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# A SURVEY ON IMAGE AND VIDEO UPSCALING AND MEASURING MATICES

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**Abstract**
Image upscaling takes a key role in the field of image processing to enhance the image and video resolution for Super Resolution (SR) in the devices such as computer system as well as in smart phone. Nowadays many remarkable machine learning based techniques of image RS are being developed. In this paper a survey on current advanced image SR techniques which use the machine learning approaches with a systematic way is presented. It is also presented other topics regarding metrics along with publicly available benchmark datasets for evaluation of the performance. Here we give the conclusion for this survey after evaluation of the results by highlighting the merits and demerits of the techniques along with potential directions.

**Keywords:** Image Super-resolution, Image Upscaling, Machine Learning, Convolutional Neural Networks (CNN).


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## INTRODUCTION

Digital photography takes a huge part of our everyday lives and we desperately need better picture quality, higher resolution and more functionality. Images having many number of pixels as much as possible within a given size of the image is called High resolution (HR) image.

Therefore, a high quality photo provides important critical information usually,for applications in various Security and civil application like surveillance monitors, medical imaging, target identification etc. However, using higher image sensors and optics is a steeply-priced and additionally proscribing manner of increasing pixel density in the photo.

An image and video scaler/up-sampling is a system converting image/video signals from one resolution to another resolution. Scalers are usually used to transform a lower resolution signal like 480pixel standard definition to a higher quality resolution like 1080pixel high definition and the process is known as "up-conversion" or "up-scaling". In contrast, converting from high to low resolution is known as "down-conversion" or "downscaling".

The operation which associates the estimation of a fine-resolution image/video from a rough-resolution input image/video is often termed as image/video frame upsampling. Since it can recover sharp edges and textures by suppressing pixel blocking means anomalies like noises and other visual artefacts from the coarse-resolution input image, it becomes an important imaging research topic in image processing.

Goal of image and video frame up sampling is to enlarge the dimension of the picture or video frame by maintaining the inherited information of the input image/video.So the term upsampling/upscaling of image or video frame refers to a process which tries to achieve a High Quality Resolution pictures through the input low Quality Resolution (LR) pictures or multiple Low Quality Resolution pictures within the same scene. Human can interpret image or video scene only on improved detail of the scene and it can be provided by HR image/video.

Furthermore, due to physical and economical limitations of cameras, higher resolution camera cannot be used in on-board circuit of satellite. A LR image/video carries less information and it is caused by low resolutioncamera. Image and video upsampling process aims to create such a High-Quality Resolution pictures and video from the available input Low Quality Resolution picture with a low cost imaging device.

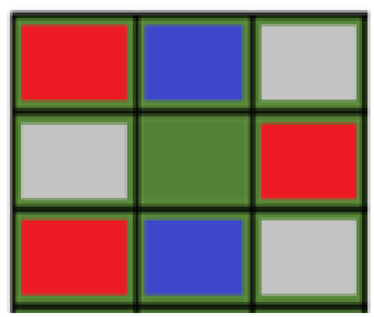
## UP-SAMPLING METHODS

Up-sampling of an image, image frame, video might be classified in the following ways.

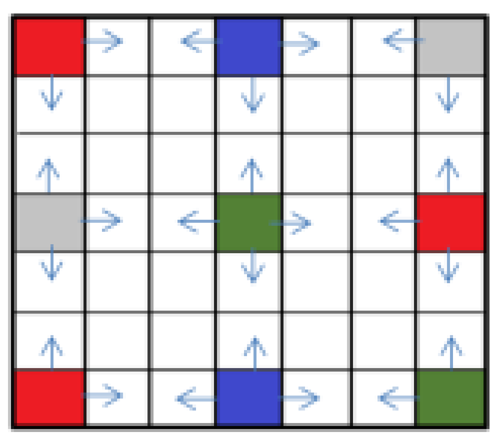
**Based on Interpolation up Scaling**

**1. Interpolation using Nearest Neighbor.**

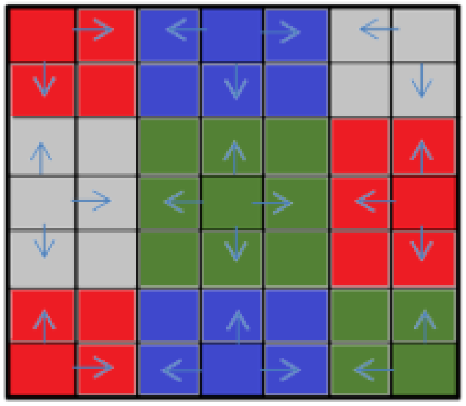
In this type of up scaling interpolation, when resize the image or image frame the missing pixels are substitute with the nearest pixel of the missing pixel.



