

# Enhancing Digital Mammogram Images using Bandpass Filters in Frequency Domain

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## Summary

In the acquisition process of digital mammogram images, several factors may affect them to be noisy or low contrast. Image filtering of digital mammograms is an important enhancement process for computerized and visual diagnosis. There a set of Bandpass frequency domain filters are more suitable to enhance edges and reducing the noise at the same time. It involves converting the digital images into frequency domains using Fast Fourier Transform (FFT); then, applying a band pass filter on the image in the frequency domain; after that, transforming the result back into the spatial domain. In this paper, the effect of filtering process on mammogram images using a band pass filter is studied and investigated. The experimental results are obtained by applying a Butterworth band pass filter on a set of mammogram breast images taken from mini-Mammogram Image Analysis Society (MIAS) database. This work gives great experience to understand the effect of band pass filtering technique for enhancing the mammogram images through a number of image quality metrics and their respective results.

## Key words:

*Mammogram image filtering, Bandpass filters, Frequency domain, Ideal filter, Gaussian filter, Butterworth filter.*

## 1. Introduction

Recently, image-processing methods have been used for medical diagnosis in many applications such as brain tumor classification [1], liver image analysing [2], breast cancer diagnosis [3], and so on. Digital Mammography is the most effective tool for early detection of breast cancer; it uses low-dose X-ray during breast examination. The types of mammography are screen-film mammography (SFM) and digital mammography (DM). The availability of inexpensive digital mammogram devices with effective image processing methods makes them effective tools for accurate diagnosis of breast cancer [4]. Breast cancer is one of the most frequent health problems that affect women aged 20–59 years, leading to female mortality worldwide. Based on breast cancer statistics, there is approximately 1.7 million of new cases in 2012 [4]. In addition, it is found that the occurrence of breast cancer is quickly growing in the Asia Pacific regions [4].

The nature of digital mammogram images is difficult for analysing by the radiologists. Moreover, during acquisition process, these images may have artefacts, noise, and low

contrasts making them hard to provide accurate diagnosis and result [5-7]. In such case, a computer-based image processing methods could be highly useful for analysing mammogram breast images by the radiologists and experts. When a better quality mammogram image is provided, diagnosis will be more accurate and no matter whether examined by a radiologist or computer-aided system. This work is focusing on image filtering of breast mammograms and its effect on their quality.

In the literature review, there is a set of conventional enhancement techniques used to enhance the contrast of masses in mammogram breast images. For as an example, Antonie et al. [8], and Bovis and Singh [9] have utilized histogram equalization for enhancing the mammograms. In addition, Schiabel et al. [10] have used a combination of histogram equalization with some techniques as a part of a pre-processing stage for mammogram images enhancement. Pisano et al. [11] introduced a study to decide whether the method of contrast-limited adaptive histogram equalization (CLAHE) can enhance the detection of breast cancer from dense mammogram images. Gumaei et al. [12] used adaptive histogram equalization for breast mammogram enhancement and proposed a new method for breast segmentation based on a mixture of gamma distribution with k-means algorithm. In [13], the authors compared the histogram-based intensity windowing (HIW) method with CLAHE method to detect masses from mammogram images.

Shelda Mohan et al. [14] proposed an approach for breast mammogram enhancement using a PSO-based CLAHE method. In this approach, the standard deviation and mean are computed to initialize the parameters of the enhancement method.

Akila et al. [15] introduced a comparative study for mammographic image enhancement using indirect contrast enhancement techniques. Abdallah et al. [16] implemented some algorithms for contrast augmentation of mammogram images such as image adjustment and noise reduction using wiener method.

In this paper, the effect of filtering process on mammogram breast images using different bandpass filters is studied and investigated. A set of filters such as Ideal, Gaussian, and Butterworth are implemented and applied on a number of mammogram breast images. The aim of this study is to give

great experience to understand the effect of bandpass filtering technique for enhancing the mammogram images based on the results of image quality metrics.

The rest of the paper is as follows: Section 2 presents gives an explanation about image filtering in frequency domain. Section 3 explains the mammograms enhancement methods. Section 4 presents the experimental results and discussion. Finally, section 4 demonstrates the conclusion and future work.

