Application Development Comparative Analysis of AI Based Upscaling and Traditional Upscaling Techniques

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Abstract. In this modern era where videos with high resolution are constantly produced and with the current technology advancement making a production of high-quality videos open to everyone and yet the older videos are facing deteriorating image and blur making it hard to recognize the content of the video anymore. In order to prevent that, people invented a method called upscaling where the video can be restored to its former form and thus expand its lifetime and prevent the video becoming a lost media. Since the old video may contain many historical values, it is necessary to preserve it for generations to come. In this paper we will analyze and compare some of the upscaling methods usually used for the video and we will determine which upscaling method offers the best value in restoring and preserving videos. In order to do that we will analyze it using experimental method and display it using a python-based application. The result of this study is that while the AI based upscaling can produce the best image fidelity compared to traditional upscaling method, The AI based method also use an extensive amount of resource making it hard for people to satisfy those demand, and thus making the traditional upscaling method easier to use for many people.

Keywords: *video; upscaling; preservation; comparative analysis.*

INTRODUCTION

As technology advances and online presence becomes common, the continuous production and consumption of media like images and videos have pushed the demand for high-resolution (HR) videos to an all-time high. The growing popularity of HR videos goes hand in hand with the availability of high-quality video capturing devices, therefore making HR videos on a daily basis are easy[1].

These HR videos are often downscaled to save more storage space or to fit screens with lower resolution, but this process comes with the cost of having loss in visual quality. On the other hand, this technology was not available in the past due to technological limitation therefore the video quality is much lower than current day video quality, and yet video has also been a foundation of visual media for over a century, capturing historical events, artistic expressions, and cultural achievements. Historical videos possess an important cultural heritage of the society but unfortunately many of them now experience degradation over time due to time and technology limitations [2].

The purpose of this paper is to determine which upscaling techniques are the most efficient with the best quality outcome between each technique. To support this analysis, an application will be developed to test and evaluate different methods. The upscaling techniques that will be used in this paper is Real-enhanced super resolution generative adversarial networks (Real-ESRGAN), bicubic interpolation, and lanczos interpolation with sharpening. This paper also will discuss the strengths and weaknesses of each upscaling techniques, aiming to contribute to the broader effort of media restoration and preservation through modern technology.

Real-ESRGAN is a deep learning model based on GANs and a more practical and robust version of ESRGAN designed to handle various degradation types (noise, blur, etc.). It improves the image by enhancing perceptual quality and reconstructing fine textures more realistically, also uses U-Net discriminator and Residual-in-Residual Dense Block (RRDB) [2].

Bicubic interpolation estimates pixel values in a larger image using a weighted average of the 16 nearest pixels from the original image, it's usually used due to its balance between simplicity and quality also preserves edges better than simple methods and also this method became standard in many application such as Adobe Photoshop and in-camera interpolation [3].

Lanczos interpolation uses a sinc function to interpolate pixels over wider range, which helps retain more detail and sharpness [4], when combined with sharpening filter, it can further enhance detail. The reason for choosing this method is because lanzcos interpolation is the best in term of minimal aliasing artifacts and detail preservation [5].

METHOD

The method used in this research will be an experimental method, where each upscaling method will be tested and evaluated to see which of each method can perform the best from visual fidelity, performance, and resource consumption. The use of experimental methods also helps to better visualize the difference between upscaling methods. And also build a simple application that applies a range of upscaling techniques to the same set of input videos. The goal is to analyze and compare the visual quality and performance of each method. To achieve that please refer to figure 1 below and the following steps will be implemented.

Figure 1. Flowchart methods

1.1 Dataset Preparation

Ten input of test videos with size of 720x340 with 10 seconds in duration will be provided and categorized based on when the video is produced. The first one is "New" category for video created 2015 – present and "Old" category for video created before 2015.

1.2 Implementation of Upscaling Methods & Application Development

A simple user interface will be developed to allow user to visualize the result of each upscaling method. This application designed to enhance the resolution of both images and videos through advanced mathematical interpolation techniques. The application implements and compares two distinct upscaling algorithms (bicubic and lanczos), providing users with detailed performance analytics and visual quality assessments.

This application addresses the problem of image super-resolution in computer vision, which aims to construct high-resolution (HR) from their low-resolution (LR) counterparts [6]. The mathematical formulation of the problem can be expressed as:

$$\mathbf{I\_LR} = \mathbf{D}\big(\mathbf{B}(\mathbf{I\_HR})\big) + \mathbf{n} \quad (1)$$

Where in equation (1) **I_LR** and **I_HR** represents low and high-resolution images respectively, **D** is the down-sampling operator, **B** represents blur degradation, and **n** represents additive noise [7].