**(a) 3x3 Pixel Image**



**(b) 7x7 up Sampled Image with Missing Pixels**



**(c) 7x7 up Sampled Image which is Filled with Missing Pixels with Nearest Neighboring Pixels**

**Fig. 1: Up sampling with nearest neighboring pixel**

**2. Interpolation using Bilinear upsampling.**

Interpolation using Bilinear is an expansion to linear interpolation for approximation functions on a rectilinear 2D grid to two variables (e.g., x and y). It uses all nearby pixels to calculate the pixel's value, using linear interpolations.

| | |
|---|---|
| 1 | 2 |
| 3 | 4 |

**(a) 2×2 Pixel Image**

| | | | |
|---|---|---|---|
| 1 | 0 | 0 | 2 |
| 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 |
| 3 | 0 | 0 | 4 |

**(b) 4×4 Upsampled image pixel withmissing gapes**

| | | | |
|---|---|---|---|
| 1 | 1.33 | 1.66 | 2 |
| 1.66 | 1.99 | 2.32 | 2.66 |
| 2.32 | 2.65 | 2.98 | 3.32 |
| 3 | 3.33 | 3.66 | 4 |

**(c) Upsampled Image Pixel**

**Fig. 2: Up-sampling by Interpolation Using Bilinear**

To solve the missing pixel for the picture

$$\textbf{Missing pixel} = \frac{d_1 - d_2}{(n+1)} \qquad (1)$$

where $d_1 - d_2$ is the differences of the neighbouring pixel.
n is the number of pixels.

**3. Up sampling using Bicubic Interpolation**

The expansion of cubic interpolation where interpolation is taking placed with data points on a regular grid of two-dimensional block is Bicubic interpolation. It can makes a surface which is moresmoothen than that of the interpolated surface produced by other techniques like bilinear interpolation or nearest-neighbor. Either one of the interpolation techniques such as Cubic convolution, Lagrange polynomials, or cubic splinescan conduct this interpolation.

If speed is not concerned, the interpolation using bicubic is preferred for resampling images over interpolation using nearest-neighbor or bilinear as it consider 16 pixels(4x4) while the other two take into account 4 neighboring pixels (2x2). It produces resampled image which is more clean and have less interpolation errors. But it is more challenging to compute.

Bicubic interpolated surface can be expressed using the unit square's four corners (0,0), (1,0), (0,1), and (1,1) assuming f asthe function values, $f_x$, $f_y$and $f_{xy}$are the derivatives, as

$$\mathbf{p(x,y)} = \sum_{i=0}^{3}\sum_{j=0}^{3} \mathbf{a_{ij} x^i y^j} \qquad (2)$$

This interpolation has to determine the 16 coefficients $a_{ij}$ by matching p(x,y) with the function values yields from four equations as:

1. $\mathbf{f(0,0) = p(0,0) = a_{00}}$ ,
2. $\mathbf{f(1,0) = p(1,0) = a_{00} + a_{10} + a_{20} + a_{30}}$,
3. $\mathbf{f(0,1) = p(0,1) = a_{00} + a_{01} + a_{02} + a_{03}}$,
4. $\mathbf{f(1,1) = p(1,1)} = \sum_{i=0}^{3}\sum_{j=0}^{3} \mathbf{a_{ij}}$

Similarly, there will be eight equations of derivations along the **x**and **y**directions as:

1. $\mathbf{f_x(0,0) = p_x(0,0) = a_{10}}$ ,
2. $\mathbf{f_x(1,0) = p_x(1,0) = a_{10} + 2a_{20} + 3a_{30}}$,
3. $\mathbf{f_x(0,1) = p_x(0,1) = a_{10} + a_{11} + a_{12} + a_{13}}$,
4. $\mathbf{f_x(1,1) = p_x(1,1)} = \sum_{i=0}^{3}\sum_{j=0}^{3} \mathbf{a_{ij} i}$,
5. $\mathbf{f_y(0,0) = p_y(0,0) = a_{01}}$ ,
6. $\mathbf{f_y(1,0) = p_y(1,0) = a_{01} + a_{11} + a_{21} + a_{31}}$,
7. $\mathbf{f_y(0,1) = p_y(0,1) = a_{10} + 2a_{02} + 3a_{03}}$,
8. $\mathbf{f_y(1,1) = p_y(1,1)} = \sum_{i=0}^{3}\sum_{j=1}^{3} \mathbf{a_{ij} j}$,