## 2. Frequency Domain Filtering

Digital image filtering in frequency domain includes transformation of images from spatial-domain to frequency-domain. It is the process of image enhancement for specific application. Fast Fourier transform (FFT) is a common tool for transforming the digital image from spatial domain to frequency domain. There are three types of filters can be applied in the frequency domain. These types are low-pass filters, high-pass filters, and band pass filters. Low-pass filters are used for image smoothing, high-pass filters are used for image sharpening, and band pass filters are used as a trade-off between image smoothing (reducing the noise) and image sharpening (reducing the blur). This means that the low-pass filters reduce the noise in the images but accentuate the blur in the images; whereas, the high-pass filters reduce the blur in the images but accentuate the noise in the images. All types filters can implemented and analyzed for Ideal filter, Butterworth filter and Gaussian filter. Image filtering in frequency-domain is performed by altering the Fourier transform of images and then recover these images in spatial-domain by using the inverse of Fourier transform to get the filtered images [17].

The main steps for image filtering in frequency domain can be listed as follows:

- 1) Input a discrete image  $f(x, y)$  of size  $M \times N$  that is in spatial domain.
- 2) Apply a zero padding method on  $f(x, y)$  to output another image  $f_p(x, y)$  of size  $W \times R$ , such that  $W = 2M$  and  $R = 2N$ . The zero padding method appends a required number of zeros to the input original image  $f(x, y)$ .
- 3) Multiply the processed image  $f_p(x, y)$  by  $(-1)^{x+y}$  to make its coordinates to be centered at  $u = W/2$  and  $v = R/2$ .
- 4) Calculate the 2D FFT of the centered image  $f_p(x, y)$  to get  $F(u, v)$ , which is the image spectrum.
- 5) Input a filter function  $h(x, y)$  of size  $W \times R$ .
- 6) Calculate the 2D FFT of the filter function  $h(x, y)$  to get  $H(u, v)$ , which is the filter spectrum.
- 7) Center the coordinate of  $H(u, v)$  at  $(W/2, R/2)$ .
- 8) Multiply the image spectrum  $F(u, v)$  by the filter

spectrum function  $H(u, v)$  to get the filtered image  $g(x, y)$ .

- 9) Multiply the filtered image by  $(-1)^{x+y}$  to reverse the centering process in step (3).
- 10) Calculate the inverse of FFT of the result of previous step to get the output image.
- 11) Crop the padded part from the output image to get the new image.

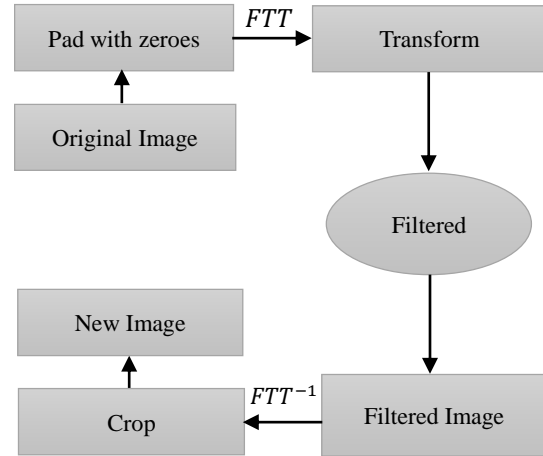


Fig. 1 Proposed methodology for orders forecasting.

The filtered image,  $g(x, y)$  is computed using the inverse of FFT. In general, the filtering process in frequency domain can effect both phase and amplitude of image spectrum  $F(u, v)$ . However, in practice, most filters change only the magnitudes and do not change the phases. These filters are called zero-phase-shift filters.

The convolution process of an image with a specific kernel has the same outcome of multiplying the image spectrum by the kernel spectrum of the Fourier transform [17]. Therefore, image filtering can be made in spatial or spectral domains. As mentioned in the beginning of this section, the three types of filters that can be applied in the frequency domain are explained in more detail as follows:

### Low-pass filters

The low-pass filters can suppress the high-frequency components, producing a smoothed image. For example, at a distance greater than a fixed value of filter radius  $r_0$  from the spectrum center  $(0,0)$ , the ideal sharp cut-off filter can block the frequencies as:

$$H(u, v) = 1 \text{ if } r(u, v) \leq r_0, \\ \text{and } H(u, v) = 0 \text{ if } r(u, v) > r_0(1)$$

