Hybrid Multi-Frequency Image Illusion

Shreena Patel, Dhyey Patel

***Abstract*—The project is a hybrid multi-frequency illusion technique of images that have been developed relying on classical image-processing methods with no machine learning/AI. The following is done to combine low-frequency components of one image and the high-frequency details of another: Gaussian filtering, frequency decomposition, morphing, and weighted blending. The test is done on grayscale images, color images and a sample of 20-30 pairs and with a demorphing step to study partial reconstruction and frequency interaction.**

***Index Terms*—Hybrid image, frequency, Gaussian filter, image processing, visual illusion, quantitative analysis, low & high Frequency, illusion, morphing, colored image illusion, demorphing.**

I. Introduction

Hybrid images are the illusion that leverages on how the human eye perceives different spatial frequencies. When viewed from a closer distance, we tend to see low frequency components prominently while viewing from afar distance the high frequency components dominate. This concept results in a single image to appear as two different images depending on the viewing distance.

In this project, hybrid images have been created without using any machine learning techniques, and completely relying on the classical image processing techniques such as Gaussian smoothing, frequency subtraction, morphing and weighted blending. Firstly, we began with grayscale images where we separated low frequency components using smoothing and high frequency via difference operations. Further these two components were combined along with adjustable weights for generating hybrid illusions of more clarity. Morphing process helped in aligning both the images appropriately for a clear hybrid image.

After developing an appropriate grayscale pipeline, a dataset of 20-30 images was tested to ensure correctness of the pipeline across different images. Further extended the learning to colour images, by applying frequency decompose separately to each RGB channel, that helped in retaining the colour while maintaining the effect of hybrid illusion. Lastly, a simple reconstruction or de-morphing process was done to study and analyse how much information the hybrid images were able to preserve. Overall, the implementation of the project demonstrated successful generation of hybrid image illusion with the help of classical image processing methods only providing understanding on frequency-based image processing.

II. Methodology

The method followed for creating hybrid multi frequency image illusion consist of three necessary steps, pre-processing, frequency, filtering, and combining image, further extended by the stage of demorphing to study the reversibility of the hybrid images. The method is as followed:

A. Preprocessing

In the first step, we give 2 input images of gray-scale or color and resize to same dimensions to make sure the spatial correspondence further, we normalize both the images to the range 021 and convert to floating point representation for accurate and precise frequency manipulation.

$$I = \frac{\text{image}}{255}$$

Here the alignment of both the images play a vital roll if they differ in the shape or structure. So, we apply precise affine morphing to ensure the facial or the objective features corresponds to each other. This is done so the low frequency image A correctly overlap the high frequency details of image B.

B. Frequency Filtering

In second step, we apply question filter to both the images. First, we apply question filter with cut-off frequency σL to produce the low frequency component.

$$I_{low} = G_{\sigma_L}(I_A)$$

Similar by subtracting original to the blood version, we get high frequency component of image B

$$I_{high} = I_B - G_{\sigma_H}(I_B) Ihigh \tag{1}$$

This technique helps to retain fine texture and edges essential for high frequency components.

C. Hybrid Image Combination

In this step, we combine the low frequency component of image A and the high frequency component of image B linearly, where k is a scale factor to adjust contrast of image B. Further output of this is clipped for valid intensity range.

$$H = G_{\sigma_L}(I_A) + k \times (I_B - G_{\sigma_H}(I_B)) \tag{2}$$

For color hybrids, equation (2) is executed independently on all three channels and then recombined into a single hybrid color image.

D. Demorphing / Reverse Frequency Extraction

As mentioned earlier to analyse the reversibility of hybrid images, the low frequency component of image A is reversed as,

$$H_{\text{low}} = G_{\sigma_L}(H)$$

while the high frequency component of image B is reversed as,

$$H_{\text{high}} = H - G_{\sigma_L}(H)$$

This method helps to get the insights that information of image A and B can be encoded in hybrid illusion. These experimental results of D morphing also validate the effectiveness of frequency, illusion and the extent to which the frequency band of hybrid image can be separated. The flowchart of methodolgy is followed in Fig 1.

