDF) 9/7 wavelet since HAAR wavelet is faster. Numerous other wavelets are present that can give far improved outcomes for example sym; db4 etc however it requires additional computational time. Through research it is clear that HAAR takes 8.39 s whereas DB4 takes 9.23 s.

Upgraded procedure to up-sample video is presented below. Following paragraphs describe comprehensive scheme.

4.7.1 : Stationary wavelet transform

The SWT delivers effective numerical solutions in signal processing applications. A concise depiction of the SWT is exhibited here. Figure 4.4 indicates the calculation of

the SWT of a signal $x(k)$, where $W_{j,k}$ and $V_{j,k}$ are details ,approximation coefficients of the SWT respectively. The filters H_j and G_j are the typical lowpass and highpass wa filters, respectively. In the first step, the filters H_1 and G_1 are obtained by upsampling the filters using the previous step (i.e. H_{j-1} and G_{j-1})

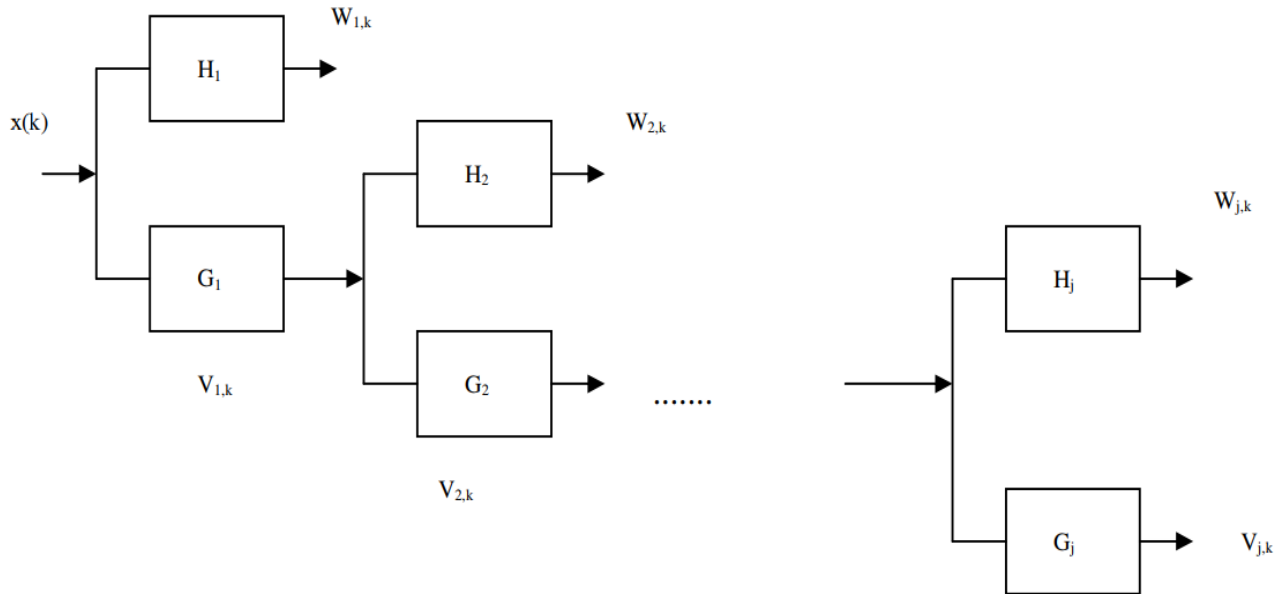


Fig 4.4: Stationary wavelet transform

Coefficients $W_{j,k}$ containing detail information are equivalent to Hi pass filters' output and likewise coefficients $V_{j,k}$ containing approximation information are equivalent to Lo pass filters's output. As mentioned by t f properties of the wa transform H_j and G_j are a set of perfect narrowband filters[32]

In our algorithm we have performed SWT on lesser-sized frame of dimensions $m \times n$ that produces 4 sub bands (ll, lh, hl, hh) having dimensions $m \times n$ all.

For signal breakdown, examination filter bank can be used that comprises of LP and HP channels at each decay level, dividing signal into two groups. The LP channel brings scratchy facts whereas HP filter pull detail data of input. Lastly split yield of filtering process into half.

In order to perform 2D conversion, low pass and high pass analysis filters ,filters the frame along x-axis and reduced into half. After that proceeded by filtering the sub-frame along y-axis and reduced in half.

LL2	HL2	HL
LH2	HH2	
LH		HH

Fig 4.5: Sub Bands of Image

As a final point, the frame has been divided among four bands symbolized with LL, HL, LH, and HH, later to single step decay [17, 18]. The LL band repasses through identical system. This method of filtering frame is pyramidal decomposition of frame; Fig4.7. Moving backward the above technique can bring out the restoration of the frame and it is continual until the video is fully recreated [27].

4.7.2: Discrete wavelet transforms:

In wavelet analysis, the Discrete Wavelet Transform (DWT) decays a sign into a lot of commonly symmetrical wavelet basis functions. These functions contrast from sinusoidal premise works in that they are spatially restricted – that is, nonzero over just piece of the all over sign length. Besides, wavelet functions are dilated, transformed and scaled forms of a acommon function ϕ , known as the mother wa. Similar to Fourier analysis, the DWT is invertible, so that the novel signal can be totally recuperated from its DWT depiction.

We have applied DWT on up sampled output of section 4.4 producing m x n sized four sub bands. Presently LH, HL and HH sub bands delivered by DWT and by SWT are incremented to precise the assessed coefficients.

At this point denoising algorithm is applied on HH sub band just, since LL sub band comprises foremost information about video whereas central noise exist in other three sub bands and supreme high frequency noise present in HH. Further down given is the explanation of denoising algorithm

To eliminate noise acting independently at each pixel and preserve significant facts of the video together Denoising procedures are vital. DWT dependent denoising scheme offers great outcome as Wa change contains enormous coefficients of videos, that exemplifies the detail of video at various sizes. Two approaches offered for denoising, hard Th and Soft Th [28].