Where  $r(u, v) = [u_2 + v_2]^{1/2}$  represents a specific distance from the spectrum's center. However, such filter yields a ringing effect nearby the edges of the image since

the inverse of FFT. To solve this problem, the transfer function of the low-pass filter must smoothly drop to zero. Some of the common known filters that use such transfer function is the Butterworth low-pass filter of order  $n$ . This filter can be computed as:

$$H(u, v) = 1/(1 + [r(u, v)/r_0]^{2n}) \quad (2)$$

Where the value of  $r_0$  is the distance in which  $H(u, v) = 0.5$  instead of the radius of the cut-off. If the value of  $n$  grows, the Butterworth filter works as the ideal filter. Alternative transfer function that performs a low-pass filtering is a Gaussian transfer, which is a Fourier transform of Gaussian function.

### High-pass filters

In image processing, it is used to suppress the low frequency components of images and enhance the edges of images. The filter that suppresses all frequencies within a border determined by a cutoff without changing the frequencies beyond this border is called an ideal high-pass filter, defined as:

$$H(u, v) = 0 \text{ if } r(u, v) \leq r_0 \\ \text{and } H(u, v) = 1 \text{ if } r(u, v) > r_0 \quad (3)$$

The ideal low-pass filter may lead to ringing effect in the processed image. This ringing effect can be removed by smoothing filter such as Butterworth high-pass filter. Butterworth high-pass filter of  $n$  uses a function can be defined as follows:

$$H(u, v) = 1/(1 + [r_0/r(u, v)]^{2n}) \quad (4)$$

In both low-pass and high-pass, the Butterworth filters make the ideal cutoff ones, if the value of order  $n$  for the filter are increased.

### Band pass filters

Band pass filters can preserve the frequencies in a specific range and suppress the frequencies of all other ranges. On the other hand, band stop filters can suppress the frequencies of a certain range and preserve the frequencies of other ranges. For instance, the band stop filtering process may contain the high-pass filter of radius  $r_{high}$  and the low-pass filter of radius  $r_{low}$ , where  $r_{low} > r_{high}$ . The Butterworth band stop filter transfer function with band width  $\Delta = r_{high} - r_{low}$  and radius  $r_0 = (r_{low} + r_{high})/2$  can be specified as  $H_S = 1 / (1 + [\Delta r(u, v) / (r^2(u, v) - r_0^2)]^{2n})$  where  $r(u, v) = [u^2 + v^2]^{1/2}$ . The equivalent band-pass filter is  $H_P = 1 - H_S$ . The versatile filtered images can be produced by editing the specific frequencies and removing the narrow spikes of periodic sinusoidal noise in the spectrum.

## 3. Proposed Approach

The proposed approach consists of four steps, which are shown in Figure 2.

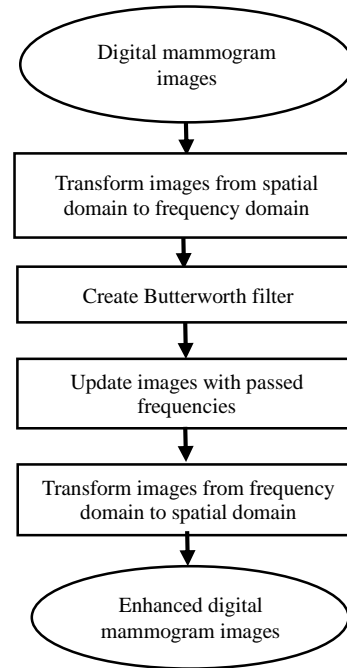


Fig. 2 Proposed methodology for digital mammogram image enhancement.

The approach starts with loading the digital mammogram images and converting these images from spatial domain to frequency domain using Fourier transform. Then, creating Butterworth filter and updating the images with passed frequencies. Finally, reconstructing the filtered images by using the inverse of Fourier transform.

The band pass filtering process of digital mammogram images uses the simple Butterworth band pass, which is computed by multiplying the high-pass filter with the low-pass filter in which the high-pass filter has a lower cut off frequency than the low-pass filter.

## 4. Experiment and Discussion

In the experiment, MATLAB programming tool is used to implement the method of proposed approach. It is a common tool in the image processing field. The experiment is conducted on ten mammogram images taken from mini-Mammogram Image Analysis Society (MIAS) database.

