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Search Based Optimization Approach for Video Super Resolution

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Abstract
Video Super Resolution (SR) is used to enhance the resolution of low resolution videos in minimum cost as compare to hardware models and it should handle noisy and blurry videos. This paper represents efficient and robust video SR model which enhance the resolution of different videos. Input video is taken from readily available standard UCSD datasets; these videos are in RGB format which are initially converted to HSV format. To achieve high resolution the V-channel is used for enhancement. Full search motion estimation is used find out matching macro blocks in a video frame. Cubic spline interpolation technique is used to find value of unknown pixel. Bilateral total variation is used for de-noising and de-blurring. Resolution factor is optimized using different optimization techniques like particle swarm optimization (PSO), Grey Wolf optimization (GWO), Whale optimization algorithm (WOA) and Lion algorithm (LA). Performance of proposed video SR is compared with existing methods and statistical analysis is done with PSNR, SSIM, SDME, ESSIM and BRISQUE parameters.

Keywords*: Video Super Resolution; Search Based Optimization Algorithm; Cubic Spline Interpolation; V-Channel Magnification.*

I. Introduction

Super resolution is well known technique in resolution enhancement of single image, multiple image and video processing. It is mainly used to reconstruct high resolution frame from noisy, blurry or down-scaled low resolution frame. In low resolution image, the components of high frequencies are missed out and those components estimated through super resolution. In image processing different hardware elements are used as a) image acquisition element which includes element as Charge coupled device (CCD) sensors, Complementary metal Oxide Semiconductor (CMOS) sensors and imagining scanners, b) image-storage devices, c) image processing elements, and d) image-display devices. Super resolution technique is used to resolve the optical issues of digital camera sensors. These techniques are not expensive as compare to hardware utilized to capture and reconstruct high resolution frame. In mutli-image super resolution, multiple images of same scene are fused together to obtain high resolution frame. The resolution of image can be improved by changing the relative motion between the scene and image plane. Super resolution technique overcomes the hardware cost and suitable for different consumer applications like video conferencing and video transmission through internet.

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Super resolution is done in two different domains as spatial domain and frequency domain. In spatial domain, the single image super resolution uses the information of current low resolution frame. This method also called as spatiotemporal, which uses information from neighboring frames to increase the quality of image. In some cases information from neighboring frames are used to reconstruct center frame. The term spatial refers to space is 2D plane in image. So, the spatial domain refers to the image plane itself and this method directly modifies the value of the pixels. Spatial domain processes are represented as,

$$Y(x,y) = T[X(x,y)]$$

Where, Y is reconstructed image and the value of a pixel with coordinate (x, y) in Y is the result of performing some operation T on the pixels in the neighborhood of (x, y) in original image X.

Frequency domain methods based on Fourier transform of an image. The term frequency in an image tells about rate of change of pixel values. It is less cheap and takes more time to compute.

The main contribution of this paper is as follows.

1. Video super resolution model is developed using cubic spline interpolation, bilateral total variation and particles warm optimization technique.
2. Input video is converted into number of frames. Those frames are converted to HSV format. Resolution of V-channel is enhanced.
3. Cubic spline interpolation technique is used to calculate pixel value of unknown location.
4. Bilateral total variation is used for denoising and deblurring.
5. Resolution factor is optimized using different search based optimization technique.
6. Statistical analysis is done with PSNR, SSIM, SDME, ESSIM and BRISQUE parameters.

The organization of this paper is in this order: Section II describes the literature work regarding video SR models. Architecture of proposed video Super resolution model is explained in Section III. The results obtained are demonstrated in Section IV and Section V concludes the paper.

II. Literature Review

Related Works

In 2013, Nafise Barzigar *et al.* [1] have developed two technique one is sparse based and other is belief propagation for video super resolution. This technique finds the candidate match pixels from multiple frames. By using Nonlocal-Means (NLM) method the information is extracted from those pixels by weight computation. Bad candidate matches are eliminates and best patches are selected with Belief propagation. This method is suitable for real time and synthetic video.

In 2016, Parisa Gifani *et al.* [2] have proposed temporal method for super resolution of echocardiographic images. Temporal information is extracted from time curve of intensity of each pixel. Active atoms and sparse coefficients are extracted to construct sparse coefficient dictionary. This method overcomes the blocking artifacts and blur of moving object.

In 2013, Zahra Ashouri *et al.* [3] have proposed countourlet transform and bilateral total variation filter to enhance the resolution of video. Compressive sensing algorithm is used to find the high resolution frame. Bilateral total variation is used in post processing to remove blurr and increase consistency.

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In 2017, Ding Liu *et al.* [4] have introduced a convolutional neural network approach for video super resolution. Temporal adaptive (TA) network is proposed to calculate the scale of temporal dependency and then spatial adaptive network (SAN) is used for motion complexity between adjacent frames.