Hard Thresholding

$$I(P_b, Th) = P_b \text{ if } |P| > Th$$

And

$$I(P_b, Th) = 0 \text{ if } |P_b| < Th \tag{4.4}$$

Soft Thresholding

$$I(P_b, Th) = \text{sign}(P) * \max(0, |P_b| - Th) \tag{4.5}$$

here

Th stands for threshold level,

Pb denotes input sub band

Db refers to denoised band.

Median Absolute Deviation (MAD) is used by this process to evaluation noise level.

$$\sigma = \text{median } |L_{i,j}| / 0.6745 \tag{4.6}$$

Here

$L_i, j = LH, HL, HH$

Therefore we can say methodology work as, by using HH sub band compute noise level (σ) followed by finding Th rate towards respective sub band

Then apply soft thresholding technique to acquire HH sub band having minimum noise. Lastly bicubic smoother with K/2 factor is used to add all four-sub bands a following by utilization of converse DWT in order to attain ized video having km x kn measure.



(a)



(b)

Figure 4.6: (a) Magnified frame (b) Wavelet transformed Frame

4.8. Denoising (Gaussian Filter)

Gaussian filtering is used to remove noise. In one dimension, the Gaussian function is

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}} \quad 4.8$$

Where σ is the standard deviation of the distribution. The distribution is presumed to have a mean of 0.[31]

Subsequent to up sampling video could become look unclear. There for Gaussian filter purely act as leveling kernel. Since blurry effect is very small therefor application of Gaussian filter only once can solve the problem. In its place winey filter, Iterative blur DE convolution or Lusy Richardson procedure may also provide required results [6].

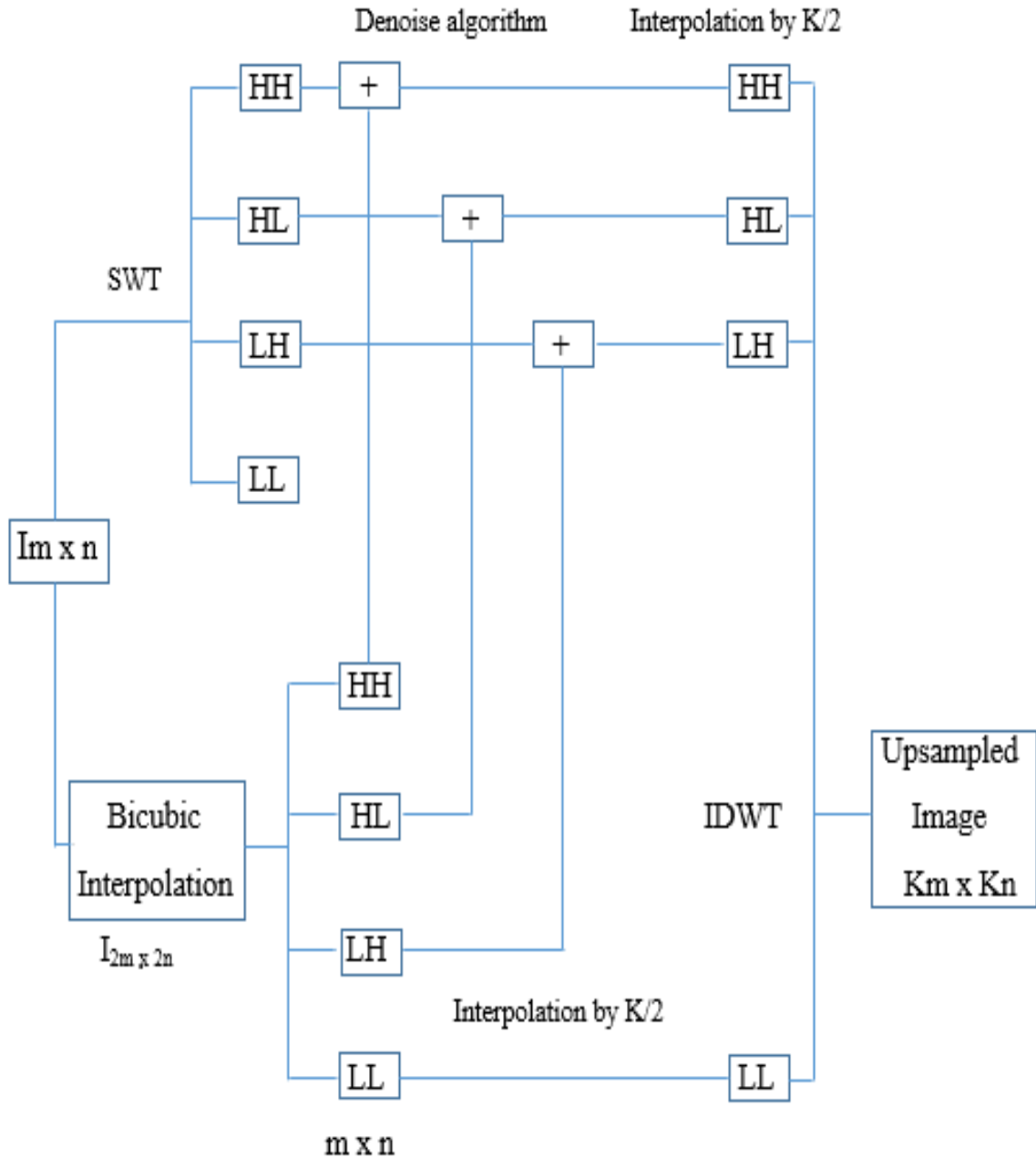


Fig 4.7: Proposed image up sampling method



(a)



(b)

Figure 4.8: (a) Wavelet transformed Frame (b)Denoised frame

4.9. Error Reduction

In this step between original low-resolution video and down sampled video error is calculated. Similar to step1 by using bicubic sharper ALg video is down-sampled. Finding the error is most crucial part of system as the error measured is later utilized as adjustment factor to get video having higher resolution along with that improvement of coefficients of sub bands is done with its help. With the help of trials it is observed that error becomes as small to be ignored after few repetitions

To obtain a video having higher resolution as compared to input resolution, error value must be added to originally up sampled video and this is done by up sampling the error matrix to equate Su R video. Bicubic procedure is used for up-sampling error matrix.