The application implements two classical interpolation methods that have been extensively studied in the literature for their effectiveness in super-resolution field:

- Lanczos Interpolation
- Bicubic Interpolation

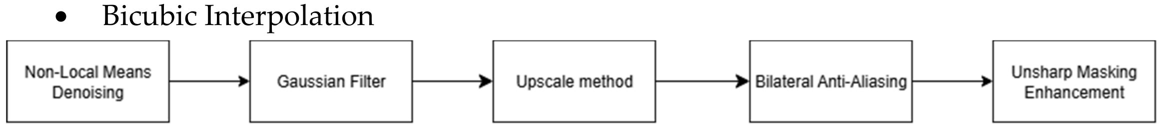


Figure 2. Process pipeline

The application also implements a process pipeline based on based on Figure 2:

Non-Local Means (NLM) algorithm deal with the denoising problem by exploiting the self-similarity property of natural images [8]. This approaches preserves texture details while effectively reducing noise, making it suitable for pre-processing in super-resolution applications [9].

The next filter used is the Gaussian filter stage implements low-pass filtering based on the Nyquist-Shannon sampling theorem [10].This filter is important because it can balance detail retention and suppress artifact. The 3x3 Gaussian kernel based on equation (2) below, with $m \approx 2\sigma$ provides optimal balance between aliasing reduction and detail preservation [11]:

$$\mathbf{G(x, y) \;=\; (1/2\pi\sigma^2)e\text{^}(-(x^2 + y^2)/2\sigma^2)} \quad (2)$$

The bilateral filter combines spatial and intensity domain filtering [12]:

$$\mathbf{I\_filtered(p) \;=\; (1/W\_p) \sum\_q I(q) G\_\sigma s(||p - q||) G\_\sigma r(|I(p) - I(q)|)} \quad (3)$$

This equation (3) reduces post-upscaling artifacts while maintaining edge sharpness, addressing the trade-off between smoothness and edge preservation in super-resolution [13].

The sharpening kernel implements a discrete Laplacian operator for edge enhancement:

$$\mathbf{K \;=\; [0 \;\; -1 \;\; 0]}$$
$$\mathbf{[-1 \;\; 5 \;\; -1]}$$
$$\mathbf{[0 \;\; -1 \;\; 0]} \quad (4)$$

This equation (4), usually used in image processing for detail enhancement [14].

1.2.1 Lanczos Interpolation

The lanczos kernel is defined as a windowed sinc function [15]:

$$L(x) = \begin{cases} 1 & \text{if } x = 0 \\ \frac{a\sin(\pi x)\sin(\pi x/a)}{\pi^2 x^2} & \text{if } 0 < |x| < a \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

Where in equation (5), **a** is the kernel size parameter, and $\boldsymbol{sinc(x) = sin(\pi x)/(\pi x)}$ [16]. This approach provides superior frequency domain characteristics compared to linear interpolation method, with reduced aliasing artifacts and better edge preservation properties [17].

1.2.2 Bicubic Interpolation

Bicubic interpolation deploy a piecewise cubic polynomial to approximate the continuous function. The bicubic interpolation kernel is given by [18]:

$$W(x) = \begin{cases} (a+2)|x|^3 - (a+3)|x|^2 + 1, & \text{for } 0 \le |x| < 1 \\ a|x|^3 - 5a|x|^2 + 8a|x| - 4a, & \text{for } 1 \le |x| < 2 \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

Where in equation (6), **a** is typically set to -0.5 or -0.75 for optimal smoothness [19].

1.2.3 User Interface and visualization Framework

This application use Tkinter-based graphical user interface that facilitates comparative analysis and result visualization.

Interface Features:

- File selection – support multiple image and video formats.
- Method selection – choice between Bicubic, Lanzcos, or all.
- Real-time Progress Tracking – Visual progress indicator and status update.
- CUDA Support – Hardware acceleration configuration.

1.3 Evaluation Metrics

Each result will be evaluated using both quantitative and qualitative metrics:

- Peak Signal-to-Noise Ratio (PSNR)
- Structural Similarity Index (SSIM)
- Visual Comparison and user feedback
- Processing time and resource consumption

1.4 Result Analysis

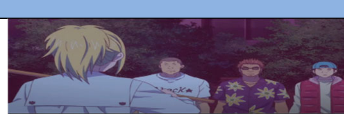
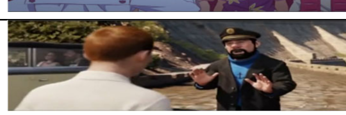
The final stage involves a detailed analysis of the compiled results to determine:

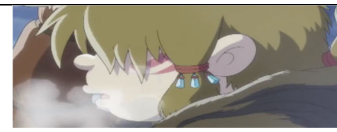
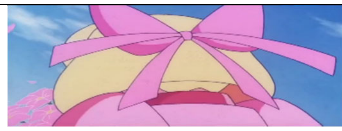
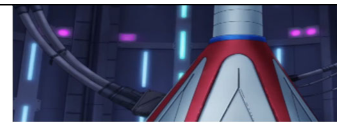
- Which method provides the highest visual fidelity
- The computational efficiency of each method
- Which offers the best balance between speed and quality
- How AI-based methods compare to traditional interpolation techniques in practical scenarios.