And four equations for the x y mixed partial derivative:

1. $\mathbf{f_{xy}(0,0) = p_{xy}(0,0) = a_{11}}$ ,
2. $\mathbf{f_{xy}(1,0) = p_{xy}(1,0) = a_{11} + 2a_{21} + 3a_{31}}$,
3. $\mathbf{f_{xy}(0,1) = p_{xy}(0,1) = a_{11} + 2a_{12} + 3a_{13}}$,
4. $\mathbf{f_{xy}(1,1) = p_{xy}(1,1)} = \sum_{i=1}^{3}\sum_{j=1}^{3} \mathbf{a_{ij} i\, j}$,

The following identities are being used by above expressions:

$$\mathbf{p_x(x,y)} = \sum_{i=1}^{3}\sum_{j=0}^{3} \mathbf{a_{ij} i x^{i-1} y^j}, \qquad (3)$$

$$\mathbf{p_y(x,y)} = \sum_{i=0}^{3}\sum_{j=1}^{3} \mathbf{a_{ij} x^i j y^{j-1}}, \qquad (4)$$

$$\mathbf{p_{xy}(x,y)} = \sum_{i=1}^{3}\sum_{j=1}^{3} \mathbf{a_{ij} i x^{i-1} j y^{j-1}} \qquad (5)$$

Using a continuous derivatives, this method produces a continuous p (x, y) surface on anunit square [ 0 , 1 ] × [ 0 , 1 ]. Bicubic interpolation can be completed through patching collectively such bicubic surfaces on an arbitrarily sized regular grid, making sure that the derivatives fit at the barriers.

**SUPERVISED SUPER-RESOLUTION**

In addition to the conventional standard techniques researchers introduced a various models regarding super resolution using deep learning. SupervisedSR is the commonly focus area where training is associated with both low-quality resolution and respectivehigh-quality resolution images. This models approach essentially through combination of a set of components like upscaling methods, model frameworks, design of networks, and learning strategies. Based on these ideas, researchers combine the components for producing integrated Super Quality Resolution model to fit specific purposes of picture or a video super quality resolution.

**Framework used in the interpolation**

Framework used in the interpolation can be classified in the following term.

**1. Super Resolution by using pre-upscaling**

In these type of framework first the image is upscale using interpolation upsampling method like bilinear, bicubic to get a coarse High resolution and then the framework applied deep CNNs for reconstructing the image into a high quality of the image as in Fig. 3.

Such Framework are implemented by Wei-Sheng Lai et al. [1] and Dong et al.[2] worked.

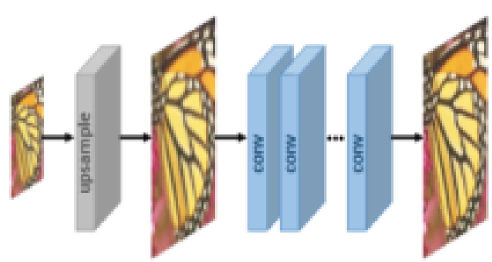



**Fig. 3: Pre-upscaling Super Resolution**

There remain issues to be addressed i.e the pre-upscaling process increases the unnecessary computational cost and couldn't give an additional high-frequency information while reconstructing the high resolution images[1].

**2. Super Resolution by Using Post-upscaling**

In these type of framework first the low resolution images are applied using deep CNNs and upscale the images using Bilinear or bicubic to get image quality at the end of the layer. Fig. 4 shows the over all process.

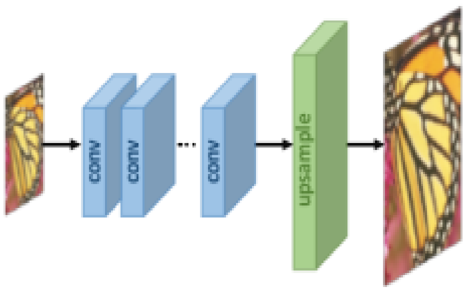



**Fig.4: Post-upscaling Super Resolution**

To address the problem faced by pre-upscaling, post-upscaling networks apply learning on the low-quality-resolution inputs images or images frames and then upscale the features close to the output of the network.This schemeresults low memory footprint with better efficiency. In the previous pioneer works[3][4] the processing function, namely post-upscaling super-resolution, the low-resolution input pictures are applied using deep Convolutional Neural Networks(CNNs) with no change in the resolution, and end-to-end intelligent upscaling layers (bilinear, bicubic) are applied at the end of the network.

