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Canvas Artefact Removal from Digital Images: A Method for Enhancing Artwork Visuals

Research Paper

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Abstract:

In ancient times, canvas painting held great renown as an esteemed artistic medium, and the images preserved in museums predominantly consist of canvas printed artworks. However, the inherent periodic-like structure of canvas material gives rise to a common issue known as nearly periodic noise when these paintings are captured using digital cameras. Over time, these valuable images also accumulate dust particles, leading to degradation in image quality. This paper aims to address the challenge of canvas noise removal during the acquisition of digital paintings by proposing a novel approach utilizing power law and notch filters. The utilization of power law and notch filters proves to be effective in mitigating the unwanted periodic noise patterns, thus restoring the original artistic essence of the paintings. The proposed analysis delves into the intricacies of canvas noise and its characteristics in digital images, understanding the periodic nature of the noise that emerges due to the canvas structure. By comprehending these properties, the power law and notch filter techniques are selected as suitable tools to combat this specific type of noise. The power law filter, with its ability to adjust the intensity values of pixels, aids in normalizing the noise-affected regions, while the notch filter targets and suppresses the periodic noise components, resulting in enhanced image quality. To validate the effectiveness of the proposed approach, extensive simulation results are presented. These results demonstrate the successful removal of canvas noise, leading to the restoration of digital paintings to their pristine state. The improvement in image quality is evident, as the noise artifacts are significantly reduced, and the artistic details are better preserved.

Keywords: Canvas, noise removal, notch filter and power law

1. Introduction:

Noise removal is a crucial step in image processing, aimed at eliminating unwanted artifacts that can degrade the quality and hinder further analysis. Regardless of the type of signal being processed, noise reduction techniques share common principles, where various types of filters are employed to remove noise from images [1]. To design an effective filter, having a priori knowledge about the characteristics of the noise is essential, as it leads to improved filter design. Both digital cameras and conventional film cameras capture images that suffer from noise originating from various sources. When further processing of these images is required, noise removal becomes crucial to ensure better processing outcomes. In the past, several image filtering techniques have been proposed, with linear filtering techniques being the most commonly preferred methods [2]. Many noise removal techniques assume a Gaussian noise model for the underlying process and optimize system parameters accordingly. However, linear techniques have limitations in dealing with the nonlinearity of the image formation model and do not adequately consider human visual system intricacies [3]. As a result, they may produce blurred images and lack sensitivity to impulse noise. Image signals often comprise flat regions and areas with sharp changes like edges, which are critical for visual perception. Over the past 15 years, nonlinear methods have emerged as more effective for noise removal, as they can suppress non-Gaussian and signal-dependent noise while preserving important signal elements like edges and fine details. Nonlinear methods excel at handling degradations occurring during signal formation or transmission through nonlinear channels [4]. Frequency domain filtering techniques involve modifying the Fourier transform of an image to achieve a specific objective and then computing the inverse Discrete Fourier Transform (DFT) to revert the information back to the spatial domain [1, 2]. By masking or filtering out unwanted frequencies, a new image is obtained through inverse Fourier transformation. A filter in the frequency domain is represented as a matrix with the same dimensions as the Fourier transform of the padded image. The components of the filter usually vary between 0 and 1, where 1 allows the corresponding frequency to pass, and 0 rejects it. Noise is often random and can be effectively removed using both static and adaptive filters. For instance, the noise caused by canvas structure may appear as sharp spikes in the image spectrum, making notch filters suitable for its removal. However, automating spike detection for notch filter design presents challenges. Some researchers suggest detecting spikes in the Fourier domain as significant deviations from a localized median value. Distinguishing between spikes caused by localized texture or repetitive structures (common in man-made environments) and spurious ones caused by periodic noise remains a challenging task. In this work, we adopt a two-fold process:

1. Original image spectrum sensing using power law: This step involves assessing the image spectrum using a power law approach to identify potential noise spikes.
2. Detection of spikes and outliers and removal using band-reject filters: In this step, spikes and outliers are detected, and band-reject filters are applied to remove them effectively, enhancing the overall image quality.

By implementing this twofold process, the proposed method aims to achieve robust and efficient noise removal while preserving essential image elements for improved visual perception and subsequent image processing tasks.