RESULT

The result of comparison is in quantitative and qualitative. Quantitative comparison method uses scale measurements such as height, width, PSNR, and SSIM, and for the qualitative comparison method uses use user preference to determine which techniques is the best for video upscaling.

Table 1. Snippet of the video used for experiments.

No Video	Snippet of the video (Old)	No Video	Snippet of the Video (New)
1		1	
2		2	

3		3	
4		4	
5		5	

The video used for this experimentation is as shown in table 1 above, where the videos are separated into two categories one is for old video made before 2015 and the other is the new video created after. As for the result of the experimentation is shown in the figure 5 below:

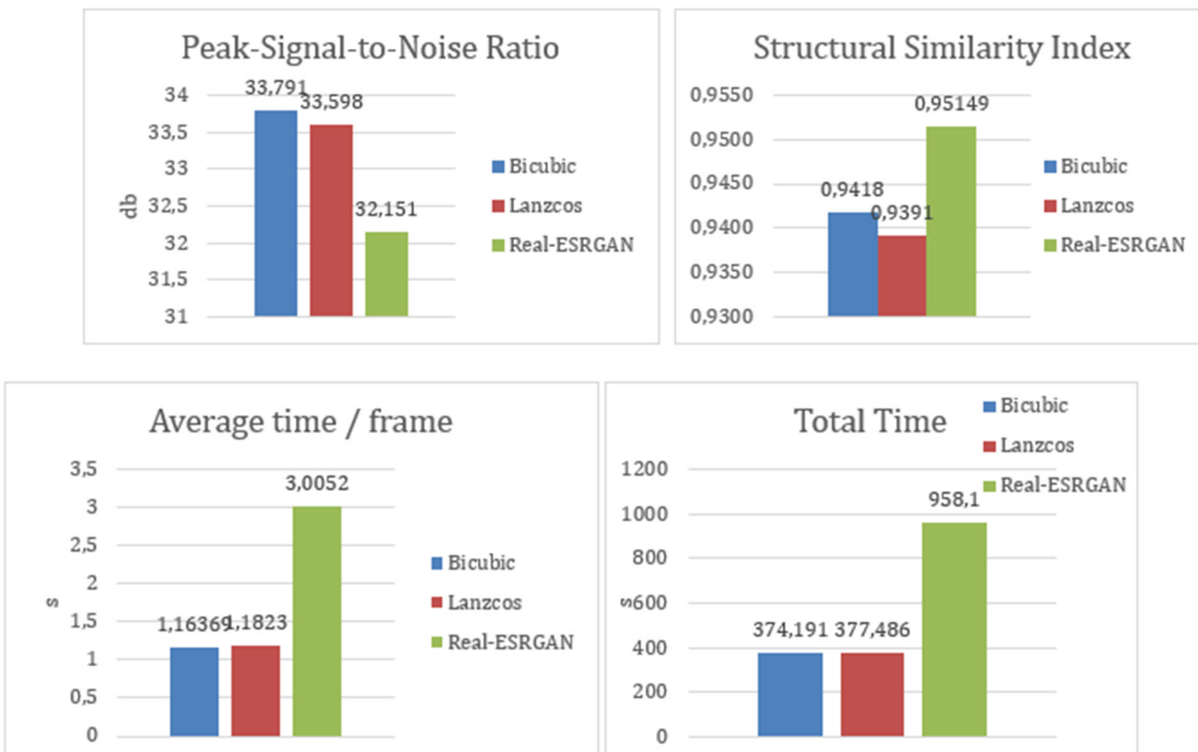


Figure 3. The results of the experimentation.

Based on the figure 3, the results of the experiment is quite fascinating. The interpolation method beat AI method almost three times in terms of processing time but rank highest in term of similarity with the original video and also the lowest in term of PSNR this mean that there is a higher chance that we will see noise or artefact in the processed video. In the other hand the interpolation methods are quite competitive while the difference between them is miniscule but bicubic interpolation is winning in all category except SSIM. This result is interesting because lanzcos interpolation should be the newer and more advanced than bicubic interpolation, and yet lanzcos is behind bicubic in term of processing time and other aspect.