### 4.1 Evaluation Metrics and Results

The experimental results are evaluated using a set of image quality measures like Structural Content (SC), Mean Square

Error (MSE), Normalized Cross-Correlation (NCC), Peak Signal to Noise Ratio (PSNR in dB), Maximum Difference (MD), Average Difference (AD), and Normalized Absolute Error (NAE).

For the SC measure, a higher value means that enhanced image is poor quality image. It can be computed using the following equation:

$$C = \frac{\sum_{i=1}^m \sum_{j=1}^n (A_{ij}^2)}{\sum_{i=1}^m \sum_{j=1}^n (B_{ij}^2)} \quad (5)$$

For NAE and MSE, they are used to measure the difference between two input images (i.e. the original and enhanced images). When the value of NAE and MSE increases, the enhanced image is increased in degradation. They computed respectively using the following equations:

$$NAE = \frac{\sum_{i=1}^m \sum_{j=1}^n (|A_{ij} - B_{ij}|)}{\sum_{i=1}^m \sum_{j=1}^n (A_{ij})} \quad (6)$$

$$MSE = \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n [A(i, j) - B(i, j)]^2 \quad (7)$$

For PSNR, it is used to evaluate the quality of the enhanced image. The higher PSNR value means higher quality image. The equation of PSNR can be written as follows:

$$PSNR = 10 \log_{10} \left( \frac{L^2}{MSE} \right) \quad (8)$$

Here, L is the maximum number of bits per pixel in an image. If there are 8 bits per pixel, then each pixel has a value in the range from 0 to 255 in the image.

The NCC values can be in the range between -1 to 1. Perfect correlation has a value of one and perfect anti-correlation has a value of minus one.

$$NCC = \frac{\sum_{i=1}^m \sum_{j=1}^n (A_{ij} \times B_{ij})}{\sum_{i=1}^m \sum_{j=1}^n (A_{ij}^2)} \quad (9)$$

For AD and MD, they provide the maximum error of the enhanced image. The higher value of AD and MD mean that the enhanced image has poor quality. The equations of AD and MD can be written respectively as follows:

$$AD = \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n [A(i, j) - B(i, j)] \quad (10)$$

$$MD = \text{Max}(|A_{ij} - B_{ij}|), \quad (11)$$

$i = 1, 2, \dots, m, j = 1, 2, \dots, n$

Table 1, Figure 3, and Figure 4 show the results of image quality metrics for enhanced mammogram images to show the effectiveness of enhancement process using Butterworth band pass filter.

Table 1: Results of image quality metrics for the selected mammogram breast images.

No.	MSE	PSNR	NCC	AD	SC	MD	NAE
1	0.00001	97.7105	1.0008	-0.00017	0.9983	0.051	0.0068
2	0.00004	92.17	1.0019	-0.00031	0.996	0.1098	0.0102
3	0.00002	94.1566	1.0011	-0.00034	0.9977	0.0824	0.0058
4	0.00002	95.1739	1.0011	-0.00021	0.9977	0.0627	0.0073
5	0.00007	89.8299	1.0022	-0.00074	0.9952	0.1059	0.0128
6	0.00002	95.4365	1.0009	-0.00032	0.9981	0.0706	0.0061
7	0.00002	95.6076	1.0012	-0.00029	0.9975	0.0549	0.0079
8	0.00001	96.4496	1.0011	-0.00024	0.9975	0.0392	0.0088
9	0.00003	93.7283	1.0009	-0.00044	0.998	0.0863	0.0064
10	0.00003	93.7286	1.0012	-0.00039	0.9975	0.0706	0.0073

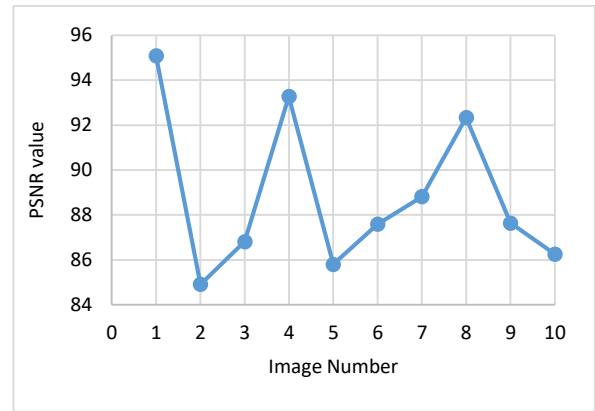


Fig. 3 The PSNR of the original and enhanced mammogram images selected randomly from mini-MIAS database.