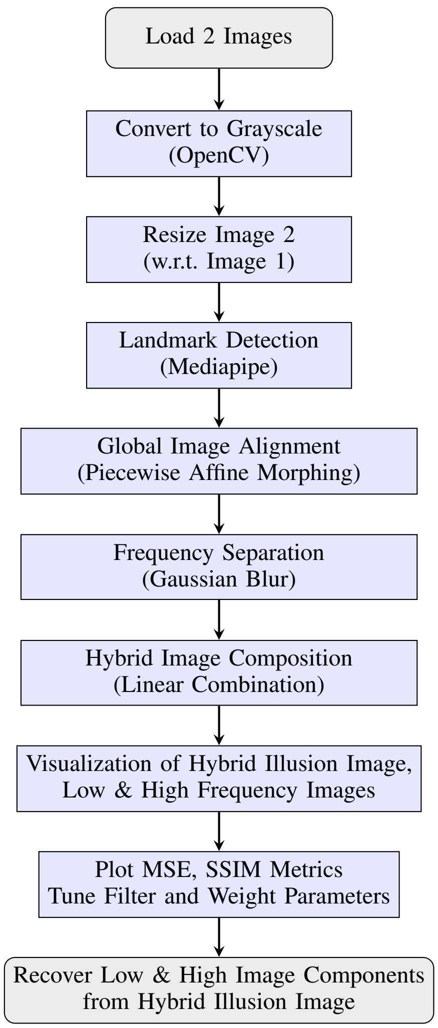

Fig. 1. Workflow of Hybrid Multi-Frequency Image Illusion: from image loading to hybrid composition.

E. Color Image Illusion

Moreover, the same methodology is followed for the color image illusion as a grayscale image illusion. In the pre-processing step, we perform it separately on RGB channels while frequency filtering is also applied individually to all three channels. The step C and D remains same for the color images.

III. Results

From the below experimental result, we obtain images Fig. 3 and 4 respectively, here figure 3 is gray-scale image illusion while figure 4 is color image illusion. Here we can observe that the gray-scale and color illusions are nearly same. Both the images show similar facial details when viewed at the near distance and show similar details of another facial structure at a far distance. From the below results, we can say that the intended perceptual illusion is highly effective. We see the low frequency image at at a far distance and high frequency image at near distance because the human human eye perceptual diminishes the details at far distance.

Fig. 2. Face 1

Fig. 3. Face 2

Fig. 4. Grey-scale hybrid image

Fig. 5. Colored hybrid image

A. Parameters to Change to Hybrid Image Quality Improvement:

Achieving good quality of a hybrid image is highly dependent on a number of tunable parameters associated with filtering, weighting, and preprocessing. These parameters are outlined in the following subsections and the effects they have on the end product. The sizes of Gaussian Kernels used in low-pass filtering are known as Gaussian kernel sizes (k).
Kernel Size k LPF1 (Low-Pass Filter applied to Image 1): The extent of smoothing of the first image is determined by the kernel size, which is $k = 65$. When you have a larger kernel,

Fig. 6. Parametric Analysis of Gray-scale Illusion Image

Fig. 7. Parametric Analysis of Color Illusion Image

the LPF1 produced is less sharp which preserves much of the low frequency information and highlights the coarse structures in the resultant hybrid picture. On the other hand, a smaller kernel has more detail of Image1. (It is important to make sure that k is always an odd number.)
kernel size k LPF2 (to obtain HPF2 out of Image 2): The cutoff frequency of Image 2 to extract high-frequency content is defined by this kernel size (e.g., $k = 31$). Reading a smaller kernel only records very sharp edges, whereas a bigger kernel records slightly lower-frequency contents in addition to the high-frequency content.
Based on blending, the weights of the two offer different selections of alpha (0.4, 0.6, 0.8) and beta (0.8, 1.0, 1.2). Weight α for LPF1: The degree of contribution made by the low-frequency representation of Image 1 is parameterised by the value of alpha. Higher values enhance the prevalence of low-frequency components that suggest Image 1 to be more prominent as one looks closer. This is minimised by smaller values. Weight β for HPF2: The parameter beta magnifies the input of the high-frequency fine-tuning of Image 2. The larger the values, the more the edges and sharp features will be visible (when viewed at a distance), whereas the smaller the value, the softer the high-frequency content. Though α and β values are usually 0 to 1, the values outside this range could also have interesting effects.
Though this is not coded as a parameter, the selection of input images is important. The structural information of the low-frequency image must be high, whereas the high-frequency image must have the sharp details clearly. Images are better suited in that they should be of similar subjects and similarly oriented to be perceived as hybrids.
The hybrid multi-frequency image system can be tuned by various low and high frequency parameters (k_1, k_2) and their respective weights (α, β). Through this experimental results, we can see how parameters variations affect the low and high frequency structure in illusion image.

B. Visual Results

The following set of images by tuning of various parameters show consistent trends:

- More the low-frequency weights $(\alpha \geq 0.6)$, the image preserves the global facial structure better, making perceptual of image at far distance more fine.
- Larger high-frequency weights $(\beta \geq 1.0)$, preserves edges such as hair strands, glasses, facial contour, which helps to get better perception at smaller distance.
- On increasing the value of k_1,we get stronger smoothing in the low-pass image, while increasing k_2 help retain sharp edges in the high-pass component.