**3. Super Resolution in Terms of Progressive Upscaling**

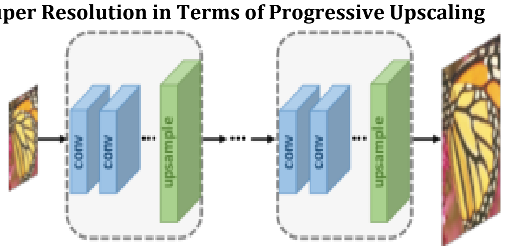



**Fig. 5: Progressive upscaling Super Resolution**

Even the computational complexity is reduced in thesementioned frameworks ( pre and post upscaling ), it used only a single upscaling convolution as in Fig.5. So it makes harder learning process for the large scaling factors. A progressive upscaling framework is introduced so as to solve the drawback by methods such as Laplacian Pyramid SR Network (LapSRN) [6], Progressive SR (ProSR) [5], and Wang [5]. In this case, the HR images or images-frame ate smaller scaling factor at each step as a result of using a cascade of CNNs progressively. Above figure shows the stages of each step of images upstaging to higher resolution and refined by CNNs usingprogressive framework of upscaling work.

**4. Super resolution in terms of Iterative up and down sampling.**

This form of framework model is in the form of hourglass (or U-Net).Several models such as the Stacked Hourglass network utilize several hourglass structures in sequence, switching successfully between the up sampling phase and down sampling phase as in Fig.6.

Within this system, the models will properly exploit the deep associations between the low-quality-resolution and high-quality-resolution picture pairs and hence provide results in better quality output.

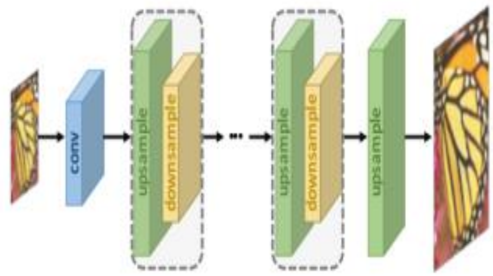



**Fig. 6: Super-resolutionusing Iterative upscaling and downscaling**

Actually, the Super-Resolution (DBPN) back-projection units used in Deep back-projection network have a very complex structure and hence it requires significant manual design. Because this technique has just been implemented into the deep learning-based super-resolution, the system has tremendous potential and requires more exploration.

**RELATED ON PREVIOUS WORKS ON UPSCALING**

**Qi- Shan et al**. [9] in 2008 they used a fast Fourier transformation operation making easy to encode an embedded with low resolution image or images frame(video) for getting quality output, the algorithm used has the limitation for using single image/video CPU and it may be enhancing by using parallel computation in multiple CPU. It also used only Low-Resolution Image/video input missing edge, textures during digitisation process.

**Ming-Sui et al**. [10] in 2009 proposed a block based up-sampling by taking many 8x8 image block of different type (smooth area, edges, and others) and applied different technique for different types of block. If a block is a mixture of smooth and edges the information for edges may be lost.

**Jianchao Yang** et. al. [11]introduces a single-image super-resolution approach in 2010, onthe basis of sparse signal representation.For each single area of thelow resolution input, it used a sparse representation, and then using the coefficients of this representation to get the better high quality resolution result. The findings from compressed sensing suggest that the sparse representation from the down-scaled signals can be properly recovered under mild conditions.By forming two dictionaries jointly for low-quality resolution and high-quality resolution image patches, then enforcethe similarity between low-resolution quality and high-resolution quality image patch pairs of sparse representations for their own dictionaries.So, to create a high-quality-resolution image patch, the sparse representation of a low-quality-resolution image patch may be apply using the high-quality-resolution image patch dictionary. In both image super-resolution and particular cases of face delusion the usefulness of such a sparsity prior is considered.In both instances, the algorithm produces high-quality-resolution pictures which are comparable or better quality to images created by other related super-resolution methods.Furthermore, the local sparse modeling method is inherently resilient to noise, and the algorithm can accommodate super resolution in a more coherent environment with noisy inputs.

However, the specification of the appropriate dictionary size for natural picture patches in terms of super resolution tasks is one of the most relevant issues for potential inquiry.