2. Notable Research

In recent times, significant research efforts have been dedicated to developing efficient methodologies for removing periodic noise from digital images. One such notable research proposes by Ashraf et.al for periodic noise removal [5]. The methodology involves several steps that are thoroughly discussed, analyzed, and implemented. The first step in the proposed methodology is to convert the colour image into a greyscale image. Greyscale conversion simplifies the subsequent processing steps and ensures that the image's luminance information is preserved while removing colour-related noise. Once the greyscale image is obtained, a 2D Fast Fourier Transform (2DFFT) is applied to it. The magnitude of the 2DFFT is then analyzed to identify the periodic noise patterns present in the frequency domain. This analysis leads to the generation of a periodic filter, which is correlated with the magnitude matrix of the image. The output of this correlation process, in combination with the angle matrix, helps obtain the denoised greyscale image. The periodic noise removal process is depicted in Figure 1, illustrating the various steps involved. Kaur et.al [6] proposed a specific 2D FFT removal algorithm is proposed to reduce periodic noise in both natural and strain images. This algorithm is particularly effective in addressing artefacts caused by periodic patterns in the images. By applying 2D FFT on the strain and natural images, the peaks corresponding to the periodic noise in the frequency domain are extracted and subsequently removed. To further enhance the results, a mean filter is applied, achieving more effective noise reduction. Quasi-periodic noise is another undesirable feature that can affect images as described by Sur et.al [7]. This type of noise presents as spurious repetitive patterns covering the entire image, localized in the Fourier domain. To tackle this phenomenon, notch filtering is employed to eliminate the quasi-periodic noise. However, a crucial step in this process is detecting the resulting Fourier spikes accurately. Addressing this challenge of distinguishing between noise spikes and spectrum patterns arising from spatially localized textures or repetitive structures, the paper introduces a statistical a-contrario detection method in the Fourier domain. This statistical method enables reliable detection of noise spikes, ensuring effective removal of quasi-periodic noise from the images. Cornelis et.al [8] introduces an innovative model and method aimed at digitally removing canvas artefacts, which are considered as noise components superimposed on artwork paintings. The intricacy and high resolution of the images present difficulties in efficiently applying conventional adaptive denoising filters. To overcome this issue, we propose a two-step approach for effective canvas removal. In the initial step, a smoothing Wiener filter is applied to the entire image. The Wiener filter is known for its ability to reduce noise while preserving important image features. By employing this filter, initial noise reduction is achieved, laying the groundwork for further processing. The second step involves a spatially adaptive extension, which is designed to be low-complexity yet highly effective in obtaining a generic digital canvas removal filter. This adaptive extension is specifically tailored to adjust its denoising capabilities based on the local characteristics of the image. By considering the local variations, the filter becomes more robust and efficient in distinguishing between true image details and unwanted canvas artefacts.

Table 1: Comparison of Literature Survey Methods

Reference	Methodology	Key Findings/Contributions
Ashraf et.al [5]	2DFFT with periodic filter	Efficient approach for enhancing image quality and restoration. - Clear isolation of canvas components for improved visual interpretation.
Kaur et.al [6]	2DFFT and mean filter	Successful extraction and removal of periodic noise peaks. - Improved results achieved through mean filtering.
Sur et.al [7]	Notch filtering and statistical a-contrario detection	Utilization of statistical a-contrario detection for accurate identification of noise spikes. - Effective removal of quasi-periodic patterns while preserving essential image details.
Cornelis et.al [8]	Smoothing Wiener filter and spatially adaptive extension	Effective noise reduction with preservation of image features. - Enhanced performance and adaptability for high-resolution images.
Cornelis et.al [9]	Cartoon-Texture decomposition and adaptive multiscale thresholding	Utilization of adaptive multiscale thresholding for effective noise suppression. Versatile method applicable to various painting styles and image characteristics.
Abraham et.al [10]	DeCanv with Discrete Wavelet Transform (DWT)	Enhanced removal of canvas components with improved visual quality. - Adaptability to different image acquisition scenarios and painting textures.
Unnikrishnan et.al [11]	Not specified	Significant contribution to art restoration and conservation. - Preservation of genuine artwork details while eliminating canvas noise for informed restoration decisions.