In 2018, Mehdi S. M. Sajjadi *et al.* [5] have developed a video super-resolution model using convolutional neural network. In this method information from previous high resolution frame is used to enhance the resolution of consecutive frame. Due to warping the computational cost is reduced. The technique does not require pre-trained database.

In 2017, Xin Tao *et al.* [6] have introduced a video super-resolution model using CNN approach using detail revelling method . In CNN frame work sub pixel motion compensation layer is included which combine multiple frames to get image detailed information.

In 2017, Wenzhe Shi *et al.* [7] have proposed super resolution technique based on efficient sub-pixel convolutional neural network for real time image and video. This method achieves good accuracy and computational performance for single image. Sub-pixel convolution layer learn array to enhance the low resolution features.

In 2018 , Ce Liu *et al.* [14] have presented a video super-resolution model which employs Bayesian technique. Video super resolution is done by jointly simulating motion, unknown blur kernel and unknown noise. Different types of blurry and noisy images are considered in single Bayesian approach.

Table I describes the different features and challenges of available video and image based super resolution methods. Those techniques are used in different applications with innovative features and with improved efficiency.

The SCoBep and NLM method [1] is suitable for real time videos and scene motion as well as well suitable for camera motion. The main challenging task of this technique is it run on complete dictionary of low resolution (LR) patches and removes bad matching conditions. The Temporal Model [2] achieves best resolution in echocardiographic images. In this technique low and high resolution dictionaries are created with prior knowledge. Challenge of this method is fractional up conversion and adapts motion of fast moving object.The CS-BTV Model [3] attains robustness for high resolution frame with selected compressive sensing. Blur in frame is removed with bilateral total variation to increase image quality. To minimize requirement of training data is challenging task and also to cover many direction with different resolution levels. The TA-SANt Model [4] obtains effectiveness in PSNR over other conventional optical flow alignment. Quality of image is improved in spatial alignment. Frame alignment is very difficult task and due to which processing time is challenging task. The FRVSR Model [5] accomplishes accuracy with video of any length can be trained on network. Previously obtained video frame is used to generate new frame. More number of frames is processed to get good resolution. The SPMC Model [6] achieves better performance using Tensor flow through which small text also covered with fine details. In which it is very difficult to handle fast motion and fusion of multiple frames. The ESPCN Model [7] efficient for motion compensation. It jointly covers video super resolution with motion compensation. It reduces motion using spatio-temporal network. Inter frame motion compensation is difficult task in the technique. The Bayesian SR Model [14] accomplishes robust complex motion and removes noise and blur conditions. To remove unknown noise and to produce sharp edges in fast moving object is challenging task of this technique.

Table 1.Features and challenges of conventional SR models in videos implemented by different techniques

Author [Citation]	Method	Features	Challenges
Nafise Barzigar et al [1]	SCoBeP, NLM	Suitable for real time video and synthetic video. Algorithm support scene motion and camera motion.	Super resolution is run on complete dictionary of LR patches. Eliminate bad matches and select best matches.
Parisa Gifani et al [2]	Temporal	Temporal technique is used to enhance echocardiographic images Low and high resolution dictionaries are designed with prior knowledge.	Suitable to any fractional up – conversion. Adaptive to fast moving object
Zahra Ashouri et al [3]	CS-BTV	HR frames are selected with compressive sensing. BTV is used to remove blur and increase image quality.	Removes requirement of training data. Cover many directions in each resolution level.
Ding Liu et al [4]	TA-SAN	Achieve highest PSNR over conventional optical flow alignment. Super resolution quality is improved due to spatial alignment.	Frame alignment Reduce processing time
Mehdi S. M. Sajjadi et al [5]	FRVSR	Network can trained on video clip of any length Previously generated HR frame is used as input for next iteration to enhance next frame.	Carry high frequency details. To get good resolution more frames are processed.
Xin Tao et al [6]	SPMC	Un-optimized Tensor flow is used Method covers the textbook character details and fine image details	Handle interframe motion Fuse image details from multiple images after SPMC arrangement.
Jose Caballero et al [7]	ESPCN	Motion compensation is jointly trainable for video SR. Reduce computational complexity by spatio-temporal network.	Estimate inter frame motion compensation Combine motion compensation and spatio temporal model.
Ce Liu et al [14]	Bayesian	Robust to complex motion. Varies noise levels and blur kernels are handled	Jointly SR simulate with unknown noise, unknown blur and complex motion Fast moving objects produces sharp edges.

Review of search optimization techniques

These techniques are more popular in many engineering problem solving because it relay on simple concept and its implementation is easy, it can bypass local optima and it used in different wide range applications. Nature inspired Meta heuristic algorithm solve optimization problems by introducing biological or physical concept. They are grouped in three categories.

