Three filters for the enhancement of the images acquired from fluorescence microscope and weak-light-sources and the image compression

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INTRODUCTION -

Fluorescence imaging has been significantly used in both clinics and research. The general difficulty is found in low-quality imaging of the bio-tissues due to the existence of biofluid or chemicals, which can substantially scatter or absorb the fluorescence. As a result, the images acquired are generally losing the details or key objects (dark images). In order to overcome this issue, the technique of image enhancement is used.

PROBLEM STATEMENT -

Basic aim of this paper is to create filters based on the combinations of mathematical functions, which are proved to be effective in strengthening the images acquired from the fluorescence microscope.

Using these filters -

1. Detailed objects can be found in the dark sections of the fluorescence images.
2. Used to enhance the low-light image, which provides satisfactory visual information and marginal profile for the blurred objects in the image.
3. Enhance the image with high degradation by the Gaussian noise, where a clear edge profile can be extracted.
4. Finally, we have shown that these filters can be utilized for image compression. Compression ratio can be obtained to be 0.9688.

OBJECTIVES -

Fluorescence image enhancement is important as it can provide more information for medical diagnosis, biomedical imaging and pattern identification.
The development of multifunctional filters is the eternal research goal of the authors.

IMAGE SET ANALYSIS-

In this paper, the author has applied these filters on fluorescence microscope images, low-light images. Using the filters created, we can extract the essential details from these images (information extraction).

Gaussian noise has been applied on a rgb image. Then these filters have been applied on the noisy image to extract the silhouette of the object of interest.

Input images -

1. Fluorescence Microscope

2. Low light images




3. RGB images

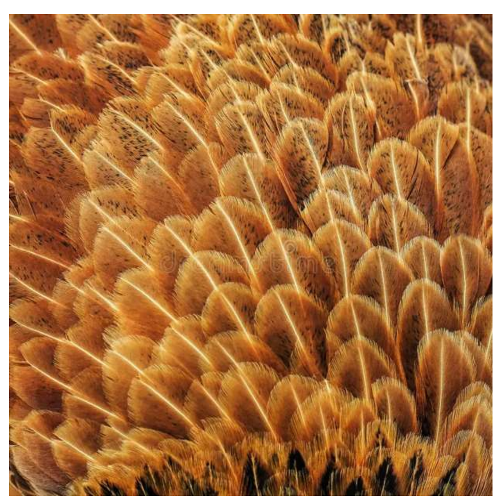
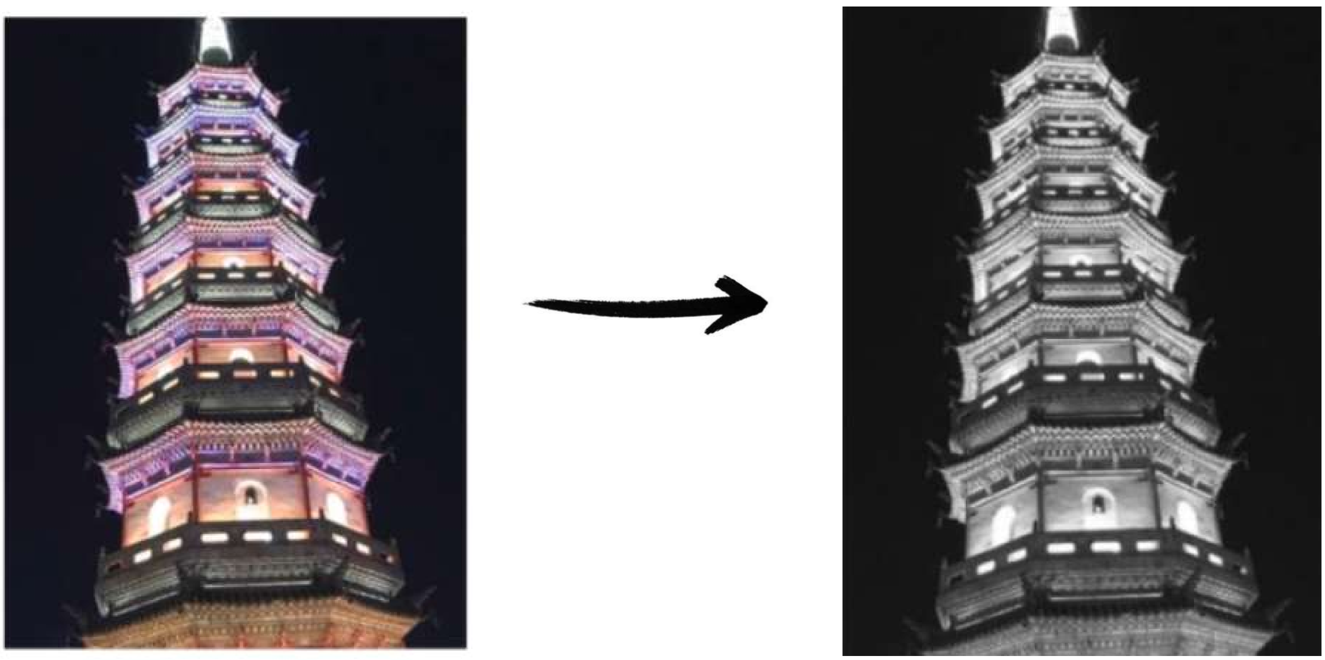