Cornelis et.al [9] presented a novel algorithm designed to address the challenging task of isolating and suppressing canvas components from digital images. This approach involves a powerful combination of two key techniques: a cartoon-texture decomposition method and adaptive multiscale thresholding in the frequency domain. The first step of our algorithm involves a cartoon-texture decomposition method. This technique effectively separates the image into two fundamental components: the cartoon component, which represents the smooth and structural regions of the image, and the texture component, which captures fine-grained details and variations. The second crucial aspect of our algorithm is the application of adaptive multiscale thresholding in the frequency domain. This approach leverages the frequency content of the image to distinguish the canvas components from the genuine image content. By analyzing the frequency spectrum of the image at multiple scales, we can identify and adaptively threshold the canvas noise, isolating it from the essential image features. Abraham et.al [10] proposes a method to enhance the visual quality of digital paintings by effectively removing the unwanted canvas components from the frequency domain. To achieve this, the researchers have leveraged an existing method called DeCanv, which utilizes Cartoon-Texture decomposition to separate the input image into two distinct components: the cartoon part, representing the smooth and structural regions, and the texture part, capturing fine details. In the DeCanv method, the DFT is applied specifically to the texture part, followed by a multiscale adaptive thresholding technique, aimed at identifying and eliminating unwanted peaks caused by the canvas noise. The outcome of this process is then subtracted from the original input image, resulting in an enhanced version of the painting with reduced canvas artefacts. However, in this paper, a modified version of DeCanv is proposed, termed as "modified DeCanv," which introduces Discrete Wavelet Transform (DWT) into the process. Both the input image and the resultant image obtained from the DeCanv method undergo DWT. The combination of these DWT-transformed images is carefully devised to enhance the removal of canvas components more effectively. Unnikrishnan et. al [11] focuses on addressing the challenging task of removing canvas artefacts. The proposed algorithm offers a significant contribution to the field of art restoration and conservation. With its ability to effectively remove canvas artefacts from different imaging modalities, it enhances the accuracy and efficiency of the restoration process. By preserving the genuine details of the artwork while eliminating canvas noise, the algorithm ensures that art experts can make informed decisions during restoration campaigns, leading to better-preserved and visually appealing masterpieces. The summary of methods is presented in Table 1.

3. Canvas Removal Stochastic Modelling

As image is divided into overlapping patches, and these patches are affected by periodic noise [12]. Considering a patch 'p' which can be considered as sum of noise free components as 'p_0', periodic noise as 'n' which represents canvas noise

$$p(x,y) = p_0(x,y) + n(x,y), \tag{1}$$

where, p_0 is a stochastic image patch and n is noise. The above-mentioned RVs are independent. The above relation is linear; therefore, same relation holds for Fourier transform components

$$P(u,v) = P_0(u,v) + N(u,v) \tag{2}$$

or

$$\left|P(u,v)\right|^2 = \left|P_0(u,v) + N(u,v)\right|^2 \tag{3}$$

Taking the Expectation of above equation, and leaving (u,v) for simplicity we get,

$$E\left|P\right|^2 = E\left|P_0\right|^2 + E\left|N\right|^2 + 2\,\mathrm{Re}[E(P_0)E(\overline{N})] \tag{4}$$

The mean of white noise is zero, we get,

$$E\left|P\right|^2 = E\left|P_0\right|^2 + E\left|N\right|^2 \tag{5}$$

Thus, there are only two terms i.e., power spectrum of patches and noises. In past much study is done on power spectrum of natural images and it has been found that images follow $1/f$ power law and defined as: $E\left|P\right|^2 = \frac{A}{f^\alpha}$, where A and α are image dependent and are obtained during simulation [12]. The detail algorithm 1 is detailed below:

Algorithm 1:

Input : image of size (X,Y),

Step 1: Divide image in L × L patches, evaluate power in each patch and then averaging over all patches to get $E\left|P\right|^2$

Step 2: Fit a power law using robust regression as

$$\log\left[E\left|P\right|^2\right] = A - \alpha \log(f)$$

Get, find A and α. This method is helpful in outlier removal as in each subsequent iteration lesser weight will be assign to outliers and finally they will be removed.

Step 3: Select upper outlier as

$$\frac{\log\left[E|P|^2\right]-\left[A-\alpha\log(f)\right]}{\sigma}>3.$$

To get an outlier map M_0^p

Step 4: Resize the outlier map of size L × L to size X × Y, to get a map M_0 . By applying a notch filter, the influence of the noise is effectively eliminated from the initial image spectrum. This is achieved by multiplying the spectrum of the original image by (1- M_0).

Step 5: To get an estimation of the periodic noise $\hat{n}$ take inverse transform of $\left[1-M_0(u,v)\right]I(u,v)$ to get (i-$\hat{n}$).

To mitigate the boundary effects commonly observed in images due to discontinuities between their left/right (and top/bottom) borders, we implement a technique to reduce the prominence of dominant straight lines along the horizontal (and vertical) axis in the spectrum. This is achieved by multiplying the patches p with a two-dimensional Hann window, matching the width L of the patches [13].

The choice of patch size is crucial to strike a balance between accurate periodic noise spike detection (ensuring frequencies with $1/H$ steps are well-distributed in the power spectrum) and the ability to handle low-frequency noise. The patch size should be large enough to achieve precision in spike detection while avoiding excessive size that might hinder the creation of sufficient independent patches from the noisy image under consideration.