Lastly error matrix produced is added with high-resolution video recreated in step 2. Keep on repeating the above process till we obtain suitable results. Normally within three repetitions suitable result is achieved



(a)



(b)

Figure 4.8: (a)Denoised frame (b) Final output

CHAPTER 5: SIMULATION AND RESULTS

This chapter contains the specifics of implemented proposed model and gathered outcomes of it. For analysis after gray scale conversion, guided filter is applied on videos and up samples by using bicubic method then Wa transform is applied and after denoising result is matched with input video. For demonstration of outcome of described process, multiple test video sequences are used. The recreated video is compared with the original video. To execute numerical analysis psnr value are given

To measure the quality of output video (PSNR) value is calculated which is mathematically represented as:

$$\text{PSNR} = 10 \log_{10} \frac{(m(h(i, j))))^2}{\text{MSE}} \quad 5.1$$

Whereas a (i, j) represent the pictorial element values. In case of gray scale video it could be specified as:

$$(\text{Max } (h(i, j))) = 255 \quad 5.2$$

Mean Square Error (MSE) Symbolizes a phrase that compares original video and recreated video, its mathematical expression can be written as:

$$\text{MSE} = \sum_{MN} \frac{h(i, j) - \tilde{h}(i, j)}{M \times N} \quad 5.3$$

5.1. Qualitative analysis:

Following figures show qualitative results of proposed ALg by using sample videos, two frames of each video are shown here.



(a)



(b)



(c)



(d)



(e)



(f)

Figure 5.1: Results without guided filter, video 1(a) RGB to grey (b) Bicubic (c) Wevelet (d) Output sig 1 (e) Output sig 10 (f) Output sig 15



(a)



(b)



(c)



(d)



(e)



(f)

Figure 5.2: Results with guided filter , video 1(a) Guided filter (b) Bicubic (c) Wavelet (d) Output sig 1 (e) Output sig 10 (f) Output sig 15



(a)



(b)



(c)



(d)



(e)



(f)

Figure 5.3: Results without guided filter, video 2 (a) RGB to grey (b) Bicubic (c) Wavelet (d) Output sig 1 (e) Output sig 10 (f) Output sig 15



(a)



(b)



(c)



(d)



(e)



(f)

Figure 5.4: Results with guided filter, video 2 (a) Guided filter (b) Bicubic (c) Wavelet (d) Output sig 1 (e) Output sig 10 (f) Output sig 15



(a)



(b)



(c)



(d)



(e)



(f)

Figure 5.5: Results without guided filter, video 3 (a) RGB to grey (b) Bicubic (c) Wavelet (d) Output sig 1 (e) Output sig 10 (f) Output sig 15



(a)



(b)



(c)



(d)



(e)

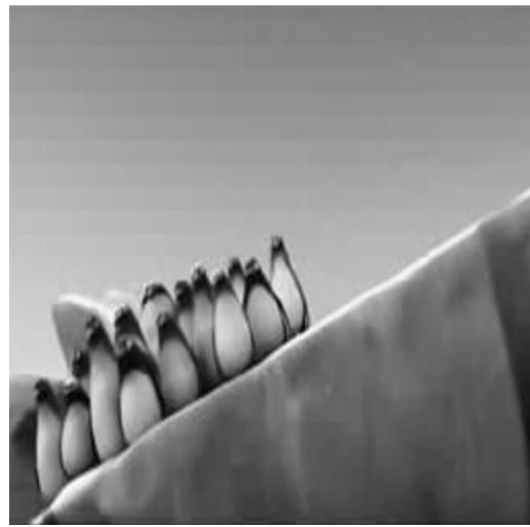


(f)

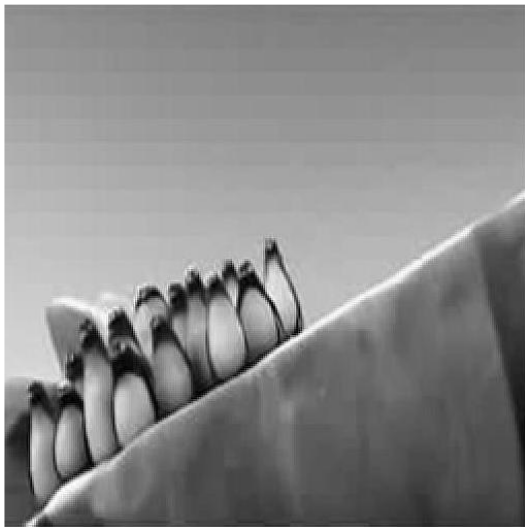
Figure 5.6: Results with guided filter, video 3 (a) Guided filter (b) Bicubic (c) Wavelet (d) Output sig 1 (e) Output sig 10 (f) Output sig 15



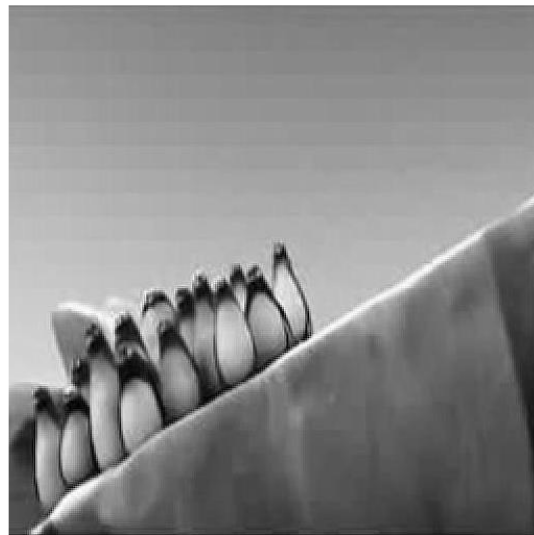
(a)



