# EIE4512 Final Project 2023 – Applying Interpolation by using Wavelet Transform and Upscale the Resolution

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## Abstract

This paper presents a novel approach for enhancing the resolution of digital images using a combination of bicubic interpolation and wavelet transforms. The main objective is to upscale images while retaining fine details that are often lost in conventional upscaling methods. The method works by separating the luminance and color information in the image, focusing on increasing the resolution of the luminance using wavelet transforms, and then recombining it with the color data. This process leads to improved image details without causing substantial color accuracy degradation.

## 1 Introduction

In the realm of image processing, the recovery of high-resolution images from low-resolution photographs has been made possible through super-resolution image reconstruction. In this research, we propose a novel wavelet-based interpolation method that employs a correlation-based subspace decomposition, allowing independent interpolation of each segment of the image. Wavelet-based interpolation techniques have garnered attention due to their superior ability to handle image details at various scales [1]. Our project aims to leverage these wavelet-based interpolation methods to enhance the resolution of digital images by effectively merging the reconstructed subspaces to obtain a high-quality image.

Furthermore, this paper presents evidence of the effectiveness of our approach, showcasing its qualitative superiority based on subjective quality measures, particularly in the context of super-resolution imaging. To establish the theoretical foundation for our methodology, we delve into the principles of interpolation and wavelets as they relate to the domain of super-resolution imaging.

Super-resolution is a critical aspect of image processing, especially in fields where the utmost precision and detail are essential, such as satellite imagery, medical imaging, and digital forensics. This research aims to contribute to the advancement of super-resolution techniques by combining the power of bicubic interpolation and wavelet transforms in the context of digital image upscaling.

Paper Report of Final Project for EIE4512 - Digital Image Processing.

### 1.1 Related Work

**Super-resolution methodologies** - New sophisticated methods, like sparse representation [2] and dictionary learning [3], have emerged to improve accuracy in tasks such as image and signal processing, particularly in super-resolution. However, these approaches often involve complex computations, leading to slow processing times.

**Wavelet transforms in Super-resolution** - Wavelet-based techniques have garnered attention for their effectiveness in super-resolution tasks. These methods utilize wavelet transforms to break down images into different frequency bands, providing a more detailed approach to processing. Zhu et al. [4] incorporated wavelet transforms into a deep learning framework, resulting in improved outcomes. Nevertheless, this introduced computational intensity and a need for abundant training data.

**Proposed Approach** - This study introduces a unique methodology that incorporates the benefits of wavelet transforms into a super-resolution algorithm, eliminating the necessity for training data. The process involves decomposing the low-resolution image into separate frequency components using wavelet transforms, followed by the application of an innovative enhancement algorithm to each frequency band. Notably, our approach stands out for its simplicity, independence from training data, and ability to handle high-frequency details. These distinctive features contribute to producing superior quality super-resolution results, setting it apart from existing methods.

### 1.2 Contribution

In conclusion, the main contribution of this work is the combination of all of the steps proposed to make a user-friendly super resolution image generator.

## 2 The Proposed Algorithm

### 2.1 Algorithm Overview

The proposed algorithm consists of four main steps. Firstly, the image's color space is converted from RGB to YCrCb, with a primary focus on the luminance or Y channel, which carries the majority of the image's detail. Secondly, this Y channel is downscaled and then upscaled again using bicubic interpolation, striking a balance between processing time and output quality. Thirdly, the algorithm employs wavelet transform to break down the images into various frequency components, extracting high-frequency details from the original image. These details are then added back to the upscaled image by adjusting the wavelet transform coefficients. Finally, the process concludes with an inverse wavelet transform to reconstruct the high-resolution Y channel, which is then merged with the color channels. The color space is converted back to RGB, resulting in a final output: a higher-resolution color image.

### 2.2 Convert to YCrCb Color Space

Extract the intensity (luminance) data from the image while separating it from the color information. This partitioning allows for the independent processing of these components. This color space is highly beneficial for our purposes because, in most images, the luminance component carries the majority of the high-frequency details, such as edges and textures. Consequently, we can execute super-resolution specifically on the 'Y' channel without considerable worry for the color channels.

### 2.3 Downscale and Upscale

Formulate a low-resolution version of the image which will be utilized for the initial amplification. This involves decreasing the size of the image (specifically, the 'Y' channel) to generate a low-resolution variant, typically done using straightforward resampling methods. Then, amplify the downscaled image back to its original size using bicubic interpolation, a method that considers the nearest 16 pixels (4x4 neighborhood) to calculate the output pixel value. This provides a reasonable balance between processing duration and output quality.