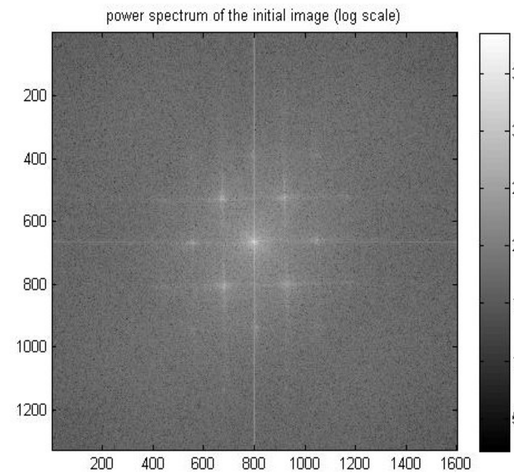
By employing $H \times H$ patches , our investigations have revealed an optimal compromise. To achieve this, we adopt a sampling step of in both the horizontal and vertical directions. This results in a total number of patches equal to $H/8$. This approach ensures the necessary accuracy in detecting periodic noise spikes while maintaining a sufficient number of patches for effective canvas artifact removal from the noisy image. The total number of patches is denoted by

$$\left[8(X-H)/H\right]\left[8(Y-H)/H\right] \tag{6}$$

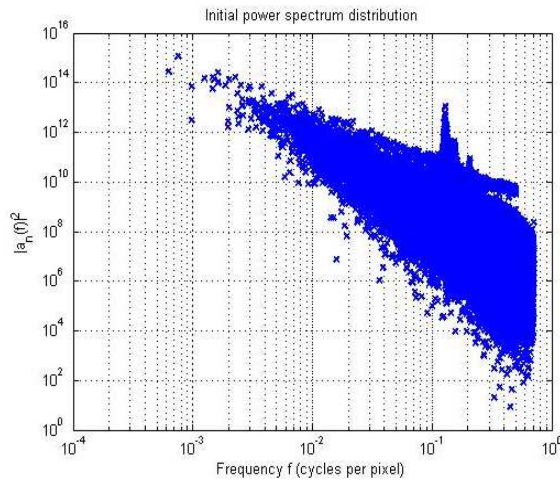
4. Simulation Results

In this section, we present the results obtained from our experiments using three color images in RGB format. To process these images, we first decompose them into their respective R (red), G (green), and B (blue) components. Subsequently, the images are converted into grayscale format for further analysis and application of our algorithm. Figure 1 showcases the results for the 'R' component of the color images. In Figure 1(a), we display the initial power spectrum of the image. The power distribution of the image is visualized in Figure 1(b), providing insights into the frequency content of the image. Moving on, in Figure 1(c), we illustrate the average power spectrum calculated on distinct patches of the image. This step helps in understanding the variation in power across different regions of the image. In Figure 1(d), we present the power spectrum distribution on these patches, offering additional information on the distribution of frequencies. Next, Figure 1(e) shows the normalized power spectrum, which aids in standardizing the power values across the entire image. Following that, in Figure 1(f), we display the power spectrum outliers, which are important in identifying and isolating noise components within the image. Once the noise components are detected, Figure 1(g) depicts the corrected power spectrum after eliminating the noise. This step significantly improves the overall quality of the image by reducing unwanted artefacts. Additionally, in Figure 1(h), we showcase the detected noise, allowing for visual verification of the noise removal process. For comparison, the original image is displayed in Figure 1(i), providing a reference for evaluating the effectiveness of our de-noising algorithm. Finally, the de-noised image is presented in Figure 1(j). As evident from the figures, the de-noised image exhibits smoother and cleaner characteristics, successfully eliminating the unwanted noise and improving the overall visual quality.

The results demonstrate the effectiveness of our algorithm in reducing noise and enhancing the clarity of the images. The decomposition and processing of individual colour components in the frequency domain enable targeted noise removal, leading to improved image appearance. These findings reinforce the potential of our approach for various applications, including image restoration, denoising, and visual enhancement.