Low pass component for large value of k_1 appears to be more blurred while for high pass component as the value of β increases the sharpening of edges is strengthened.

C. Quantitative Results

The variation for high performing parameter combinations are summarized in below Table I. This metrics table include Structural Similarity (SSIM), Peak Signal-to-Noise Ratio (PSNR), and Mean Squared Error (MSE).

TABLE I
QUANTITATIVE PERFORMANCE METRICS FOR SELECTED PARAMETER COMBINATIONS.

Parameters	**SSIM**	**PSNR**	**MSE**
k1=65, k2=15, α=0.8, β=0.8	**0.8289**	17.5267	1149.24
k1=45, k2=15, α=0.8, β=0.8	0.8282	17.5416	1145.30
k1=25, k2=15, α=0.8, β=0.8	0.8198	17.5100	1153.65
k1=65, k2=15, α=0.8, β=1.0	0.8003	17.4476	1170.38
k1=45, k2=15, α=0.8, β=1.0	0.7999	17.4623	1166.41
k1=25, k2=15, α=0.8, β=1.0	0.7927	17.4313	1174.76
k1=65, k2=31, α=0.8, β=0.8	0.7914	17.3242	1204.09
k1=45, k2=31, α=0.8, β=0.8	0.7911	17.3367	1200.64
k1=25, k2=31, α=0.8, β=0.8	0.7844	17.3048	1209.49
k1=65, k2=45, α=0.8, β=0.8	0.7839	17.2129	1235.35

1) Key Observations:

a) 1. Best Structural Similarity: The combination of following parameters resulted in the highest SSIM of **0.8289** are as follows:

$$k_1 = 65, \quad k_2 = 15, \quad \alpha = 0.8, \quad \beta = 0.8$$

This combination yields the most balanced hybrid image, preserving both smooth structure and fine edges.

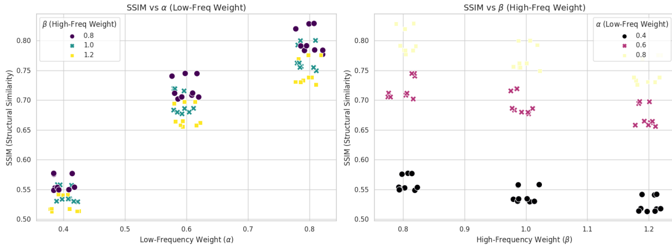

Fig. 8. Quantitative Analysis Graphs (SSIM vs α and SSIM vs β)

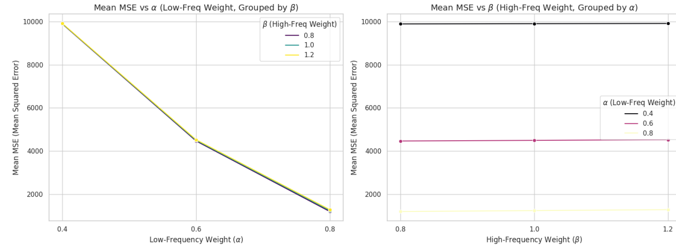

Fig. 9. Quantitative Analysis Graphs (MSE vs α and MSE vs β)

b) 2. Effect of Increasing High-Frequency Weight β: On increasing the value of β from 0.8 to 1.0 (for $\alpha = 0.8$) showed the drop in SSIM value:

$$0.8289 \rightarrow 0.8003 \quad (k_1 = 65)$$

This indicates that excessive sharpening introduces noise-like artifacts that reduce structural similarity.

c) 3. Effect of Stronger High-Pass Filtering: On increasing the value of k_2 from 15 to 45 shows steady drop in SSIM value:

$$0.82 \rightarrow 0.78$$

While higher value of k_2 shows reduce in perceptual stability of hybrid image, more sharpened edges.

D. Scatter Plot Analysis

The above SSIM vs. α plot shows that the value of SSIM increases monotonically as the value of α becomes larger, and $\alpha = 0.8$ consistently giving the highest similarity values. The points form three cluster based on different value of β, and $\beta = 0.8$ performes best of all.

Similarly, the SSIM vs. β plot shows a downward trend as β increases, supporting that for strong high-frequency weights results in degarded quality of hybrid image. Overall, these results shows that a balanced weights of $\alpha = 0.8$ and $\beta = 0.8$, combined with moderate filter sizes ($k_1 = 45$–65, $k_2 = 15$), produces the most perceptually accurate hybrid images.