1. Evolution Based algorithms
2. Physics based algorithms
3. Swarm Based algorithms

Evolution based techniques are motivated by the law of natural evolution. The hunt procedure begins with a randomly produced population that developed over the subsequent generation. Genetic algorithm, probability-based gradual learning, Genetic programming and Biogeography based optimizer are few algorithms are come in evolution based system. Material science-based techniques emulate the physical standards in the universe. Simulated Annealing, Gravitational nearby search, Central force optimization are nearby algorithms that come under material science-based system. The nature-inspired method likewise incorporates swarm-based strategies that mimic the social behaviour of groups of animals. Molecule swarm optimization, ant colony optimization, and whale optimization are a few algorithms of swarm-based technique. The benefits of a swarm-based algorithm are which save search space data over subsequent iteration while an evolution-based algorithm disposes of any data when another population is framed. incorporate fewer operators contrasted with transformative methodologies.

Methodology and Implementation

Proposed video super resolution algorithm consists of multiple steps as RGB to HSV conversion, full search motion estimation, cubic spline interpolation, bilateral total variation and particle swarm optimization. Input low resolution video is converted to multiple frames. Each frame in Red, Green, Blue (RGB) format, which is converted to Hue, Saturation, Value (HSV) format. V channel is further used for enhancement. Full search motion estimation technique is used for motion estimation between current and reference frame. Cubic spline interpolation is used to find unknown value of pixel. V channel frame is deblurred through bilateral total variation and resolution factor is optimized using particle swarm optimization (PSO), Grey wolf optimization algorithm (GWO), Whale Optimization Algorithm (WOA) and Lion Algorithm (LA). Finally H channel, S channel and enhanced V channel are combined together to form high resolution (HR) frame.

Full Search Motion Estimation

It is utilized to discover coordinating macro blocks in a video frame if there should be an occurrence of motion estimation. Motion estimation is utilized in which patterns identified with the objects and background in a casing of video sequence move inside the edge to shape relating objects on the consequent frame. The block matching technique partitions the present edge of video into macro blocks and contrasts each and a comparing block and its adjoining neighbors in a close-by frame of video. A vector is created which models the development of a macro block starting with one area then onto the next. This vector is determined for all macro blocks of the frame. Search parameters are utilized to choose the search area in which the number of pixels on all sides of the macro blocks of the previous frame. Evaluation metrics utilized for movement compensation are Mean absolute difference (MAD), Mean square error (MSE) and Peak Signal to Noise Ratio (PSNR).

Mean absolute difference (MAD),

$$MAD = \frac{1}{N^2}\sum_{i=0}^{n-1}\sum_{j=0}^{n-1}\left|(C_{ij} - R_{ij})\right| \quad (1)$$

Where, N is size of macro lock, C_{ij} is pixels compared with current macro block and R_{ij} is pixels compared with reference macro block.

Cubic Spline Interpolation

Interpolation is a process which generate new pixel by analyzing nearby pixels. Interpolation techniques are used to attempt balance between undesirable artifacts edges halos, blurring and aliasing. The cubic spline interpolation technique is used to draw smooth curves through various points. The spline comprises of loads joined to a level surface at the points to be

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associated. An adaptable strip is then twisted over every one of these loads, bringing about a pleasingly smooth curve. The numerical spline is comparable on a fundamental level. The points, for this situation, are numerical information. The weights are the coefficients on the cubic polynomials used to add the information. These coefficients 'twist' the line so it goes through every one of the information points without any erratic behavior or breaks incoherence. The primary use of cubic spline interpolation strategies is bend fitting.

$$S_i(x) = p_i(y-y_i)^3 + q_i(y-y_i)^2 + r_i(y-y_i)^3 + d_i \quad (2)$$

For i=1, 2…n-1

The first and second derivatives of these n-1 equations are fundamental to this process, and they are

$$S_i^{'}(x) = 3p_i(y-y_i)^2 + 2q_i(y-y_i) + r_i \qquad (3)$$

$$S_i^{''}(x) = 6p_i(y-y_i) + 2q_i \qquad (4)$$

In cubic spline interpolation following conditions are followed

a. Function S(x) will interpolate all data points.

b. In interval [x_1, x_n], S(x), S'(x) and S''(X) are continuous.

Regularization

Regularization process is used to add information to solve the ill opposed problem or to prevent over fitting. It calculate cost function which compares the low resolution and high resolution frame.