**Gilad freedman et al. [12]**in 2011 adopted a localized self-similarity principle on natural images and retrieved patches in the input images from highly localized areas, enabling the nearest patch search time to be shortened considerably without losing the accuracy of most pictures. It indicates that for small scaling factors the local self-similarity principle holds stronger.Then use nondyadic filter banks that model the upscaling mechanism, to incorporate such small scales. In fact, the new filters are almost biorthogonal and generate high-quality-resolution artifacts that are strongly compatible with the input picture without computing implied equations of back-projections. Fine-detailed cluttered regions, though, are not realistically reproduced and look somewhat faceted.

**Xinbo Gao** et. al.[13] in 2012, Xinbo Gao developed a joint learning method train two projection matrices in combination and map the original Low Resolution and High Resolution feature spaces to a single subspace.Subsequently, to estimate the reconstruction weights, the K-nearest neighbor choosing the input low-resolution image patches is performed in the selected area. Locally, joint learning benefits from a coupled constraint by linking low-quality-resolution and high-quality-resolution counterparts with K-nearest patch grouping pairs used to accommodate a wide number of samples.

To further refine the initial SR estimation, they impose on the SR result a global rebuilding constraint based on the posteriori maximum framework.

**Weishing Dong et al. [14]** in 2013 incorporated the non-local self-similarity of images into sparse representation model (SRM) for interpolation of pictures. In sparse representation model, a non-local autoregressive model (NARM) is developed and taken as the term for data fidelity, which has little coherence with the dictionary of representation, thereby making sparse representation model higher efficient for approximation of pictures. Their findings indicate the non-local autoregressive model based picture interpolation method can efficiently restore the edge features of the image as well as it removes noisy parts, producing the strongest PSNR-based image interpolation findings so far as perceptual accuracy metrics like SSIM and FSIM are concerned.

**Xiaoyan Li et al.** [15] proposed a novel SR method in the year 2015. The developed a super-resolution method is focused on the two points:1) the majority of sharp edges are focussed on such a less number of directions; 2) The pixel value may be determined byits neighbors' weighted mean.

Keeping these findings into account, the curvelet transform was implemented to get directional features that are then used in the weight estimation and region selection. A Combined Total Variation (CTV) Regularizer is used that implies the gradients in the given pictures have a direct sparsity group feature.Furthermore, a regularization concept for directional non-local means (D-NLM) takes image pixel values and spatial details to remove unnecessary artefacts. Through assembling the planned regularization words, they overcome an energy function's SR issue with limited reconstruction error by implementing a modeling structure for first-order conic solvers (TFOCS).

**Chao Dong et al. [16]** in the year 2016 proposed a Single Image Super-Resolution (SR) Deep learning method.In a picture with low resolution, the SRCNN's first convolutionary layer extracts a group of feature maps. The next layer nonlinearly maps these feature maps to patch representations in high quality resolution and the final layer combines the predictions to generate high quality resolution picture in a spatial neighborhood. In addition, the proposed structure may be extended to certain low-quality vision like removing the visual blurring as well as removing noises, with its benefits of flexibility and robustness. It also may analyze a network for coping with different upscaling factors.

**Mehdi S.M. Sajjadi et al.** [17] Proposed an end-to-end trainable video recurrent super-resolution framework in 2018 utilizing the HR estimate previously inferred to super-resolve the resulting frame. This naturally encourages temporally consistent outcomes and minimize the cost of computation by warping only one picture in each step.

**I**n 2019, **S. Muthuselvan et al.** [18] proposed a work of fiction algorithm called Super Interpolation(SI) to achieve the low complex upscaling of High Resolution (HR) video frames. The method of Super Interpolation consists of two phases: Phase of Up-scaling and Phase of training. A large set of external training images / video frames undergo edge orientation analysis during the training phase. The primary, upscaling phase, the Low-Resolution picture, video frame is upscale and interpolated by using bicubic interpolation method. Then the interpolated frame is subjected to edge detection by canny edge detector for frame smoothing. Frame sharpening is by local laplacian filter with edge preservation technique to get the reconstructed HR video frame.

**Soo Ye Kimet al. [19]** Proposed 3DSRnet in 2019, maintaining the temporal depth of spatiotemporal feature maps to maximize the capture temporal nonlinear properties between low resolution and high resolution frames, and adopting residual learning in conjunction with sub-pixel results.

**3DSRnet is comprised of two subnets:**
**(i) Video Super Resolution subnet.**

The video super-resolution subnet takes in a sliding time window a sequence of consecutive LR input frames, and generates an HR output frame in the sliding time window corresponding to the middle frame.