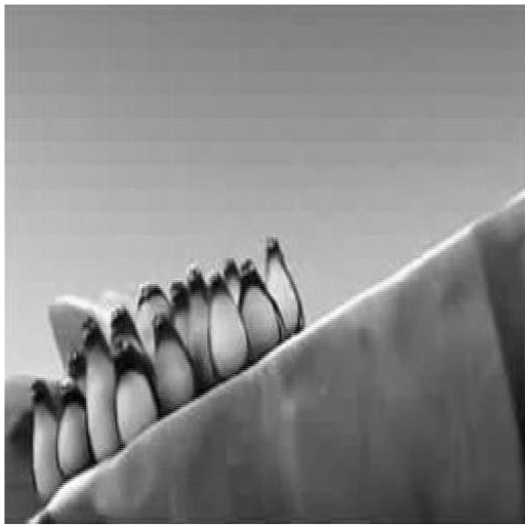
(b)



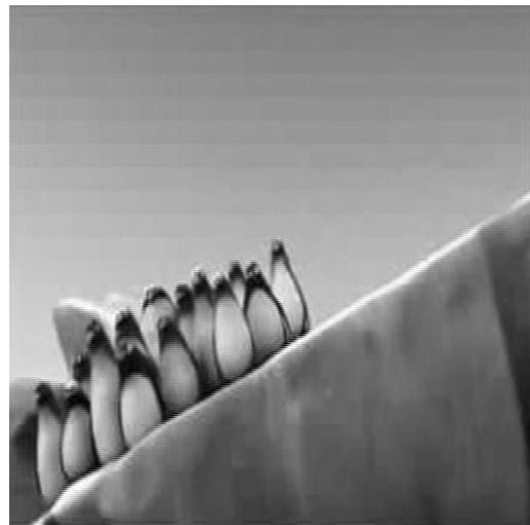
(c)



(d)



(e)



(f)

Figure 5.7: Results without guided filter, video 4(a) RGB to grey (b) Bicubic (c) Wavelet (d) Output sig 1 (e) Output sig 10 (f) Output sig 15



(a)



(b)



(c)



(d)

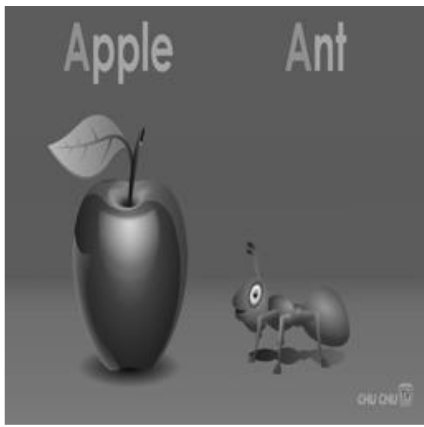


(e)

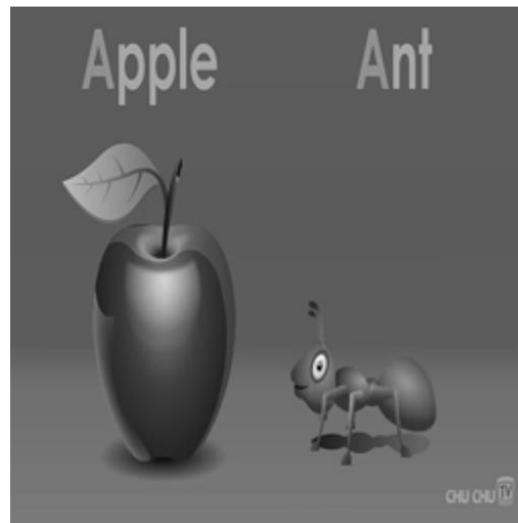


(f)

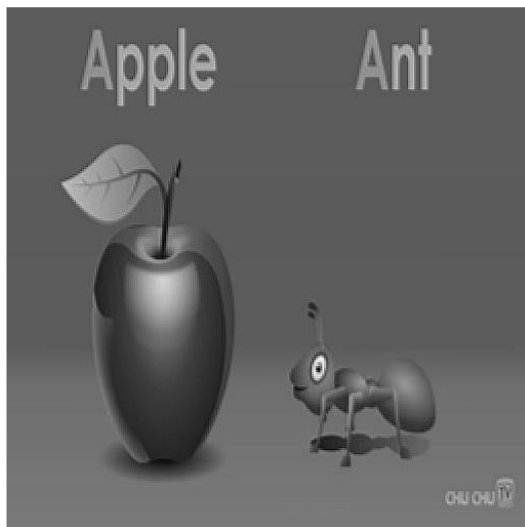
Figure 5.8: Results with guided filter, video 4 (a) Guided filter (b) Bicubic (c) Wavelet (d) Output sig 1 (e) Output sig 10 (f) Output sig 15



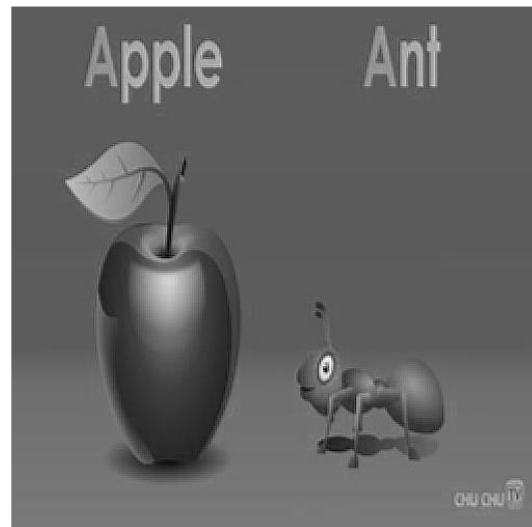
(a)