Regularization follows few steps

1. L1 norm

2. Bilateral total variation

3. Steepest Descent minimization

L1 norm minimization technique is used to measure distance between vectors, that the sum of absolute difference of component vectors.

$$\hat{X} = \overset{\arg\min}{X}\left[\sum_{k=1}^{N}\left\|H_k X - Y_k\right\|_1\right] \qquad (5)$$

Where, $\hat{X}$ is estimated image

H_k is Point spread function

$H_k X$ is blurred image

Y_k is LR image

X is original frame (Real world scene)

(H_k = H assume common PSF as all images are acquired by unique camera)

Bilateral total variation is used to remove blur and noise from frame. The frame obtained from cublic spline interpolation is deblurred to obtain enhanced high resolution frame with better visual quality. BTV criterion penalizes the total amount of change in image measured by L1 norm.

The cost function Γ(X) of BTV regularizing function looks like,

$$\hat{X} = \overset{\arg\min}{x}\left[\sum_{k=1}^{N}\left\|H_k X - Y_k\right\|_1 + \lambda\Gamma(X)\right] \qquad (6)$$

Where,

$$\Gamma(X) = \left[\underbrace{\sum_{la=-t}^{t}\sum_{ma=0}^{t}}_{la+ma\geq 0}\alpha^{|ma|+|la|}\left\|X - S_x^{la}S_y^{ma}X\right\|_1\right]$$

Where, α is a scalar weight applied to give a spatially decaying effect to the summation of regularization term, 0< α<1.

$\left\|X - S_x^{la}S_y^{ma}X\right\|$ is photometric distance,

$\alpha^{|ma|+|ia|}$ is geometric distance

S_x^{la} is horizontal shift x by l pixels,

S_y^{ma} is vertical shift y by m pixels,

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P is window size

λ is metric for weighting the likeness cost over the regularization cost

$$\hat{X}_{n+1} = \hat{X}_n - \left[\sum_{k=1}^{N} \left\| H_k X - Y_k \right\|_1 + \lambda \underbrace{\sum_{la=-t}^{t} \sum_{ma=0}^{t}}_{la+ma \geq 0} \alpha^{|ma|+|la|} \left(\hat{X} - S_x^{la} S_y^{ma} \hat{X} \right) \right] \times \beta \quad (7)$$

Where, β indicates the cubic spline estimation parameter

The high resolution (HR) frame generated from multiple low resolution frame using full search motion estimation and cubic spline interpolation.

Particle Swarm Optimization

Particle swarm optimization technique is used to find the optimal solution. It is population based technique which consists of multiple particles in search space. Each particle having random position and velocity. These particles move in search space to find global best with definite velocity. To find best solution each particle shares information with all other particles. The velocity of each particle is updated based on its previous experience and the experience all other particle.

Each particle i consists of a y-dimensional position vector

$Xi = [Xi_1, Xi_2, Xi_3, \cdots , Xi_y]$ and

Velocity vector

$Vi = [Vi_1, Vi_2, Vi_3, \cdots, Vi_y]$

The two equations used in the algorithm for updating the velocity and position of the particles are:

$$V_i\,(t+1) = wV_i\,(t) + C_1(P_i\,(t) - X_i\,(t)) + C_2(g(t) - x_i\,(t)) \quad (8)$$

$$P_i\,(t+1) = P_i\,(t) + V_i\,(t+1) \quad (9)$$

Particle swarm optimization is a search streamlining procedure used to find the ideal arrangement spurred by the behavior of bird flocking. Each swarm has a population of N particles, which are consistently instated alongside the they-dimensional search space, having arbitrary positions and speeds. These particles search alongside the whole space by moving at a specific speed to find the worldwide best position. Every molecule works together with different particles and offers its encounters with every one of them. For every molecule, the new speed is refreshed utilizing its very own experience and the entire swarms' best experience.

PSO Parameters

- Number of particles usually between 10 to 50.
- C1 is the significance of individual best value.
- C2 is the significance of neighbourhood best value.
- Usually $C_1+C_2=4$ (experimentally picked value)
- If velocity is too low- algorithm is slow
- If velocity is high- algorithm is unstable

Algorithm Outline

- The particle swarm algorithm begins starts by making the underlying particles and allocating them introductory velocities.
- It assesses the target work at every molecule area and decides the best capacity value and the best location.
- It picks new velocities, in light of the present velocity, the particles' individual best areas, and the best areas of their neighbors.
- It then iteratively refreshes the molecule areas, velocities, and neighbors.
- Iterations continue until the algorithm arrives at a halting criterion.

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Grey Wolf Optimization (GWO)

This is another search based technique for hunting. The group of wolves are divided into four groups as alpha, Beta, Delta and Omega. Alpha is also called as leader which may be male or female which is responsible for all types of decisions. Beta is second level wolves which helps Alpha in decision making. Beta will take position of Alpha, when Alpha passes away or become old. Delta helps Beta and Alpha in hunting and follows instructions of both Alpha and Beta. Omega is last category in wolves which include small and very old wolves; they are very week in fitness. In hunting process they work in three steps searching, encircling and attacking the prey. Alpha, Beta and Delta works together and update their positions to attack on prey or goal.