E. Line Graph Analysis

The mean Mean Squared Error (MSE) changes with the Line length and this is shown in the line graphs below. That is the change in low frequency weight (α) and high frequency weight (β). These trends can be used to identify that a lower MSE indicates a higher quality of illusion.

1. Mean MSE vs. α (Low-Frequency Weight): This is the most vital analysis finding. There is a dramatic and non-linear reduction of MSE with the increase in value of α. The curves show a very steep drop that took place between $\alpha = 0.4 and \alpha = 0.6$, then MSE reaches its minimum value = 0.8 at any values of β. These findings are a clear indication that the parameter that is more dominant is alpha. Gain in α would result in increasing low-frequency contribution.

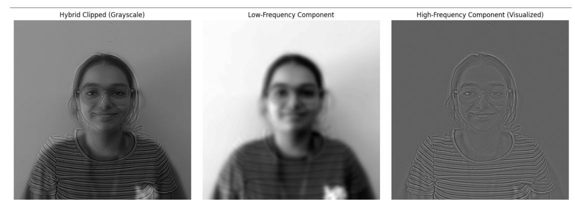

Fig. 10. Demorphed Illusion Image (grayscale)

2. Mean MSE vs. β (High-Frequency Weight): Unlike in the case of the alpha, the mean MSE changes with respect to β gradually. The line which represent the case of every α are nearly horizontal.

Sensitivity to β is not observed till the alpha is small. At the values of $\alpha = 0.4$, as we increase the value of β, the MSE increases slightly, which implies that high-frequency amplification is adding more error as a result of the high-frequency amplification.

F. Quantitative Analysis

The summary of Quantitative Analysis with respect to MSE and PSNR is discussed in the below table

Parameter Increase	**MSE**	**PSNR**
Increase α	$\downarrow$ Strong decrease	$\uparrow$ Strong increase
Increase β	$\downarrow$ Moderate decrease	$\uparrow$ Moderate increase
Low α **+ High** β	$\uparrow$ High error	$\downarrow$ Low PSNR
High α **+ High** β	$\downarrow$ Lowest MSE	$\uparrow$ Highest PSNR

TABLE II

COMPARISON OF THE EFFECTS OF α AND β ON MSE AND PSNR.

G. Demorphing

The results of demorphing of illusion image in Fig 5 shows the significance of the reversibility and the extent to which the high-frequency and low-frequency images can be recovered from the illusion image. In addition, it also signifies missing details and structure while recovering the image, with potential signs of improvement in later stages. Also, the recovered images are not 100 per cent accurate because of the blending of these images.

IV. DISCUSSIONS

The experimental results successfully validate the project's core objective: creating effective hybrid multi-frequency illusions using only classical image processing methods. The

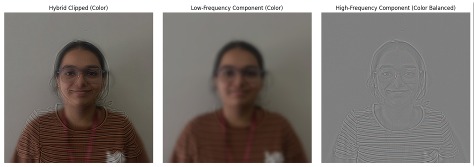

Fig. 11. Demorphed Illusion Image (color)

illusions, demonstrated in both grayscale (Fig. 3) and color (Fig. 4), confirm that the perceptual shift from high-frequency to low-frequency details with viewing distance is reliably achievable. This supports the underlying theory of the human visual system's frequency sensitivity. The extension to color, by processing RGB channels independently , proved effective and enhanced the "realistic" nature of the distant percept.
A key finding stems from the demorphing analysis (Fig. 5). While it successfully re-isolated the constituent frequency components, validating the encoding process. This confirms the process is not perfectly reversible due to information loss. From a practical viewpoint, the results were critically dependent on parameter tuning. The manual, trial and error selection of Gaussian kernel sizes (k) and blending weights (α, β) are essential for a clear illusion. Furthermore, the project underscores that precise spatial alignment of the source images is non-negotiable; poor alignment directly results in "poor performance" and breaks the illusion.

V. Conclusion

This project was able to show how hybrid multi-frequency image illusions can be created solely based on classical processing methods, which met the main goal of the project which was not to employ AI/ML models. The grayscale illusion (Fig. 3) and the color illusion (Fig. 4) were successfully created and confirmed the approach with the help of producing the required distance-related alteration in perception. The methodology was also confirmed by the succinct re-isolation of the frequency components of the constituents, as in the demorphing analysis (Fig. 5). The overall conclusion is that the classical approach is solid, but its effectiveness rides heavily on two manual elements namely the accurate spatial correspondence of the original images and the trial-and-error optimization on the filter parameters. It is a good base of the frequency based visual processing and reaffirms the persistence of classical image processing as a whole.

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