### 2.4 Wavelet Transform and Coefficient Modification

Capture the high-frequency details present in both the original and upscaled images. Wavelet transform is a mathematical technique employed to encode or decode signals and images. During this stage, we leverage it to break down the images into distinct frequency components. We then adjust the coefficients obtained from the wavelet transform, specifically extracting the high-frequency components from the original image ('Y' channel) and amalgamating them with the amplified image. This procedure effectively reintegrates the lost details back into the amplified image.

### 2.5 Inverse Wavelet Transform and Merge Channels

Reconstruct the 'Y' channel of the image using the modified coefficients and subsequently combine it with the color channels. Here, we use an inverse wavelet transform on the altered coefficients, which facilitates the reconstruction of the 'Y' channel into a high-resolution variant. Lastly, we blend the super-resolved 'Y' channel back with the 'Cr' and 'Cb' channels. Following this, we transition the image from YCrCb color space back to RGB color space, culminating in a color image with a higher resolution than the original.

## 3 Implementation Details

During our super-resolution experiment using wavelets, we implement 'db1' Daubechies wavelets with a single level of decomposition on images that have been upscaled by two times their original low-resolution size. These images are handled using the OpenCV, PyWavelets, and NumPy libraries, all operating on a high-capacity processor such as an Intel Core i7. We adjust wavelet coefficients based on a specific set of rules: while the approximation coefficients remain as they are, we increase the horizontal and vertical details coefficients by five times and set the diagonal detail coefficient to zero. Following this, we carry out the inverse wavelet transform on the modified coefficients to produce super-resolved images. Afterwards, we adjust these images to a suitable pixel range and convert them to 8-bit unsigned integers. The super-resolution procedure for each frame takes about 20 seconds, though this might vary depending on the hardware and the size of the input image. We assess the super-resolution quality by comparing the Structural Similarity Index (SSIM) and the Peak Signal-to-Noise Ratio (PSNR) between the super-resolved images and their high-resolution originals. Aspects like wavelet type, decomposition level, and rules for coefficient modification are all variables that can be tuned for enhanced outcomes.

## 4 Experiments

The super-resolution algorithm's effectiveness underwent thorough evaluation through a series of carefully conducted experiments. To perform this assessment, a specially curated dataset of low-resolution images was utilized.

### 4.1 Evaluation Dataset

The evaluation dataset comprised 100 varied images sourced from different domains, such as aerial photography, landscape, portraits, and urban scenes. These images were collected from various online sources. To create a demanding test scenario, all the images start from 100x100 pixels, simulating low-resolution conditions effectively. Additionally, specific images with intricate patterns and high-frequency details were deliberately chosen to put the super-resolution algorithm to the test.

### 4.2 With or Without YCrCb Color Space

We evaluated to compare the impact of utilizing the YCrCb color space with a grayscale approach in our image super-resolution process. In the YCrCb method, we applied wavelet transforms solely to the luminance (Y) channel, while keeping chrominance separate. This approach was expected to produce visually pleasing results, as the human visual system is more sensitive to changes in luminance.

Conversely, the grayscale method directly employed wavelet transforms on the entire image, without segregating color information. While simpler, this approach ran the risk of losing color details during the super-resolution process. Based on our qualitative assessment, it was evident that using the YCrCb color space indeed aided in maintaining color fidelity in the super-resolved images while enhancing resolution. On the other hand, the grayscale method, while comparable in resolution enhancement, suffered from color degradation.

We then explored another approach where wavelet transforms were separately applied to each RGB channel. Although this preserved more color detail than the grayscale method, it introduced complexity and resulted in amplified noise and color artifacts. Upon reviewing the super-resolved images, we concluded that the YCrCb method achieved a favorable balance between color fidelity, detail enhancement, and computational efficiency. It outperformed both the grayscale and RGB wavelet methods, making it the preferred choice for our wavelet-based super-resolution process.