Algorithm Outline

- The Grey wolf optimization starts by initializing the wolf population as Xi (i=1, 2, 3,….n)
- Initialize coefficient vectors ai, Ai and Ci, Where, the values of $\vec{a}\,i$ are linearly decreased from 2 to 0 over the course of iteration

  $\vec{A}i. = 2\vec{a}\,i.rand_1 - \vec{ai}$ $\vec{C}i. = 2.rand_2$
- Find the fitness of each search agent as follows:

$$\vec{D} = \left|\vec{C}.\vec{G}_p(t) - \vec{G}(t)\right| \qquad \vec{D}(t+1) = \vec{G}_p(t) - \vec{A}.\vec{D} \tag{10}$$

$$\vec{D}_\alpha = \left|\vec{C}_1.\vec{G}_\alpha - \vec{G}\right| \qquad \vec{D}_\beta = \left|\vec{C}_2.\vec{G}_\beta - \vec{G}\right| \qquad \vec{D}_\delta = \left|\vec{C}_3.\vec{G}_\delta - \vec{G}\right| \tag{11}$$

$$\vec{G}_1 = \vec{G}_\alpha - \vec{A}_1.(\vec{D}_\alpha) \qquad \vec{G}_2 = \vec{G}_\beta - \vec{A}_2.(\vec{D}_\beta) \qquad \vec{G}_3 = \vec{G}_\delta - \vec{A}_3.(\vec{D}_\delta) \tag{12}$$

$$\vec{D}_\alpha = \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right| \qquad \vec{D}_\beta = \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right| \qquad \vec{D}_\delta = \left|\vec{C}_3.\vec{X}_\delta - \vec{X}\right| \tag{13}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.(\vec{D}_\alpha) \qquad \vec{X}_2 = \vec{X}_\beta - \vec{A}_2.(\vec{D}_\beta) \qquad \vec{X}_3 = \vec{X}_\delta - \vec{A}_3.(\vec{D}_\delta) \tag{14}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{15}$$

Where, X_α is the best search agent, X_β is the second best search agent and X_δ the third best search agent, t is current position, t+1 is next position

- Update the position of the each search agent, ai, Ai and Ci and evaluate the fitness of all search agents.
- Modify X_α, X_β and X_δ and execute second iteration, similarly proceed for number of iteration until stopping condition.

Whale Optimization Algorithm (WOA)

Whale is very intelligent animal. They live alone or in a group. WOA is based on hunting behavior of whale specially Humpback whale. They use bubble-net hunting technique. They kill school of fish

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at the surface of water. For hutting they use 9-shaped path or circular bubble shaped structure. Humpback whale find the loation of school of fish and goes down almost 12m and create bubbles in spiral shape and attck on fish.

Algorithm Outline

- Start algorithm by initializing input data, Number of maximum iteration and Population.
- Initialize the whale population as Xi (i = 1, 2, ..., *n)* and coefficients ai, Ai, Ci, li and pi.
- Evaluate the fitness of each search agent and find the best search agent.
- Update the current search position of each agent if there is a better solution.
- Execute second iteration t=t+1 and update next location and update ai, Ai, Ci, li and pi.
- Execute all iteration till stopping condition at maximum level.

Lion Algorithm

Lions survive with different social behavior as compare to other cat species. This algorithm involves six stages as Pride generation, Fertility evaluation, Mating, Territorial defense, Territorial takeover and Termination. The initiating step of lion algorithm is pride generation, in which the female attend males to give birth to offspring. In second step after fertility evaluation, mating is main step for growing cubs. As compare to other optimization technique Territorial defense and territorial takeover are known as the distinctive processes. These steps are required to find optimal solution from search space. Stopping condition or termination of Lion algorithm is based on optimum solution.

Algorithm Outline

- Start algorithm by initializing pride generation male, female and nomadic vector L^{male}, L^{female} and $L^{nomadic}$.
- Fertility evaluation process find $f(L^{male})$, $f(L^{female})$ and $f(L^{nomadic})$.
- After mating and cub growth, check survival fight.
- Check nomadic lion is defeated or not. Update nomad coalition.
- Check cub is matured. If mature check cub is eligible to takeover pride. If matured go for next iteration. If not matured check maximum generation is achieved. If it is achieved terminate else go for next iteration.

Result and Discussion

Experimental Setup

The proposed video super resolution algorithm is implemented in MATLAB 2018a for different videos of UCSD dataset. Proposed video SR method with different search techniqure particle swarm algorithim algorithm, Grey Wolf Optimization (GWO), Whale Optimization Algorithm (WOA) and Lion Algorithm (LA).

Performance Measure Parameters

Performance of proposed algorithm is measured by means of performance measures such as Peal Signal to noise ratio (PSNR), Structural Similarity Image Index (SSIM), Second Derivative Like measure of enhancement (SDME), Edge Strength Similarity for Image Quality (ESSIM) and Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE).