Not only that a simple python-based application is also developed alongside this experiment. A GUI is also used to help other people use it more easily. The application offers two interpolation method; bicubic and lanzcos.

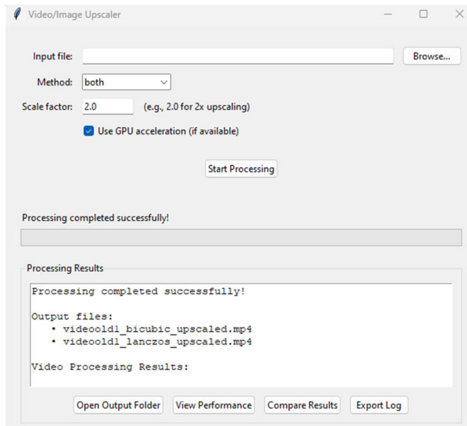


Figure 5. Application GUI

The application offers various feature that allow user to freely choose the method used for upscaling their selected media such as “Input file”, “Method”, and “scale factor”. Not only that there are other features that allow user to see the difference between each method such as “View Performance” and “Compare Results”. There are also “Open Output Folder” which help user to locate their processed media, and lastly “Export Log” for debugging purposes.

And that is all the feature it has from the simple python application, with hope that this application can raise the awareness about preserving media for future generations to come, and also encourage many people to contribute to preserving and restoring media even if it just a little, it still means a lot for the next generation.

DISSCUSSION

In term of visual fidelity, Real-ESRGAN provide the best visual fidelity among other method by quite a large margin. To prove this a survey is conducted where a user will be given 3 different photo from the same video each representing different method used to processed the video *Gambar 1* representing bicubic method *Gambar 2* representing lanzcos method *Gambar 3* representing Real-ESRGAN method and the user need to select the best image out of all three. The interesting part is all of them choose *Gambar 3* or Real-ESRGAN method as shown in table 2:

Table 2. Top 10 result of the survey

Video 1 (New)	Video 2 (New)	Video 3 (New)	Video 4 (New)	Video 5 (New)	Video 1 (Old)	Video 2 (Old)	Video 3 (Old)	Video 4 (Old)	Video 5 (Old)
Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3
Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3
Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3
Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3
Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3
Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3
Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3
Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3
Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3
Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3	Gambar 3

From there it is clear that *Gambar 3* or the video processed using Real-ESRGAN method provide the best visual fidelity. This also backed up by the fact that Real-ESRGAN's SSIM is the highest among other method.

In term of computational efficiency, bicubic offers the fastest processing time averaging 1,16369 seconds per frame and average total processed time for 10-seconds video with 20-60 frames per second is 374,191 seconds or 6,2365 minutes. Next is lanzcos with 1,1823 seconds per frame and 377,486 seconds or 6,2914 minutes for each video. Lastly is Real-ESRGAN with 3,0052 seconds per frame on average and 958,1 seconds or 15,9683 minutes for each video, and the scale is set to 4.0 for all method.

In term of the best balance between speed and quality Real-ESRGAN is the recommendation since it gives the user the best visual fidelity among other method, if supported by powerful GPU in the process. If not then the bicubic method is the recommendation, while it has very little difference between lanzcos method the bicubic method is better in performance and visual fidelity.

While AI based technique has the best visual fidelity it also requires an extensive amount of resource like hardware and software, and sadly not all people can afford the hardware and thus making difficult to use AI based upscaling technique in everyday life since it will take very long time to upscale the video. In the other hand traditional upscaling method such as bicubic and lanzcos doesn't need an expensive GPU to run it, all it need is just a CPU and thus making it very accessible to a lot of people.

CONCLUSION

The result of this study is interesting because while the AI based upscaling is superior than the traditional method is also uses a lot of computing power making it hard for people to satisfy the requirement of computing power to run AI based upscaling. In the other hand the traditional upscaling method has lower requirement for computing power making it very accessible to a lot of people since they can run it in their own device without needing upgrade or expensive GPU. Traditional upscaling method is also easy to use than the AI based upscaling method sing it already integrated in a lot of software such as in video editor there is a feature that can use bicubic or lanzcos while exporting the video and thus improving the video quality in the process.

For future research directions should focus on optimizing the balance between computational efficiency and quality enhancement, potentially using adaptive processing strategies that can dynamically adjust algorithm based on content characteristic and hardware capabilities. This study can serve as a benchmark for developing next-generation super-resolution solutions that can implement classical methods with upcoming technologies to achieve optimal performance across diverse multimedia enhancement application while maintaining practical viability in-real world scenarios.

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