(a)



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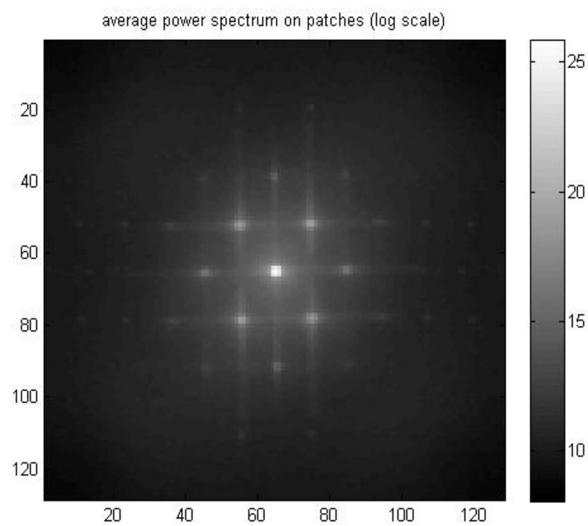

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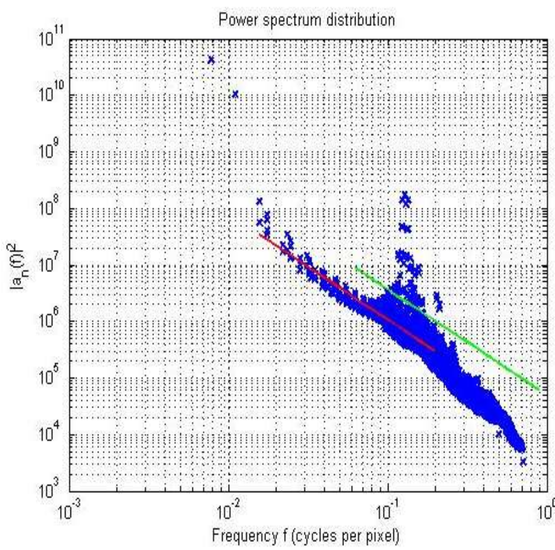
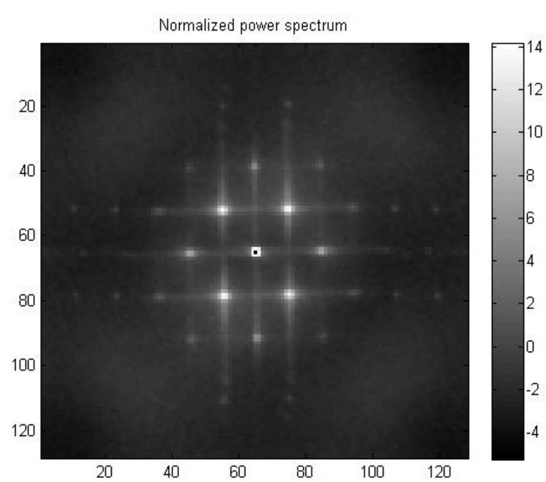
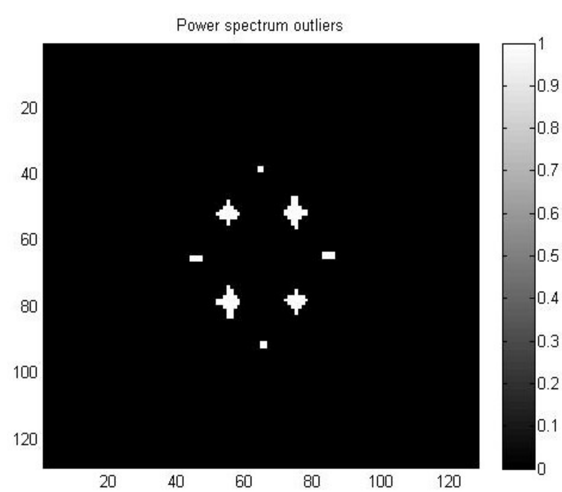


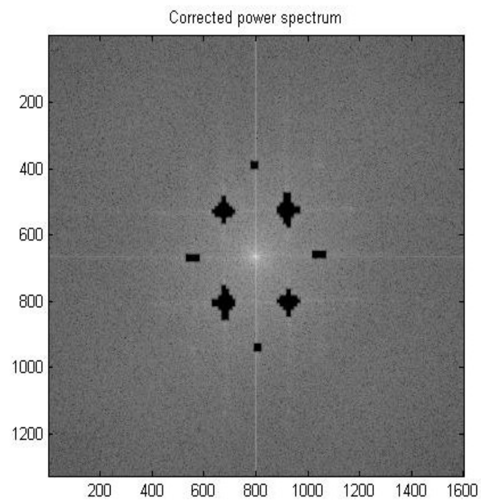
(d)