1. Second Derivative Like measure of enhancement (SDME)

$$SDME = \frac{-1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} 20\ln\left|\frac{I_{\max,i,j}^{SR} - 2 * I_{Centr,i,j}^{SR} + I_{\min,i,j}^{SR}}{I_{\max,i,j}^{SR} + 2 * I_{Centr,i,j}^{SR} + I_{\min,i,j}^{SR}}\right| \quad (16)$$

Where, M x N- Size of Block

$I_{\max,i,j}^{SR}$, $I_{\min,i,j}^{SR}$, $I_{centr,i,j}^{SR}$ are maximum, minimum and centre intensity values of pixels in each block.

2. Edge based structural similarity (ESSIM)

ESSIM pays more attention to the edges and details in images, which represents the higher layer image structure information.

$$ESSIM(x,y) = [l(x,y)]^{\alpha}.[c(x,y)]^{\beta}.[e(x,y)]^{\gamma} \quad (17)$$

Where, $l(x,y)$ is luminance comparison,

$c(x,y)$ is contrast comparison.

$$e(x,y) = \frac{\sigma'_{xy} + C_3}{\sigma'_x \sigma'_y + C_3}$$

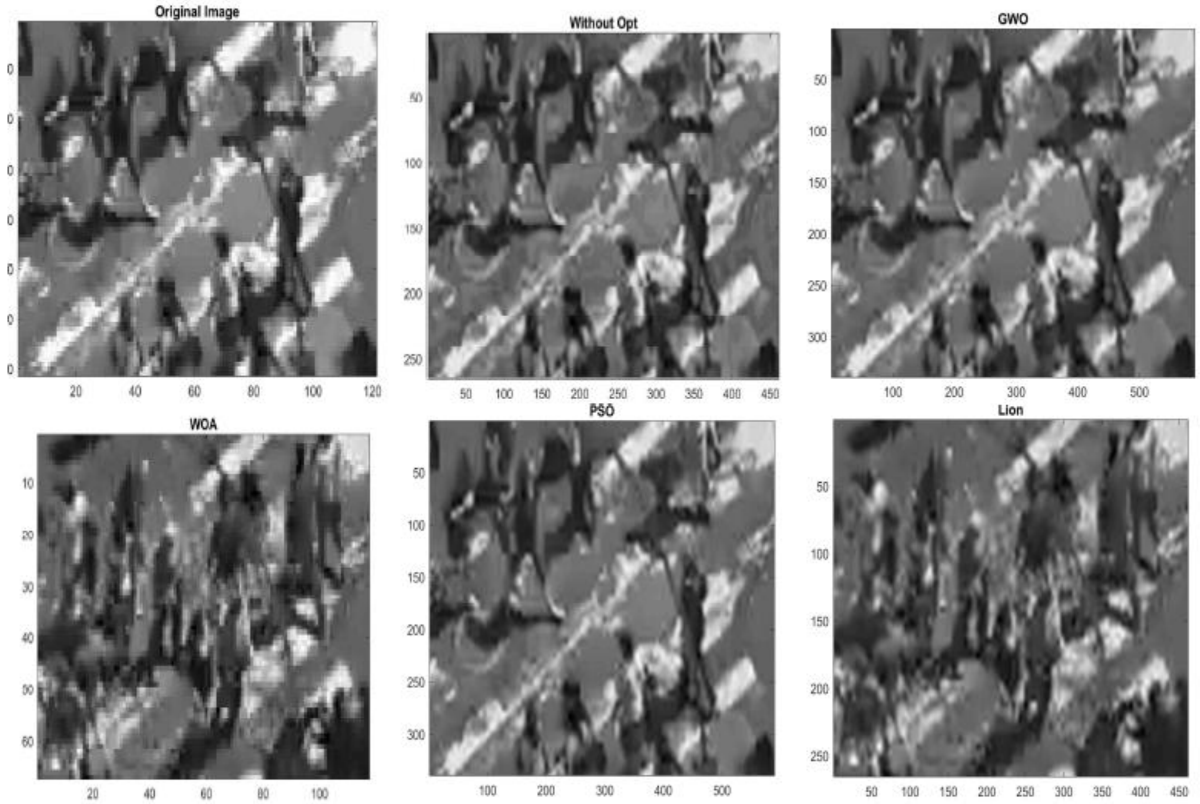
Where, σ'_x and σ'_y are standard deviation of direction vector D_x and D_y σ'_{xy} is covariance of vector D_x , D_y and C_3

Experimental Results

Fig. 1 shows the result of three different videos for single LR frame. It consists of low resolution (LR) original frame, high resolution (HR) frame without optimization, HR frame with Grey wolf optimization [28], HR frame with Whale optimization [29], HR frame with Particle swarm optimization [27] and HR frame with Lion algorithm [26]. Visual quality of PSO and Lion is good as compare to GWO and WOA.