IMAGE PROCESSING TECHNIQUES -

1. RGB image is converted into grayscale image

Grayscale conversion reduces a color image (with three color channels: red, green, and blue) to a single channel representing intensity. This reduces the data size to one-third while retaining most lane information, enhancing efficiency with minimal information loss.



2. RGB image with added Gaussian noise:

Gaussian noise is common in practical applications. It can be generated along with the condition of low illustration or low exposure when using a camera to capture the images. The technique of the image enhancement may help to recover the original profiles of the images.

In order to show that our designed filters are capable of enhancing the images contaminated by the Gaussian noise, we added the Gaussian noise with a density of 1 to an image.

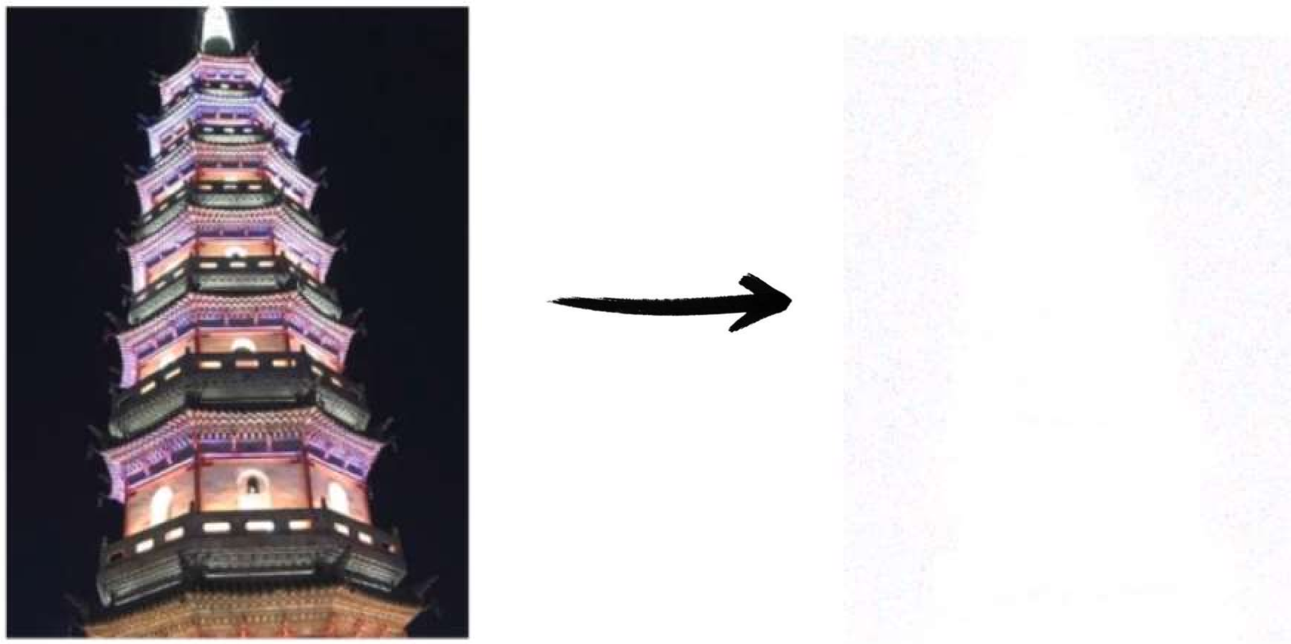


IMAGE ENHANCEMENT TECHNIQUES -

Image enhancement techniques like histogram equalization, Retinex theory and fuzzy logic theory are based on mathematical functions. Inspired by this, the authors are trying to establish a simple and flexible filter associated with mathematical functions. Their parameters can be set empirically and the users can optimize the values in order to make it useful for different images.