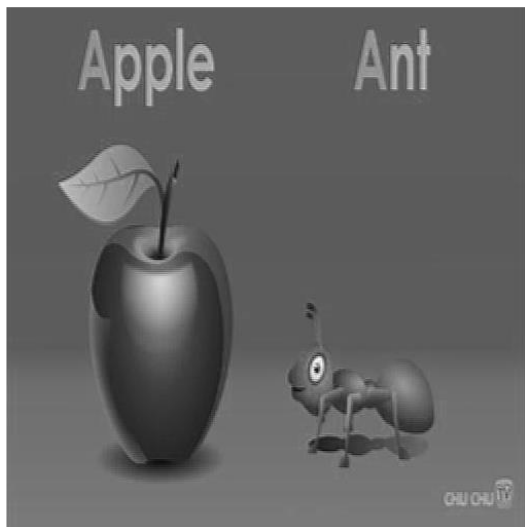
(b)



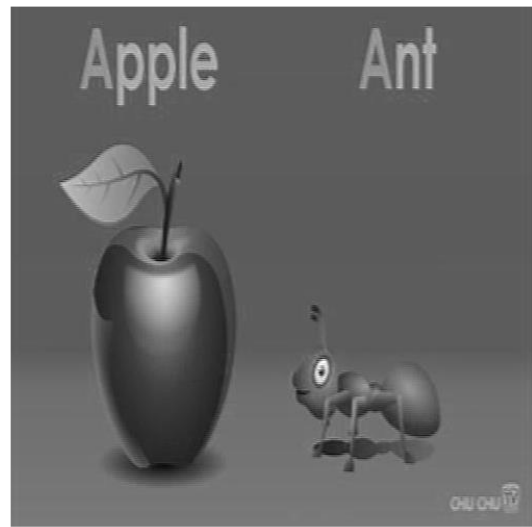
(c)



(d)

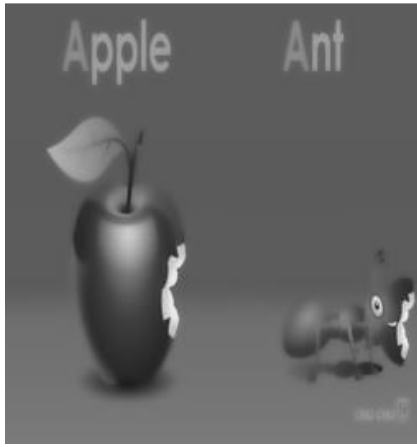


(e)

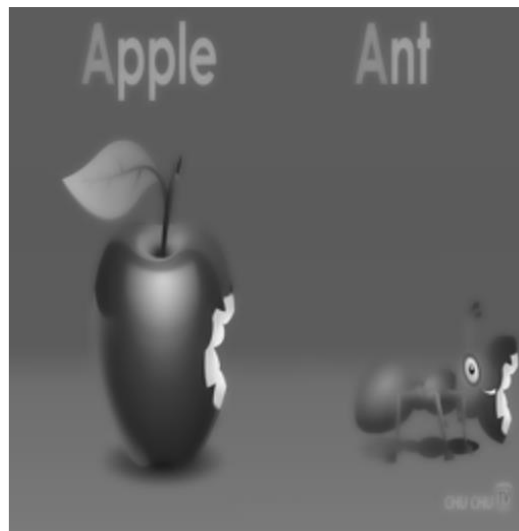


(f)

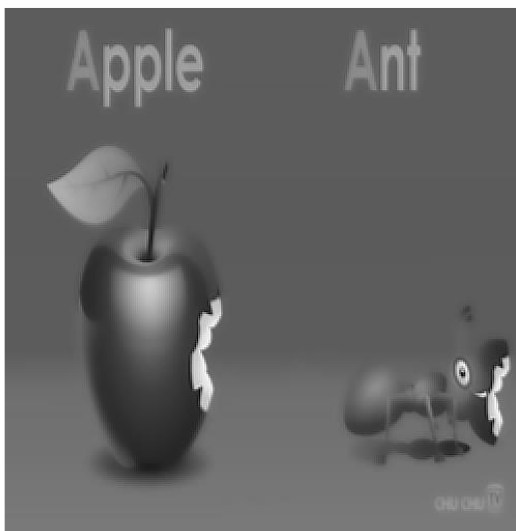
Figure 5.9: Results without guided filter, video 5 (a) RGB to grey (b) Bicubic (c) Wavelet (d) Output sig 1 (e) Output sig 10 (f) Output sig 15



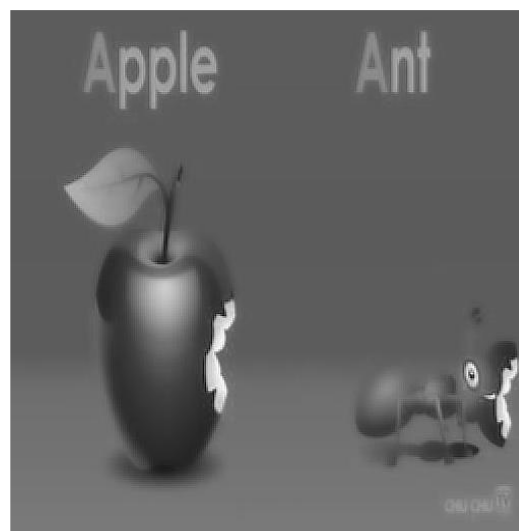
(a)



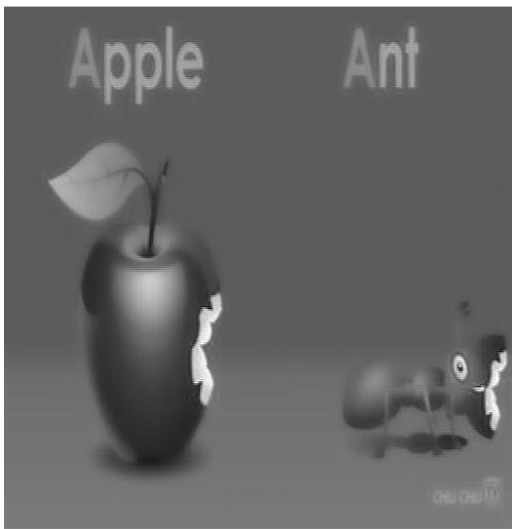
(b)