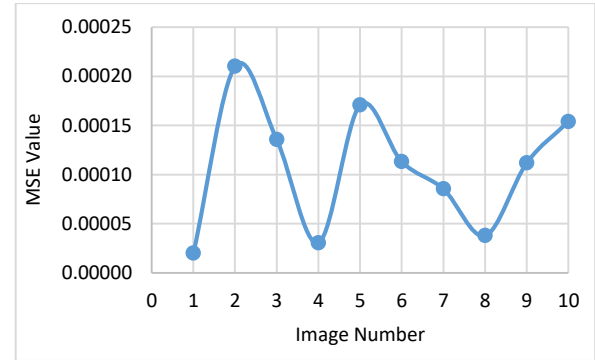


Fig. 4 The MSE of the original and enhanced mammogram images selected randomly from mini-MIAS database.

As shown in Table 1, the values of structural content of samples are low, which indicated a good quality image.

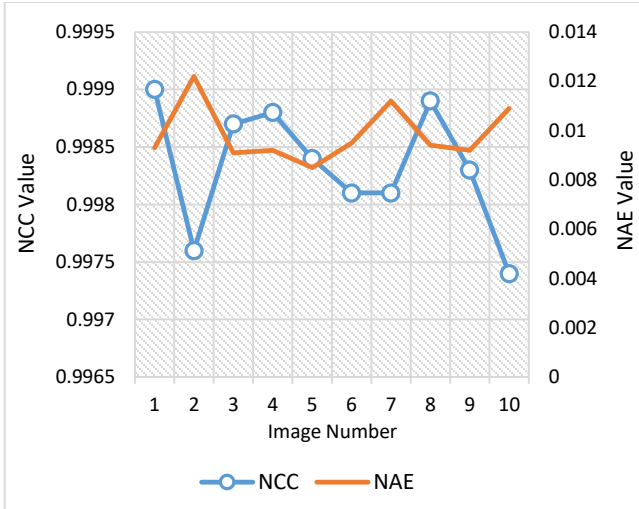


Fig. 5 The NCC and NAE of the original and enhanced mammogram images selected randomly from mini-MIAS database.

Typically, NCC and NAE measures reflect the normalized correlation and normalized error between the original and enhanced images. As shown in Figure 5, the normalized correlation between the original and enhanced images are very high and close to one and the normalized error is very small and close to zero. In addition, the value of NAE increases when the value of NCC decreases.

### 4.2 Comparisons

In this subsection, the results of Butterworth filter that adopted in this study are compared with the results of median filter in terms of MSE, PSNR, NCC, and AD image quality metrics on the same images. Figures 6-9 demonstrate the results of these metrics and reveal the effectiveness of adopted filter to enhance the mammogram breast images without much loss of images information.

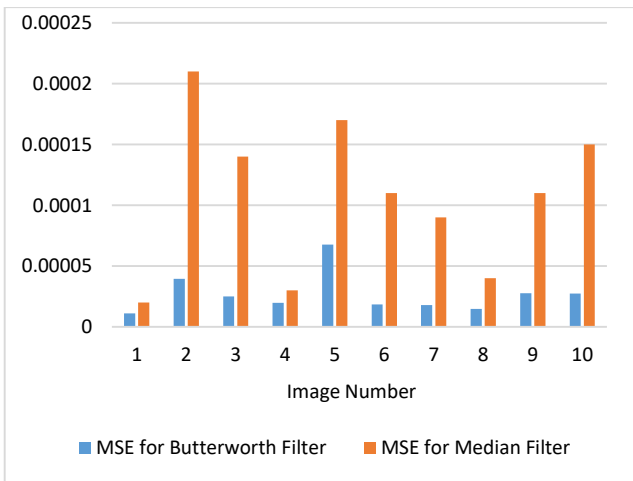


Fig. 6 MSE results of adopted Butterworth filter compared to median filter on selected mammogram images.