**(ii) Scene shift detection and frame replacement (SF) subnet**

The 3DSRnet's SF subnet is responsible for scene shift detection in the sliding time window, and substitutes the frames of a different scene with the frame that is temporarily closest to the same scene as the middle frame.

**EVALUATION MATRIC**

Evaluation matric are important in dealing with image processing, it check how much has the image been change or regain.
If the metrics cannot accurately measure the model performance of the image, it may be difficult to verify improvements while image processing. Super-resolution metrics further require to perform experiments.
Some of the Evaluation Matric are as follows:

**PSNR (Peak Signal to noise Ratio)**

The peak signal to noise ratio does smoothing, and the outputs often vary wildly between pictures that are almost different.

$$\mathbf{PSNR = 20\log_{10}\left(\frac{MAX_f}{\sqrt{MSE}}\right)} \tag{6}$$

Where MSE (mean square error) is:

$$\mathbf{MSE = \frac{1}{mn}\sum_0^{m-1}\sum_0^{n-1}||f(i,j) - g(i,j)||^2} \tag{7}$$

$\mathbf{MAX_f}$is the maximum signal value in the picture, "proven to be fine".
**f**is a matrix of the initial picture data.
**g**is matrix data of the deteriorated image.
**m**is the pixel number of row of the images and i is the index of that row.
**n**is the number of pixel columns of the picture, and j is the index of that column.

**SSIM (Structural Similarity Index Metrics)**

The SSIM evaluates brightness, contrast and structure, however it does not compute image perceptual quality accurately.

$$\mathbf{SSIM(x,y) = l(x,y).\,c(x,y).\,s(x,y)} \tag{8}$$

Where $l(x,y) = \frac{2\mu_x\mu_y+C_1}{\mu_x^2+\mu_y^2+C_1}$, l is the luminance change.

$c(x,y) = \frac{2\sigma_x\sigma_y+C_2}{\sigma_x^2+\sigma_y^2+C_2}$, c is the contrast change.

$s(x,y) = \frac{\sigma_{xy}+C_3}{\sigma_x\sigma_y+C_3}$, s is the structural change.

$\mu_x$ and $\mu_y$ are the local means, while $\sigma_x$ and $\sigma_y$ are the standard deviation and $\sigma_{xy}$is the sequential cross-covariance for the x and y pictures.

If $= \beta = \gamma = 1$ , then If the index is simplified as the following form using Equations

$$\mathbf{SSIM}(\mathbf{x},\mathbf{y}) = \frac{(2\mu_x\mu_y+C_1)(2\sigma_x\sigma_y+C_2)}{(\mu_x^2+\mu_y^2+C_1)(\sigma_x^2+\sigma_y^2+C_2)} \quad (9)$$

**MOS (Mean Opinion Score)**

Mean Opinion Score is a technique that evaluates Image Quality Assessment. People has to give ratings for the output by allocating perceptual content scores to the checked items while using this method. The ratings range usually from 1(bad quality) to 5 (excellent quality). And the final MOS is determined by human raters as the arithmetic mean of ratings.

The value of the rating is given below.

**Table 1: Performance Rating**

| Rating Point | Performance Label |
|---|---|
| 5 | Excellent |
| 4 | Good |
| 3 | Fair |
| 2 | Poor |
| 1 | Bad |

For computing MOS the formula is:

$$\mathbf{MOS} = \frac{\sum_{n=1}^{N}\mathbf{R_n}}{\mathbf{N}} \quad (10)$$

Where $R_n$ is the individual ratings of N subjects for a given stimulus.

**Other Image Quality Assessment Methods**

There are infrequently used metrics for computing super-resolution performance. MS-SSIM i.e Multi-scale structural similarity has greater flexible for incorporating the variations in viewing conditions than single-scale Structural Similarity Index Metrics does.

**CONCLUSION AND SUGGESTION**

The main purpose of this survey is to provide an introduction to the problems and the approaches of the upscaling of images. In this paper, theoretical aspects regarding the interpolation and previous paper based on upscaling of images or image frames, filtering of images and the evaluation metric for the images are considered. Image upscaling is an important in the image processing approach for improving the images and videos resolution to get super quality resolution in the devices such as computer system as well as in smart phone. Recent years have seen impressive developments in super-resolution of the image using machine learning approaches.Through this paper, we aim to provide an article about recent developments through super-resolution image techniquesusing systematic machine learning techniques and issues, like performance evaluation metrics are also discussed. For removal of noises and blurring in the image, we agree that the advancement of the theory and implementation of image upscaling will require more detailed effort.

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