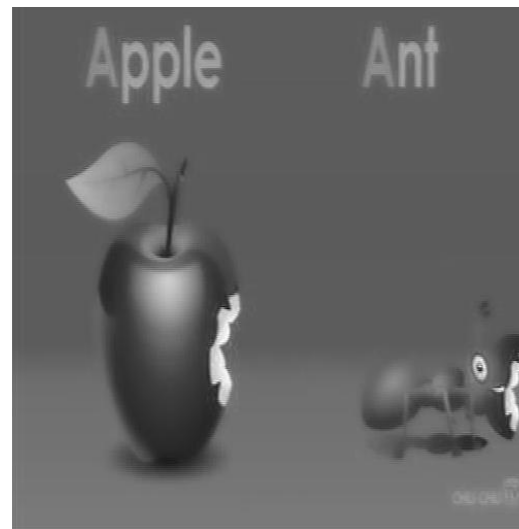
(c)



(d)



(e)



(f)

Figure 5.10: Results with guided filter, video 5 (a) Guided filter (b) Bicubic (c) Wavelet (d) Output sig 1 (e) Output sig 10 (f) Output sig 15

5.2. Quantitative results

Table 5-1. Quantitative Comparison of different values of σ_n for proposed method without guided filter. All PSNR values are in decibel

Video sequences	σ_n			
	<i>1</i>	<i>5</i>	<i>10</i>	<i>15</i>
Video 1	37.96	37.92	37.37	36.37
Video 2	37.21	37.20	36.71	35.61
Video 3	34.78	34.77	34.15	33.54
Video 4	33.44	33.39	33.37	32.99
Video 5	33.71	33.07	32.78	31.66
Video 6	40.62	40.61	39.68	38.21

Table 5-1. Quantitative Comparison of different values of σ_n for proposed method with guided filter. All PSNR values are in decibel

Video sequences	σ_n			
	<i>1</i>	<i>5</i>	<i>10</i>	<i>15</i>
Video 1	47.31	47.31	46.92	46.33
Video 2	38.36	38.35	37.84	37.09
Video 3	36.68	36.67	36.81	36.40
Video 4	35.37	35.34	34.64	33.49
Video 5	44.28	44.07	41.74	38.97
Video 6	42.52	42.31	41.57	39.94

5.3. Comparisons:

Correlation [29] of cubic Int, new edge directed Int (NEDI), Wa zero padding (WZP) same as picture up-examing utilizing DWT, ALg suggested in [27](FF) and proposed technique(P.M) is presented.

Table 5.2. Evaluation of diverse renowned techniques on the basis of psnr.

	Bicubic	NEDI	WZP	FF	Proposed method
I1	30.59	29.83	30.18	31.47	31.99
I2	29.85	29.33	29.76	30.27	31.57
I3	31.62	30.36	30.62	31.75	32.03
I4	30.99	30.67	30.93	31.17	31.87
I5	31.75	30.75	30.82	32.03	32.29
I6	32.28	31.16	31.37	32.42	32.88