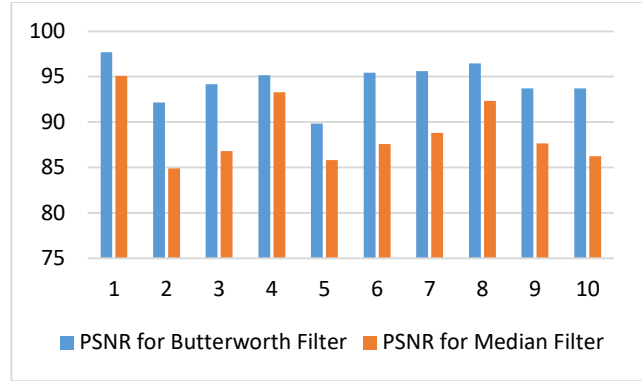


Fig. 7 PSNR results of adopted Butterworth filter compared to median filter on selected mammogram images.

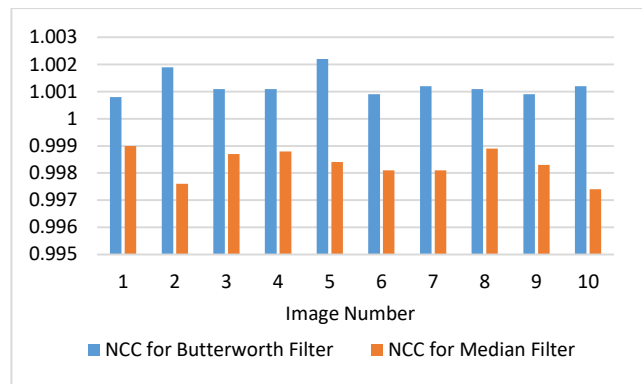


Fig. 8 NCC results of adopted Butterworth filter compared to median filter on selected mammogram images.

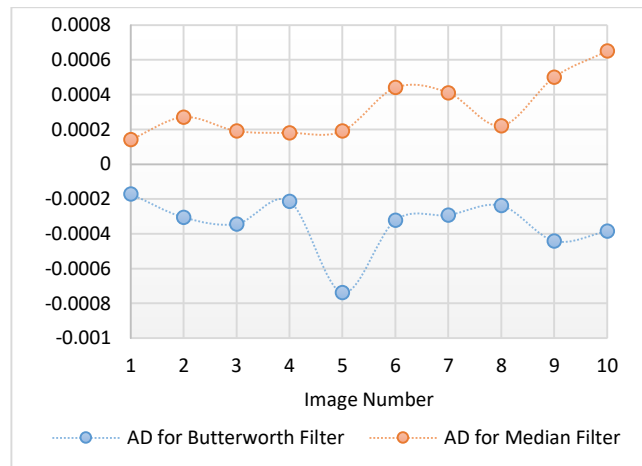


Fig. 9 AD results of adopted Butterworth filter compared to median filter on selected mammogram images.

The results shown in Figures 6-9 demonstrate that the proposed approach using Butterworth achieves the best results compared to the median filter in terms of MSE,

PSNR, NCC, and AD image quality metrics on the same images.

## 5. Conclusion and future work

The study introduced a brief background on the enhancement filters of images in frequency domain. In addition, the study proposed an approach to use Butterworth bandpass filter for enhancing digital mammogram breast images in frequency domain without much loss of images information. To evaluate the proposed approach, ten images are selected randomly from the mini-MIAS database, enhanced based on the proposed approach, and then computed the results using a set of image quality metrics. These image quality metrics are Structural Content (SC), Mean Square Error (MSE), Normalized Cross-Correlation (NCC), Peak Signal to Noise Ratio (PSNR in dB), Maximum Difference (MD), Average Difference (AD), and Normalized Absolute Error (NAE). The experiment is implemented using MATLAB programming tool. The results of Butterworth band pass filter used in the proposed approach are compared with the results of median filter for enhancing digital mammogram breast images. The comparison results revealed that the proposed approach using Butterworth achieves the best results compared to the median filter in terms of MSE, PSNR, NCC, and AD image quality metrics on the same images. In the future work, the proposed approach will be used to improve the detection rate of breast cancer diagnosis using Machine learning algorithms.

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