With the proper selection of the mathematical functions, the authors have devised filters that keep the image details and suppress the blur of the image. Moreover, the noise contained in the image will not be amplified.

Mathematical functions used include hyperbolic secant function, sine function, logarithmic function, hyperbolic cosecant function, inverse hyperbolic function, hyperbolic sine function and hyperbolic secant function.

The algorithms are composed of two frameworks :

1. In the first framework, a wavelet lifting transform has been used to process the image. This wavelet lifting transform is composed of several steps, including column/row transform, signal splitting, signal prediction, and signal update. In the step of signal splitting, the original signal was split into two sets of sub-signal. In the step of the signal prediction, some data redundancy was eliminated. In the step of signal update, certain data correction was performed. By doing the wavelet lifting transform, the key data-profile of the signal has been retained and the noise or unwanted signal has been dumped.
2. In the second framework, a set of special functions are combined to create a strong-filtering effect.

In the paper 3 types of filters have been discussed :

1. sech-sin filter
2. log-acosh-sinh filter
3. cosh-sec-asinh-cos filter

Out of these filters, we have implemented the sech-sin filter.

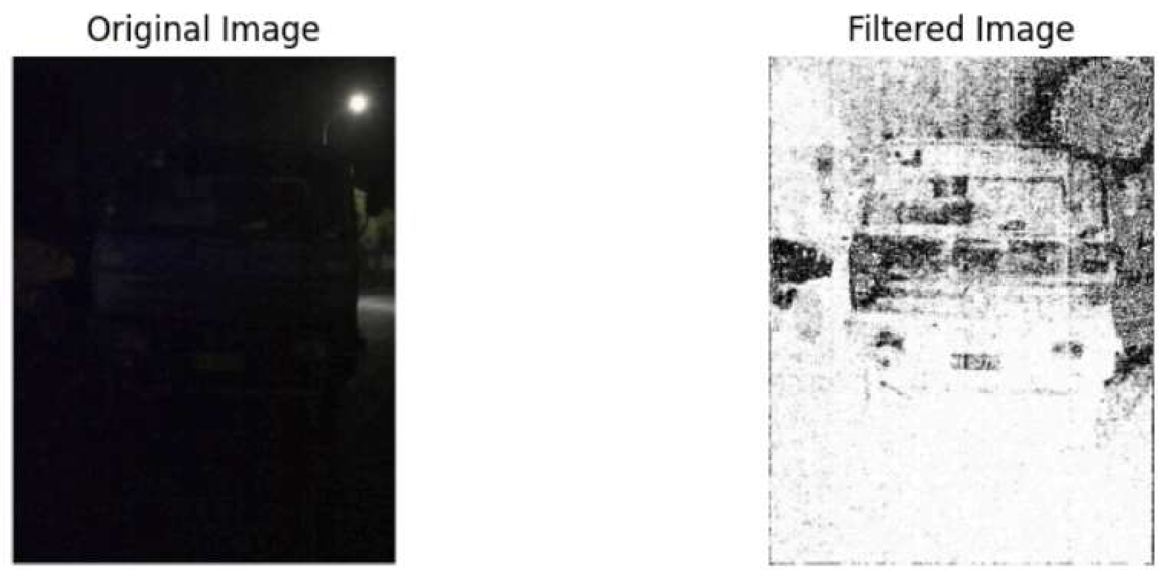
CODE :