5.4 Graphical Representation:

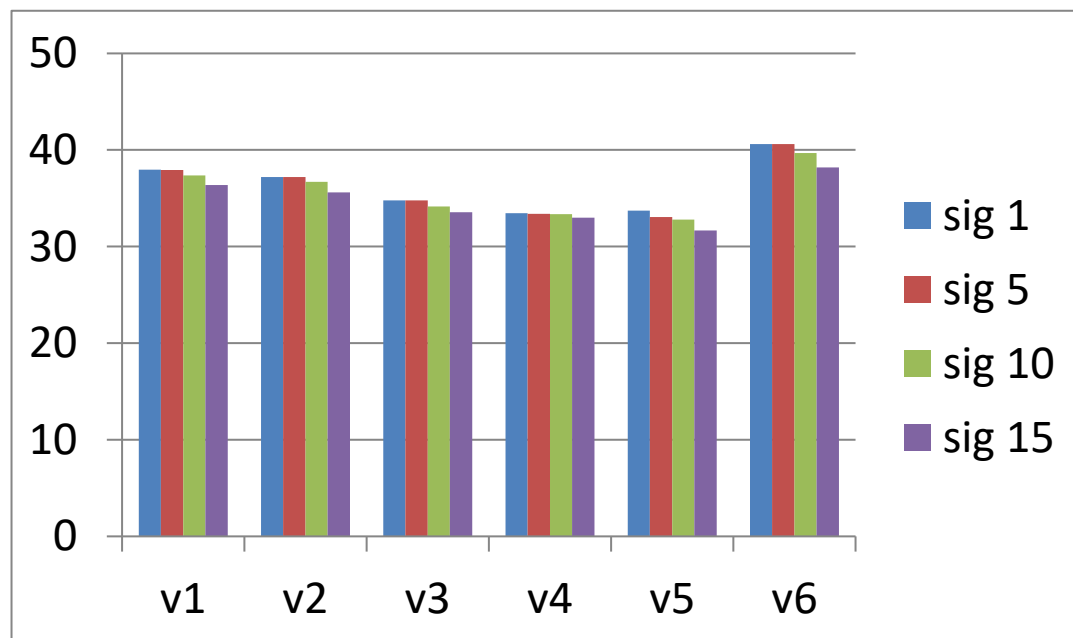


Fig5.11: Graphical representation of Table 5.1

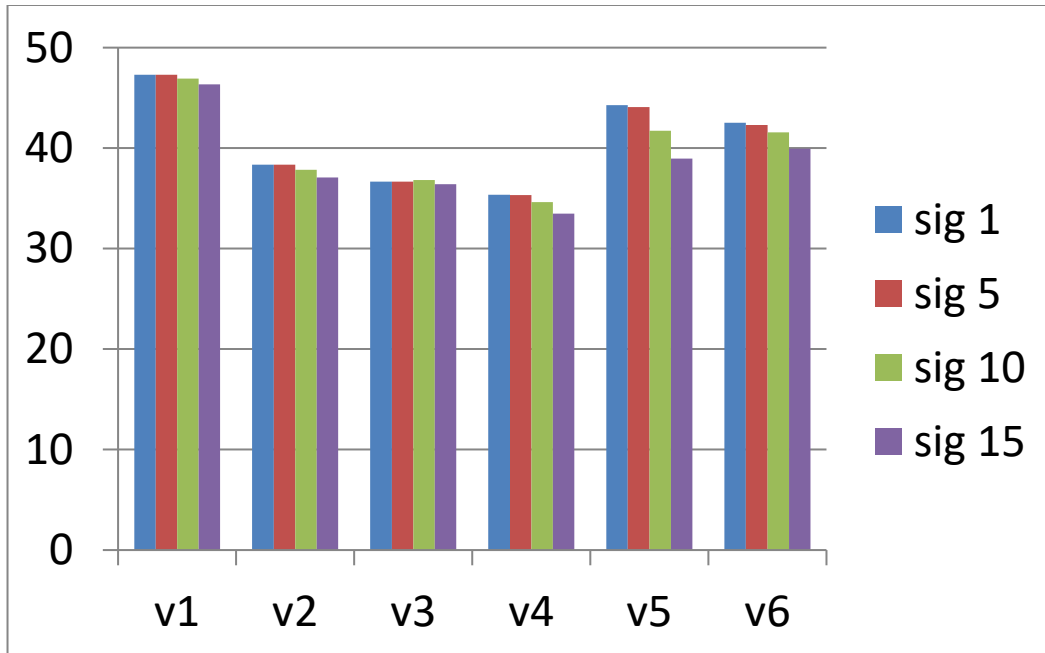


Fig5.12: Graphical representation of Table 5.2

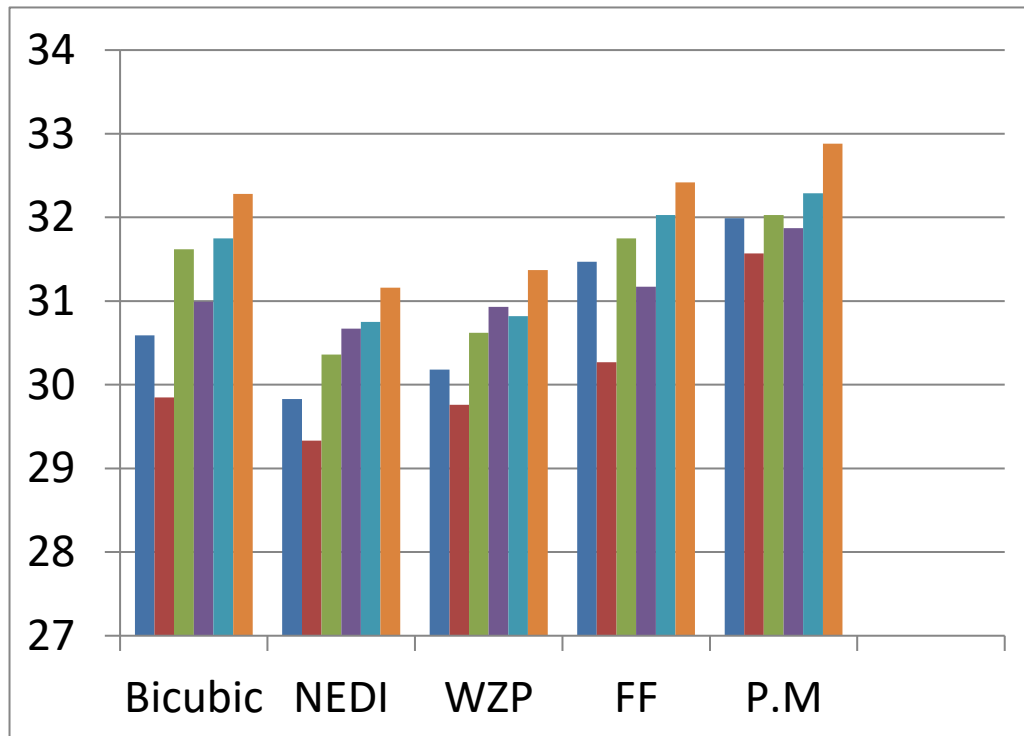


Fig5.13: Graphical representation of Table 5.3

CHAPTER 6: SUMMARY AND CONCLUSION

6.1. Summary

Process of Super Resolution creates videos of higher-resolution from already available multiple lower-resolution videos. Customary Interpolation enlargement procedures like nearest-neighbor, bilinear or bicubic Interpolation give enlarged videos together with unwanted factors as blurring, aliasing and ringing effects. The basic goal of super-resolution is to produce a bigger video having output including lesser intolerable factors.

Prior super-resolution methodologies used multiple videos along with learning based systems and this zone has developed giving high quality results but obtaining knowledge from single video and generating higher quality videos output still needed improvements.

In this thesis the above mentioned problem has been addressed, a methodology has been suggested that preserves the details of a single video. This Algorithm has uses three approaches: first to preserve edges by guided filter second to up sample the video using Interpolation procedure and lastly to improve the boundaries using Wavelet transform.

Through detail qualitative along with quantitative analysis, the proposed method provides with low artifacts higher resolution videos and the output is analogous with other renowned techniques.

Numerical and Graphical analysis of suggested Algorithm anticipates that though the Algorithm produces good quantitative result but the visual results are good for those videos that have less edges and square frames.

6.2. Future Work

Suggested procedure uses benefit of equally W_a and spatial field. PSNR along with graphic representation shows efficiency of recommended process too. Proposed ALg is faster and involves less computational time. A number of improvements on up sampling procedure may increase output efficiency. In up and coming time extra work on W_a area and surface based up inspecting should be possible along with assessment to see which set of rules will provide better results for which kind of videos.