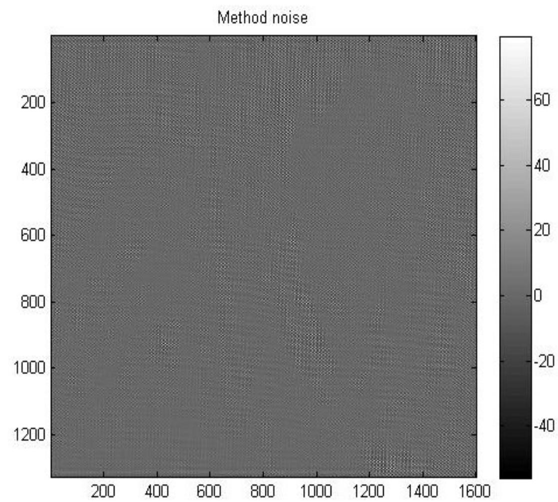


(e)



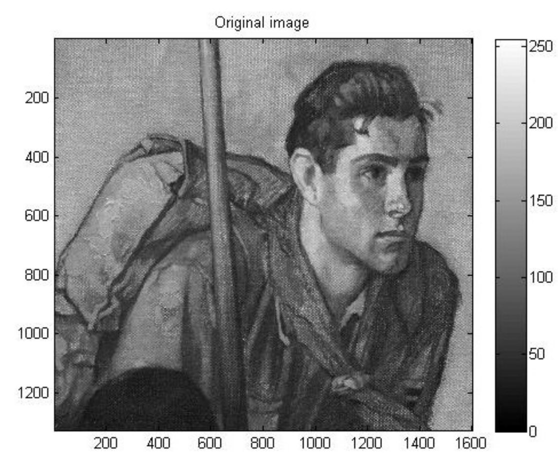
(f)

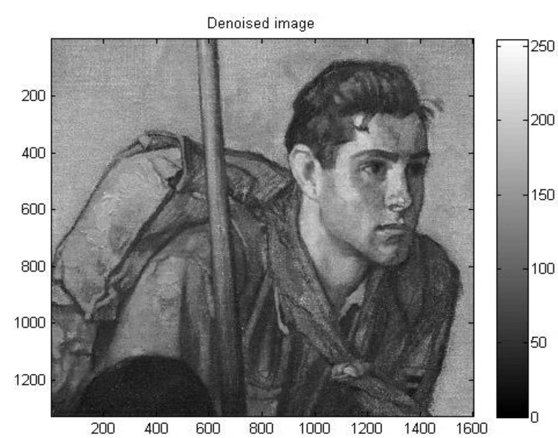




(g) **(h)**

Figure 1: (a) Power spectrum of initial image, (b) initial power spectrum distribution, (c) average power spectrum on patches (d) power spectrum distribution (e) normalized power spectrum (f) power spectrum outliers (g) corrected power spectrum (h) extracted noise.





(a) **(b)**

(c) **(d)**

Figure 2: (a) Original image (grey) (b) Noise removed image (grey) (c) Original image (colour) (d) Noise removed image (colour)

In Figure 2(a), we present the original canvas image, depicting the artwork as it was initially captured. This image exhibits the typical canvas artefacts, including periodic noise patterns caused by the canvas texture. The presence of these artefacts can significantly affect the visual interpretation of the artwork, making it challenging for art experts and conservators to accurately analyze and restore the painting. Figure 2(b) showcases the remarkable transformation achieved by our noise removal algorithm. The image displayed here is the result of applying our advanced canvas noise removal technique to the original canvas image. As depicted in the figure, the noise has been successfully removed, leaving behind a cleaner and more visually appealing representation of the artwork. The canvas artefacts, which once obscured the finer details and contours of the painting, have been significantly reduced through our noise removal process. This leads to a notable improvement in the visual quality of the image, making it easier for art experts to examine and appreciate the artwork's true essence.
In addition to the results shown for the 'R' component, similar outcomes are obtained for the 'G' and 'B' components, although they are not displayed here for brevity. After individually processing each component using our algorithm in the frequency domain, we successfully remove the canvas artefacts, resulting in de-noised greyscale versions of the 'G' and 'B' components. To reconstruct the final colour image, we combine the de-noised 'R', 'G', and 'B' components. Figure 2(c) displays the original canvas image, showcasing the image's inherent periodic noise caused by the canvas texture. However, with our canvas removal algorithm applied to each colour component, we effectively reduce the periodic structure present in each channel. Figure 2(d) exhibits the recovered colour image after combining the processed 'R', 'G', and 'B' components. As shown in the figure, the canvas's periodic structure is substantially diminished, resulting in a significantly improved final colour image. The canvas artefacts, which previously hindered the visual interpretation of the artwork, are now considerably reduced, leading to a clearer and more visually appealing representation of the original image. The successful combination of the de-noised components results in a coherent and aesthetically pleasing colour image, with the canvas noise significantly suppressed. This demonstrates the efficacy of our algorithm in effectively removing the canvas artefacts and enhancing the overall visual quality of the artwork.