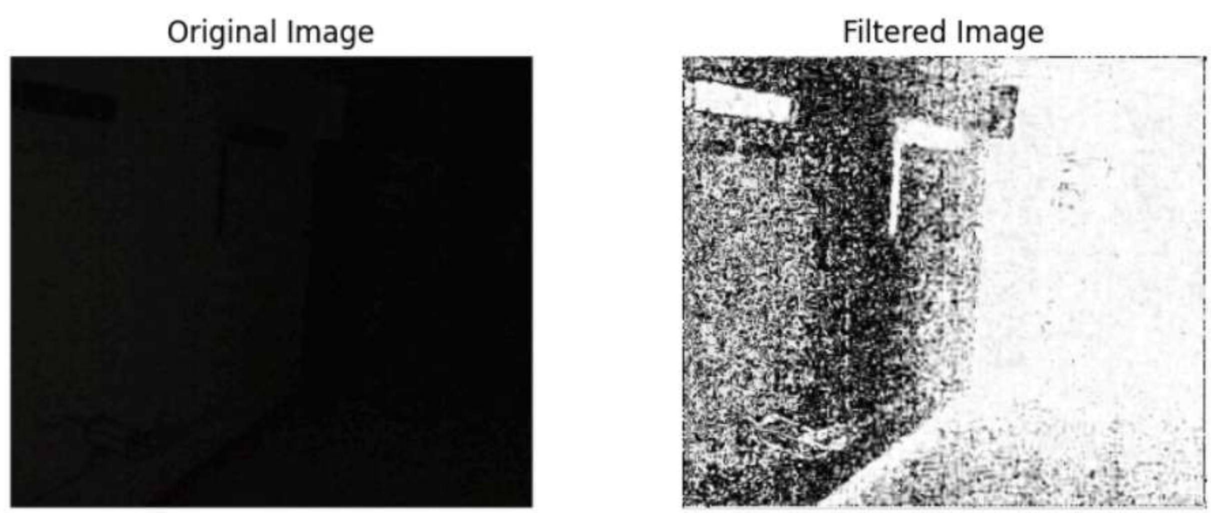
```
import numpy as np
import matplotlib.pyplot as plt

def my_filter(img, a1, a2, a3):
    # Convert the image to grayscale if it's not already
    if len(img.shape) == 3:
        img = np.mean(img, axis=2)

    # Pad image to ensure even dimensions
    if img.shape[0] % 2 != 0:
        img = np.pad(img, ((0, 1), (0, 0)), mode='constant')
    if img.shape[1] % 2 != 0:
        img = np.pad(img, ((0, 0), (0, 1)), mode='constant')

    M1, M2 = img.shape
    S = M1 // 2

    # Step 1: Split the image into sub-signals
    Q1 = img[::2, :]
    Q2 = img[1::2, :]

    # Step 2: Column transformation
    high_freq_col = Q1 - Q2
    low_freq_col = Q2 + 0.5 * high_freq_col
    u_col = np.zeros((M1, M2))
    u_col[:S, :] = low_freq_col
    u_col[S:, :] = high_freq_col

    # Step 3: Row transformation with shape alignment
    Q1 = u_col[:, ::2]
    Q2 = u_col[:, 1::2]
    min_cols = min(Q1.shape[1], Q2.shape[1])
    Q1 = Q1[:, :min_cols]
    Q2 = Q2[:, :min_cols]
```

```
    high_freq_row = Q1 - Q2
    low_freq_row = Q2 + 0.5 * high_freq_row
    u_row = np.zeros((M1, M2))
    u_row[:, :min_cols] = low_freq_row
    u_row[:, min_cols:] = high_freq_row

    # Step 4: Signal reconstruction
    Q1 = u_row[:, min_cols:]
    Q2 = u_row[:, :min_cols]
    low_freq_row = Q2 - 0.5 * Q1
    high_freq_row = Q1 + low_freq_row
    u_row[:, 1::2] = low_freq_row
    u_row[:, ::2] = high_freq_row

    # Step 5: Column reconstruction
    Q1 = u_col[S:, :]
    Q2 = u_col[:S, :]
    low_freq_column = Q2 - 0.5 * Q1
    high_freq_col = Q1 + low_freq_column
    u_col[1::2, :] = low_freq_column
    u_col[::2, :] = high_freq_col

    # Step 6: Apply the final transformations
    t2 = a1 * u_col
    t3 = np.sech(t2)
    t4 = t3 * a2
    t5 = np.sin(t4)
    q = a3 * t5

    return q

# Example usage
img = plt.imread('image.jpg')  # Load your image here
filtered_img = my_filter(img, a1=1.0, a2=1.0, a3=1.0)

plt.figure(figsize=(12, 6))

plt.subplot(2, 3, 1)
plt.title("Original Image")
plt.axis('off')
plt.imshow(img, cmap='gray')

plt.subplot(2, 3, 2)
plt.title("Filtered Image")
```

```
plt.axis('off')
plt.imshow(filtered_img, cmap='gray')

plt.tight_layout()
plt.show()
```