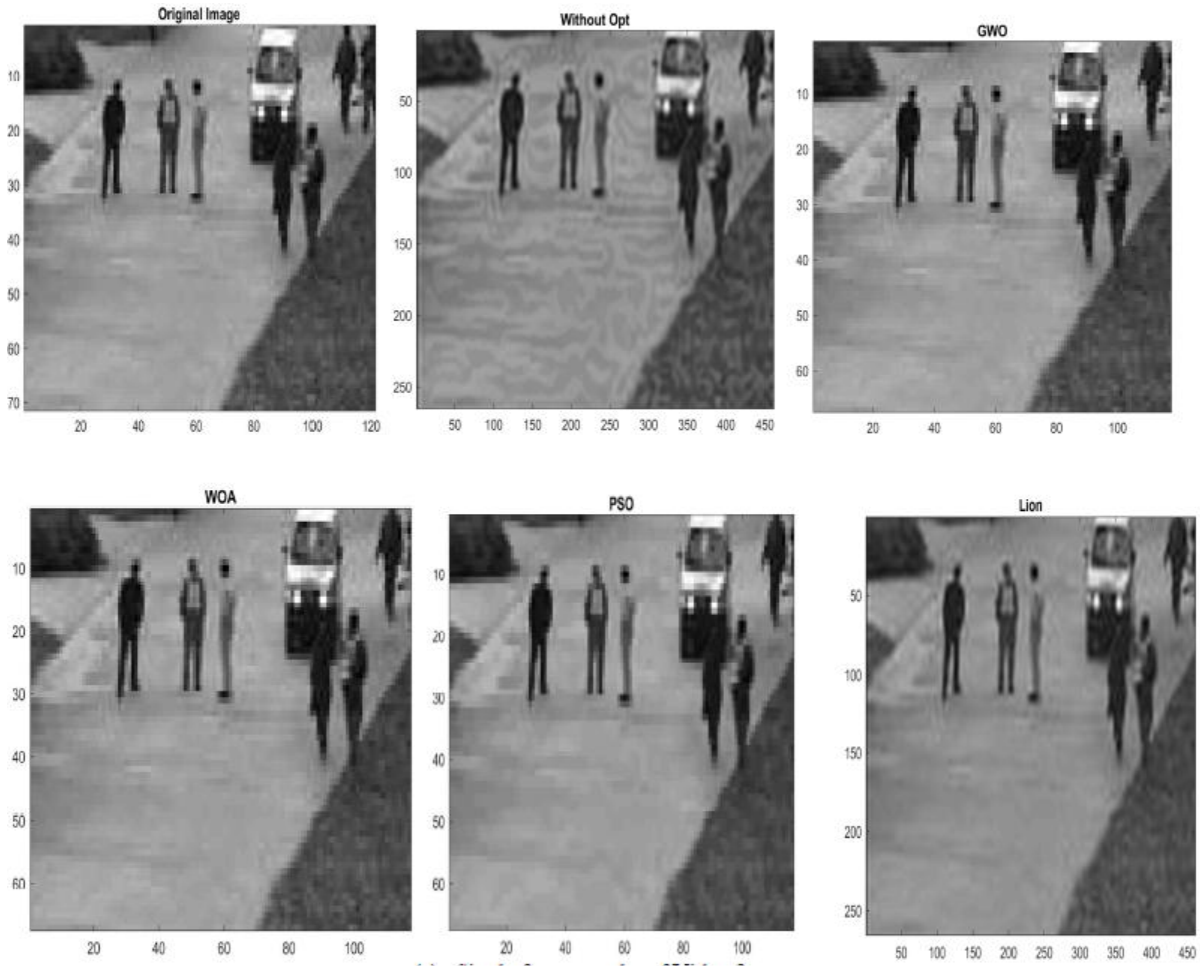
Statistical Analysis

This section describes the statistical analysis of proposed video super resolution technique with different search based optimization algorithm such as particle swarm optimization (PSO), Grey Wolf Optimization (GWO), Whale Optimization Algorithm (WOA) and Lion Algorithm. Table II shows the statistical performance of the video 1, video 2, video 3, video 4, video 5 and video 6 of minimized value of BRISQUE, maximized SDME and ESSIM. For video 1 minimized BRISQUE value is 43.958 in GWO, maximized SDME is 0.082968 in PSO and maximized ESSIM is 15.995 in GWO. Similarly, for video 2 minimized BRISQUE value is 43.476 in PSO, maximized SDME is 0.066774 in PSO and maximized ESSIM is 11.975 in GWO. For video 3 PSO achieves minimized BRISQUE value is 43.476, maximized SDME is 0.17946 and maximized ESSIM is 14.339 as compare to GWO and WOA. In video 4 minimized BRISQUE value is 39.317 in GWO, maximized SDME is 0.22906 in PSO and maximized ESSIM is 39.893 in PSO. For video 5 minimized BRISQUE value is 43.27 in PSO, maximized SDME is 0.16585 in WOA and maximized ESSIM is 21.776 in PSO. In video 6 minimized BRISQUE value is 45.29 in PSO, maximized SDME is -0.01803 in PSO and maximized ESSIM is 7.9723 in PSO. This analysis shows that PSO gives better results as compare to other two so PSO will be considered for modification to improve results.