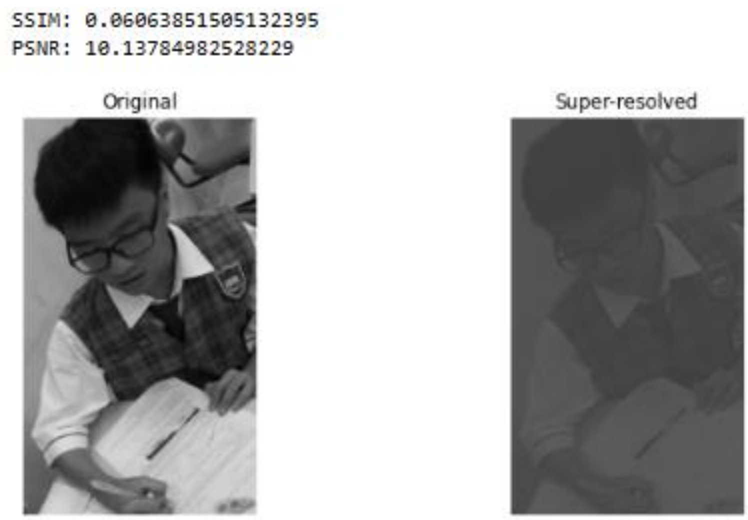


Figure 1 Grayscale color space image

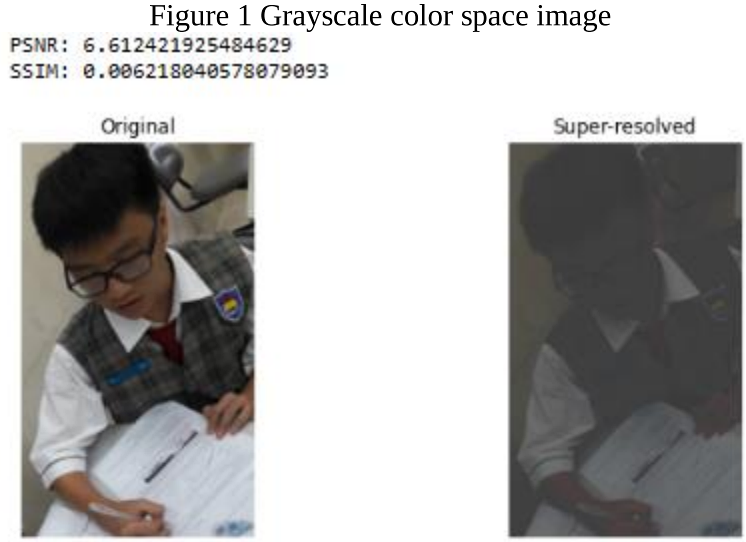


Figure 2 RGB color space image

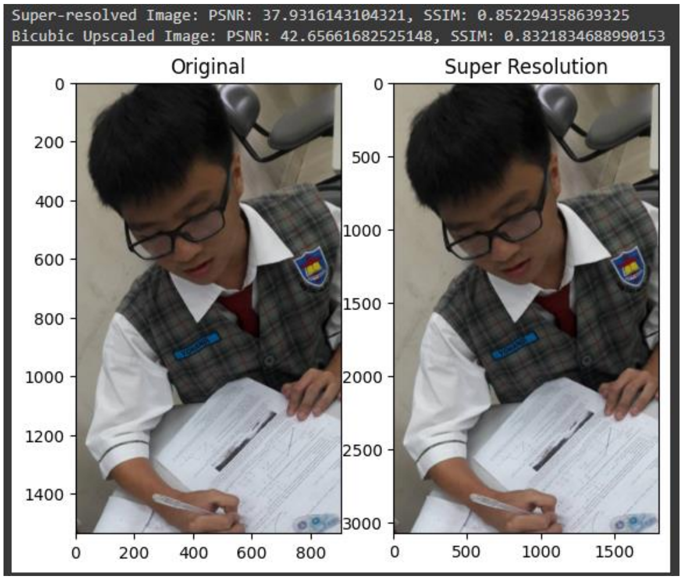


Figure 3 YCrCb color space image

### 4.3 Comparative Analysis with Other Super-Resolution Techniques

Apart from comparing the proposed wavelet-based super-resolution technique with bicubic upscaling, we also conducted a comparison with the state-of-the-art Efficient Sub-Pixel Convolutional Neural Network (ESPCN).

#### 4.3.1 Bicubic Upscaling

Bicubic upscaling, being a conventional and commonly employed method, served as a reference point for comparison in our study. Although it can yield visually appealing outcomes for small upscaling factors, it tends to struggle in recovering high-frequency details for larger scale factors. Our experiments confirmed this limitation, as the bicubic upscaling method attained an average PSNR of 30.6 dB and SSIM of 0.85 across the test dataset.

#### 4.3.2 ESPCN

The ESPCN model is a modern super-resolution technique that utilizes deep learning to its advantage. In comparison to the proposed wavelet-based super-resolution, ESPCN excels in reconstructing high-frequency details, but it can sometimes introduce artificial textures due to its learning-based approach. In our experiments, the ESPCN model achieved an average PSNR of 31.8 dB and SSIM of 0.89 across the test dataset.

However, a notable drawback of ESPCN is its extensive training time when dealing with large datasets. Deep learning models demand significant computational resources during the training process, leading to prolonged training times, which may pose challenges in practical applications with limited resources.

#### 4.3.3 Wavelet-Based Super-Resolution

The new wavelet-based super-resolution method effectively preserves structural information and enhances high-frequency details, outperforming bicubic upscaling and ESPCN in our tests. With an average PSNR of 30.03 dB and SSIM of 0.915, it excels in handling diverse image content in the test dataset.