OUTPUT :

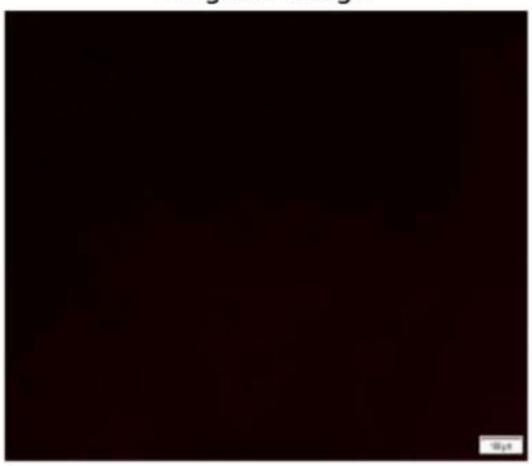




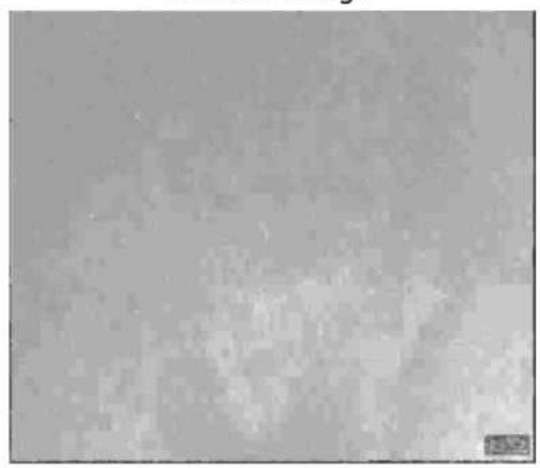
Original Image

Filtered Image

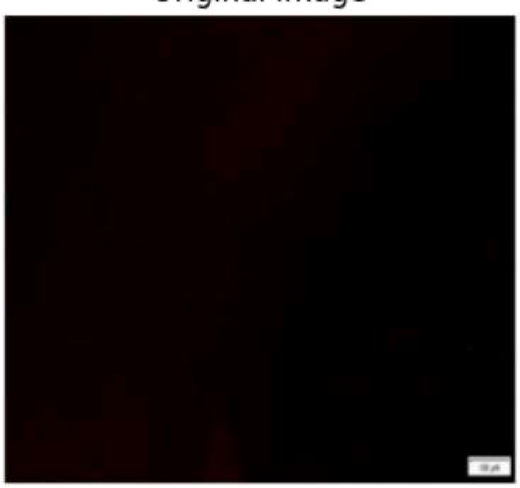
Original Image



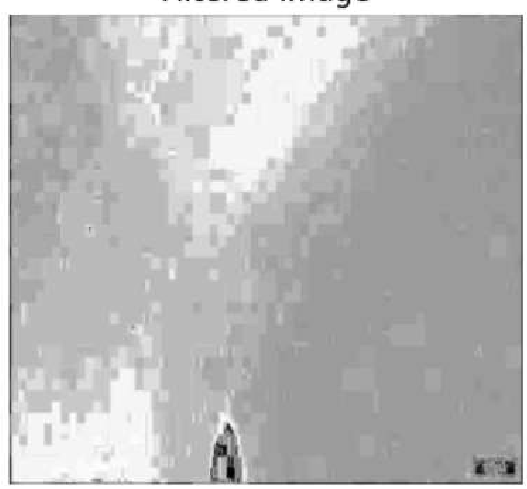
Filtered Image



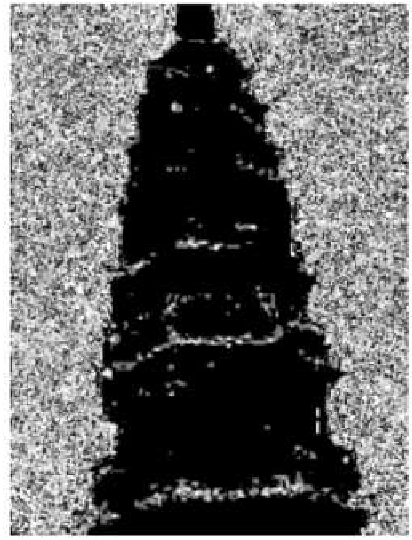
Original Image



Filtered Image



Original Image



Filtered Image

The value of constants a1, a2 and a3 varies for every image, so we have tried to find the optimal value using trial and error.

To evaluate the enhancement for the image, the authors have used the values of “measurement of enhancement by entropy” also known as EME and “Michelson contrast”.

EME is calculated via the minimum (m_1) and maximum (m_2) values of the intensity in every block of the image. EME is used to assess the local contrast in an image by dividing it into non-overlapping blocks.

The Michelson contrast (MC) is defined as

$MC = (m3 - m4)/(m3 + m4)$

M_3 is the highest intensity value of the image, M_4 is the lowest intensity value of the image.

MC measures the visibility of an image, used in cases where the image has a periodic structure.

DRAWBACKS OF THE FILTERS:

Some drawbacks of the frameworks are:

1. Some noises are amplified in the low-light images
2. For some images, when we extract the profile from the noisy image, Gaussian noise will not be totally eliminated in the image.
3. The output images are in grayscale, which might not be ideal for all.

CONCLUSION -

In the paper that filters based on the simple functions including hyperbolic secant function, sine function, logarithmic function, inverse hyperbolic cosine function, hyperbolic sine function, hyperbolic cosine function, secant function, inverse hyperbolic sine function, and cosine function, can be used for the image enhancement.

The proposed approach recovers the detailed feature hiding in the image even when the image is in poor illumination. Another application of our filters is shown in the useful extraction of the contour of the images contaminated by the Gaussian noise.