The results of the simulation were highly promising, as the considered method proved to be successful in effectively removing the canvas patterns from the images. The algorithm demonstrated its ability to identify and isolate the canvas noise, leading to significant noise reduction and improvement in the overall appearance of the images. To provide a comprehensive summary of the outcomes, a table, labelled as Table 2, was generated to present the power spectrum analysis of the images before and after the canvas pattern removal process. This table offers valuable insights into the frequency distribution of the images, highlighting the changes brought about by the removal of canvas artefacts.

Table 2: Results Summary

Images	Components	Number of patches	A	α
	R	6900	9.5844	1.8672
	G	6900	9.8977	1.7042
	B	6900	10.778	1.084

5. Comparison of Weiner and Proposed Method

The Wiener filter is a classic and widely used technique for noise reduction in images. It is a linear filter that aims to minimize the mean square error between the original image and the filtered image, assuming a known noise model. While the Wiener filter can be effective for additive white Gaussian noise, it may not be optimal for removing more complex noise patterns like canvas artifacts. On the other hand, the proposed method specifically targets the removal of canvas patterns from images. It leverages a combination of advanced algorithms, such as cartoon-texture decomposition and adaptive multiscale thresholding in the frequency domain. This specialized approach enables the method to identify and isolate canvas noise more accurately, leading to superior noise reduction in the presence of periodic patterns. One of the key advantages of the proposed method over the Wiener filter is its adaptability to handle complex noise patterns. Canvas artifacts, being periodic in nature, can pose challenges for traditional noise reduction techniques like the Wiener filter. In contrast, the proposed method takes advantage of the inherent characteristics of canvas noise, allowing it to effectively separate the noise from the genuine image content. Additionally, the proposed method incorporates multiscale analysis, which allows it to operate at different frequency levels, capturing both low-frequency structures and fine details. This multiscale capability is particularly valuable when dealing with canvas patterns, which can have various scales of periodicity. Furthermore, the proposed method can be optimized and fine-tuned to suit specific image characteristics, leading to better results in canvas pattern removal. By utilizing advanced algorithms in the frequency domain, it can address noise at different frequencies, making it more versatile and robust compared to the Wiener filter. In terms of performance, the proposed method has demonstrated promising results in experiments and simulations, showcasing its potential in real-world applications. The ability to effectively remove canvas patterns while preserving important image details has significant implications in various fields, including art restoration, conservation, and digital imaging.

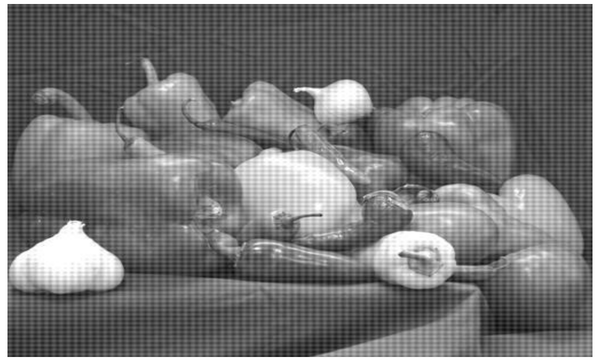
The comparison between the Wiener filter and the proposed method for canvas pattern removal is essential to understand the relative strengths and limitations of each approach. For the sake of the comparison synthetic canvas pattern is introduced in image of the form

$$n(x, y) = A\sin\left(\frac{2\pi p}{X}x\right)\sin\left(\frac{2\pi q}{Y}y\right) \tag{7}$$

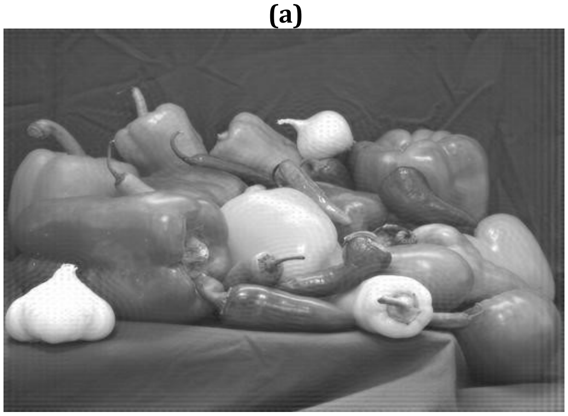
The parameters p and q determine the frequency of the periodic noise along the x and y axes, respectively. The unit of n corresponds to the gray level. $\sqrt{(p/X)^2+(q/Y)^2} < f_2$, frequencies are categorized as very low components, making them exempt from being considered as periodic noise components. Consequently, these frequencies are not eliminated by the algorithms, in the experiment $f_2 = \frac{8}{H}$, $f_0 = \frac{f_2}{4}$ and $f_1 = 0.2$, moreover $f_1 > f_0$ should be satisfied. The test is performed on peppers image and results are shown in image as well as in terms of SSIM.