(A)Single frame results of Video 1

(B)Single frame results of Video 2



(C)Single frame results of Video 3

Figure 1.Image Results of original image, image without optimization, GWO, WOA, PSO and Lion algorithm model by considering the frame of (a) video 1, (b) video 2 and (c) video 3

Table 2.Statistical Performance of Different Search Methods in terms of BRISQUE, SDME, and ESSIM for Different Video

	GWO			**WOA**			**PSO**		
Performance Measures	**BRISQUE**	**SDME**	**ESSIM**	**BRISQUE**	**SDME**	**ESSIM**	**BRISQUE**	**SDME**	**ESSIM**
Video 1	43.958	0.07806	15.995	44.123	0.077979	15.759	44.952	0.082968	11.768
Video 2	43.59	0.060566	11.975	43.575	0.060516	11.961	43.476	0.066774	11.768
Video 3	43.594	0.17465	13.876	43.56	0.17461	13.62	43.476	0.17946	14.339
Video 4	39.317	0.22846	31.014	40.033	0.22843	31.232	41.421	0.22906	39.893
Video 5	45.216	0.16576	17.54	44.952	0.16585	15.084	43.27	0.16429	21.776
Video 6	45.873	-0.01828	6.6424	45.655	-0.01829	6.7499	45.29	-0.01803	7.9723

Table III shows the statistical performance Peak Signal to Noise Ratio (PSNR) and Structural Similarity Image Index (SSIM) for six different videos frames for without optimization, GWO,

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WOA, PSO and Lion algorithm. For video 1 PSO achieved maximum PSNR as 29.3996 and maximum SSIM as 0.7749 compare to other algorithm. For video 2 maximum PSNR achieved by GWO is 0.7995 and SSIM is 0.7995 which are nearly equal to PSO. Similarly in other cases PSNR and SSIM of PSO is maximum. The highest value of PSNR achieved by PSO is 35.9002 and SSIM is 0.9007 for video 6. So as per the statistical analysis PSO will be considered for further modification for significant achievement in enhancement.

Table 3.Statistical Performance of Different Search Methods in terms of PSNR and SSIM for Different Video

	Without Optimization		**GWO**		**WOA**		**PSO**		**LA**	
Performance Measures	**PSNR**	**SSIM**	**PSNR**	**SSIM**	**PSNR**	**SSIM**	**PSNR**	**SSIM**	**PSNR**	**SSIM**
Video 1	29.366	0.7551	29.3961	0.7748	28.5979	0.7378	29.3996	0.7749	28.3875	0.6866
Video 2	33.2441	0.7788	34.5978	0.7995	32.959	0.7737	34.3595	0.7997	31.4348	0.7515
Video 3	33.3053	0.815	35.2833	0.8373	33.5293	0.8179	35.2991	0.8372	27.0166	0.7862
Video 4	26.5463	0.8165	26.4148	0.8682	26.504	0.864	26.4076	0.8665	29.1631	0.8363
Video 5	34.9137	0.8208	35.2591	0.8419	35.5343	0.8256	35.2564	0.8418	32.4444	0.7498
Video 6	34.9346	0.8787	35.8396	0.901	34.9673	0.8853	35.9002	0.9007	27.949	0.865

III. Conclusion

Video super resolution technique is proposed in this paper. This algorithm is optimized with various search based optimization techniques like particle swarm optimization (PSO), Grey Wolf optimization (GWO), Whale optimization algorithm (WOA) and Lion algorithm (LA). This technique is used to enhance resolution of single image as well as video. The main need of super resolution algorithms is to reduce hardware cost. The challenge of this algorithm is to handle noisy and blurry videos with good visual quality. The algorithm includes RGB to HSV conversion, full search motion estimation, cubic spline interpolation, regularization and optimization. Enhancement of frame is processed on V-channel by converting RGB frame to HSV form. Unknown pixel value is estimated using motion estimation and cubic spline interpolation technique. The enhanced high resolution frame is further optimized using different optimization techniques to improve resolution factor. Performance analysis all technique is done with performance parameters such as PSNR, SSIM, BRISQUE, SDME and ESSIM.

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