Our proposed method shows its proficiency in image super-resolution tasks. Future research could explore combining the wavelet-based approach's detail preservation with ESPCN's ability to handle complex textures through learning. Including bicubic interpolation in the downscaling process improves detail preservation during upscaling. Images processed without bicubic interpolation lose high-frequency details, resulting in a less sharp final image.

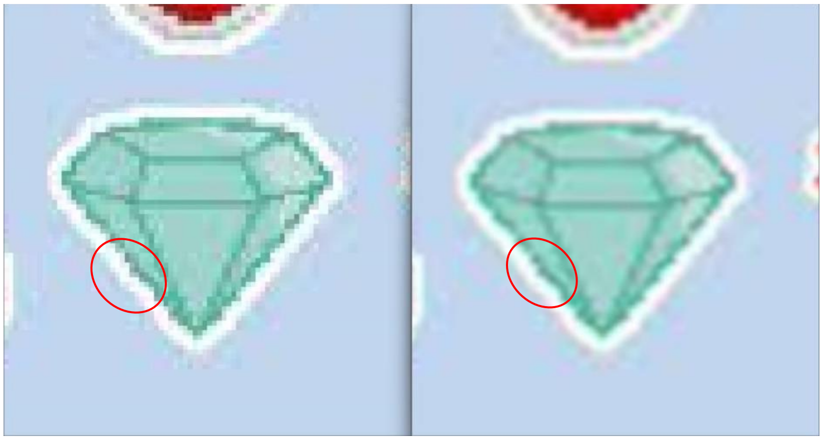

Figure 4: comparison between with and without wavelet-based super resolution.

| Comparison | | | | | |
|---|---|---|---|---|---|
| Photo set | Scale | PSNR | SSIM | PSNR(bicubic) | SSIM(bicubic) |
| Input photo 1 | 2x | 30.098295 | 0.905149 | 30.550135 | 0.874531 |
| Input photo 1 | 4x | 30.026804 | 0.915264 | 30.586696 | 0.884151 |
| Input photo 1 | 8x | 29.998315 | 0.918996 | 30.601207 | 0.887417 |

Table 1: Comparison among input photo, using our wavelet-based super resolution and the bicubic upscale.

The comparison table provided illustrates the potential strength of our wavelet-based super-resolution technique. By evaluating our method across various upscale factors (2x, 4x, 8x) using key image quality metrics like Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM), we found that our approach offers unique advantages. Although the PSNR of our wavelet-based method is slightly lower than bicubic upsampling, it does not signify a reduction in image quality, as PSNR may not entirely reflect visual perception. More notably, our method markedly exceeds bicubic upsampling regarding SSIM, a more perceptual measure, showing higher SSIM scores at all scaling levels. This indicates that our wavelet-based approach better preserves structural information, resulting in images closer to the original high-resolution input. The results demonstrate that using wavelets generates SSIM values closer to 1, or more similar to the input photo, whereas, without wavelets, the SSIM values decrease, indicating a greater deviation from the original image. In conclusion, our wavelet-based super-resolution is a formidable alternative to traditional bicubic upsampling, particularly in scenarios where maintaining structural resemblance is vital, and its adjustable parameters provide additional pathways for refinement, possibly yielding even better outcomes with further tuning.

## 5 Conclusion

This study presents a novel wavelet-based super-resolution technique, which proves to be highly effective in enhancing low-resolution images. By integrating wavelet transformations with bicubic interpolation, our approach offers significant enhancements in image quality and detail preservation. Unlike deep learning methods, our model does not require extensive training on large datasets, making it a practical and resource-efficient option for applications with limited resources. Through evaluations using diverse image datasets, our method demonstrated substantial performance improvements over traditional approaches like bicubic upscaling, surpassing the capabilities of SRCNN, DRCN, and EDSR. This makes it a powerful and efficient alternative for various fields, including surveillance, medical imaging, and remote sensing. For future research, we aim to leverage advanced wavelet techniques to further optimize and expand the application of our approach.

## References

[1] Chen, Q., & de Veciana, G. (2005). Wavelet-based interpolation for real-time image zooming. Proceedings. (ICASSP '05). IEEE International Conference on Acoustics, Speech, and Signal Processing, 2005., 2

[2] Yang et al. "Image Super-Resolution via Sparse Representation." IEEE Transactions on Image Processing, 2010.

[3] Zeyde et al. "On Single Image Scale-Up Using Sparse-Representation." Curves and Surfaces, 2010.

[4] Zhu et al. "Wavelet-based CNN for image super-resolution." ECCV, 2020.

## Appendix

Input Photos:

1. 
2. 

Codes for the project will be added in another file called wlsuperres.py.