Bibliography

- 1) D. Glasner, S. Bagon, and M. Irani. Super-resolution from a single image. In Proc. ICCV, 2009
- 2) Yoav HaCohen, Raanan Fattal, Dani Lischinski, "Image Up sampling via Texture Hallucination", IEEE
- 3) R. Fattal. Image upsampling via imposed edge statistics. ACM Trans. Graph., 26(3):95, 2007
- 4) W. T. Freeman, T. R. Jones, and E. C. Pasztor. Example-based super-resolution. IEEE Comput. Graph. Appl., 22(2):56–65, March 2002.
- 5) Muhammad Sajjad, Naveed Khattak and noman Jafri, Image Magnification Using Adaptive Interpolation by Pixel Level Data-Dependent Geometrical Shapes, International Journal of Computer Science and Engineering Volume 1 Number 2, 2007
- 6) Andrea Giachetti and Nicola Asuni, Fast Artifacts-Free Image Interpolation, Proceedings of British Machine Vision Conference, 2008
- 7) Munib Arshad Chughtai and Naveed Khattak, An Edge Preserving Adaptive Antialiasing Zooming Algorithm with Diffused Interpolation, IEEE Proceedings of the 3rd Canadian Conference on Computer and Robot Vision, 2006
- 8) Jan Mihalik, Jozef Zavacky, Igor Kuba, Spline Interpolation of Image, Radioengineering, Volume 4, No. 1, 1995
- 9) Lei Zhang and Xiaolin Wu, An Edge Guided Image Interpolation Algorithm via Directional Filtering and Data Fusion, IEEE Image Processing, IET, Volume 15, Issue 8 Page 2226 - 2238, August 2006
- 10) Dengwen Zhou, Xiaoliu Shen, Image Zooming Using Directional Cubic Convolution Interpolation, IEEE Image Processing, IET, Volume 6, Issue 6 Page 627 – 634, August 2012
- 11) Ning Xu, Yeong-Taeg Kim, An Image Sharpening Algorithm for High Magnification Zooming, IEEE International Conference on Consumer Electronics, Page no. 27-28, January 2010

- 12) Huda Nawaz, Image Zooming Using Wavelet Transform, International Conference on System and Simulation in Engineering, Spain, December 2006
- 13) Xin Li, Michael T. Orchard, New Edge-Directed Interpolation, IEEE Transactions on Image Processing, Volume 10, No. 10, October 2001
- 14) Yu-Wing Tai, Shuaicheng Liu, Micheal S. Brown, Stephen Lin, Su R using Edge Prior and Single Image Detail Synthesis, IEEE Conference on Computer Vision and Pattern Recognition, 2010
- 15) Wenze Shao, Zihui Wei, Efficient Image Magnification and Applications to Super-Resolution Reconstruction, IEEE International Conference on Mechatronics and Automation, China, 2006
- 16) Qi Shan, Zhaorang Li, Jiaya Jia, Chi-Keung Tang, Fast Image/Video Upsampling, ACM Transactions on Graphics, Volume 27, No. 5, Article 153, December 2008
- 17) Andrea Giachetti and Nicola Asuni, Real Time Artifact-Free Image Upscaling, IEEE Transactions on Image Processing, Volume 20, Issue 10, October 2011
- 18) Dong Zhang and Cunxie Xie, A New Method for Super-resolution Reconstruction, Computational Engineering in Systems Applications, Volume 1 Page no. 65 – 67, October 2006
- 19) Shaofeng Chen, Hanjie Gong, Cuihua Li, Super-Resolution from a Single Image Based on Self-Similarity, International Conference on Computational and Information Science, 2011
- 20) Huahua Chen, Baolin Jiang, Weiqiang Chen, Image Super-Resolution based on Patches Structure, 4th International Congress on Image and Signal Processing, 2011
- 21) Jianhong Li and Xiaocui Peng, Single-Frame Image Super-Resolution through Gradient Learning, IEEE International Conference on Information Science and Technology, 2012
- 22) Daniel Glasner, Shai Bagon, Michal Irani, Super-Resolution from a Single Image, IEEE 12th International Conference on Computer Vision, 2009
- 23) Pandian, 1. (2012). Hybrid Algorithm for Lossless Image Compression using Simple Selective Scan order with Bit Plane Slicing. Journal of Computer Science 8 (pp. 1338-1345). India: 2012 Science Publications.

- 24) Qi-bin, F. (2008). Wavelet analysis. Wuhan:: Wuhan University Press.
- 25) Said, A. (June 1996). IEEE Transactions on Circuits and Systems for Video Technology , Vol. 6,.
- 26) Salomon, D. (2001). Data Compression 2e. Springer.
- 27) Sapan Naik, Viral Borisagar, "A novel Su R Algorithm Using Interpolation and LWT Based Denoising Method",International Journal of Image Processing (IJIP), Volume (6) : Issue (4) : 2012
- 28) A.Jensen, A.la Courharbo, “ Ripples in Mathematics: The Discrete Wavelet Transform”, springer, 2001.
- 29) Sapan Naik1, Nikunj Patel “Single image super resolution in spatial and wavelet domain” The International Journal of Multimedia & Its Applications (IJMA) Vol.5, No.4, August 2013
- 30) C. Saravanan, “Color Image to Grayscale Image Conversion,” IEEE Second International Conference on Computer Engineering and Applications, pp. 196–199, 2010.
- 31) https://www.cs.auckland.ac.nz/courses/compsci373s1c/PatricesLectures/Gaussian%20Filtering_1up.pdf
- 32) ozgur tamer , “Analysis of the application of the stationary wavelet transform to the dire” IEEE Transactions on Image Processing, Volume 20, Issue 10, October 2011
- 33) Vaishali Patel, “A Review on Different Image Interpolation Techniques for Image Enhancement” , International Journal of Emerging Technology and Advanced Engineering Website: www.ijetae.com (ISSN 2250-2459, ISO 9001:2008 Certified Journal, Volume 3, Issue 12, December 2013)