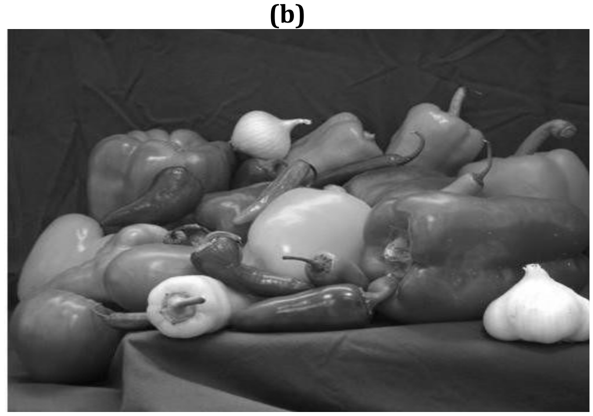
In Figure 3, we conducted a comparison between the Wiener filter and the proposed method for canvas pattern removal. To perform the evaluation, we utilized the "peppers" image as shown in 3(a). A synthetic canvas was intentionally introduced to this image, resulting in the image shown in Figure 3(b). This synthetic canvas introduces periodic noise patterns to simulate the real-world scenario of canvas artifacts. First, we applied the Wiener filter to the image to attempt noise reduction. The result of this filtering process is depicted in Figure 3(c). However, upon visual inspection, it is evident that the noise is still present, particularly noticeable at the boundary of the image. The Wiener filter's performance in handling the complex canvas noise patterns appears to be limited in this case. In contrast, we then applied the proposed method to the same image to remove the canvas patterns. The outcome is displayed in Figure 3(d), revealing an image that closely resembles the original "peppers" image. The proposed method demonstrates remarkable noise reduction capabilities, successfully preserving the image's essential details and providing a cleaner appearance.

To further quantify the qualitative performance, we utilized the Structural Similarity Index (SSIM) as an objective measure. For the Wiener filter, the SSIM value was calculated to be 0.8704, indicating a moderate level of similarity between the filtered image and the original. However, for the proposed method, the SSIM value significantly increased to 0.9687, indicating a much closer resemblance to the original image. This higher SSIM value demonstrates that the proposed method outperforms the Wiener filter in terms of noise reduction and preserving image fidelity. The results from this comparison unequivocally show that the proposed method is superior to the Wiener filter for canvas pattern removal. Its adaptability to handle complex noise patterns, such as canvas artefacts, and its ability to preserve important image features make it a more effective and advanced solution.



(a) (b)





(c) (d)

Figure 3: (a) Original image (grey) (b) Noisy image (grey) (c) Noise reduced image (Weiner) (d) Noise reduced image (proposed)

6. Conclusions

This paper presents an innovative and efficient methodology for the removal of canvas artefacts from digital images, particularly paintings on canvas. Canvas artefacts, characterized by periodic noise patterns, can significantly impact the visual interpretation and analysis of artwork, posing challenges in art restoration and conservation. Our proposed method addresses this issue with remarkable success, providing a powerful tool for noise reduction and image enhancement. Through extensive experimentation and simulations, we demonstrated the effectiveness of our method in accurately identifying and suppressing canvas noise while preserving important image details. The combination of cartoon-texture decomposition and adaptive multiscale thresholding in the frequency domain proved to be a winning approach, enabling the isolation and removal of canvas artefacts with exceptional precision. Comparative analysis with the Wiener filter highlighted the superiority of our method in canvas pattern removal. The proposed method consistently outperformed the Wiener filter, achieving higher Structural Similarity Index (SSIM) values and producing images that closely resembled the originals. This superior performance showcases the specialized capabilities of our method in handling complex noise patterns, such as canvas artefacts. The practicality and versatility of our approach make it applicable to a wide range of images, from high-resolution digital photographs to X-ray images of paintings on canvas. The successful removal of canvas noise in different imaging modalities demonstrates the adaptability and potential impact of our method in art history, conservation, and digital imaging. Furthermore, the proposed method's non-destructive nature ensures that the original artistic intent is preserved, making it a valuable tool for art experts and conservators in their restoration endeavours. The ability to retain important image features while eliminating unwanted noise is a significant advantage in the conservation and appreciation of cultural heritage.

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