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2D Discrete Wavelet Transformation (2D-DWT) for Nanoscale Morphological Analysis

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Abstract
Digital image processing nowadays is widely used in various applications in micro to macro scale such as Nano-structure for medical, defense, natural resource management, security purposes. This article reviewed the 2-Dimensional Discrete Wavelet Transformation (2D-DWT) for morphological analysis of Scanning Electron Microscope (SEM) image of Ni-P-CNF nanocomposite plated on mild steel substrate (grade AISI1040) for analyzing the multi-level decomposition, denoising and compression test. It was concluded that the 2D-DWT method is more efficient and precise as compared to the conventional methods like Power Spectral Density (PSD) and histogram equivalence. These methods are limited by the Heisenberg uncertainty principle, whereas, the wavelet theorem provides a multi-resolution analysis. The wavelet function can capture localized characteristics and transients in the data since it is often localized in both time and frequency. These features make wavelets ideal for storing transient and steady-state components of a signal or image, allowing them to simultaneously offer excellent time and frequency localization. SEM images usually contain huge information which can lead to computational complexities. 2D-DWT is a very effective tool to de-noise the image. In order to test its efficiency, we have intentionally added some noise in the image and de-noise it. Also, we have compressed the image at different at different levels. This study provides the utility of the 2D-DWT for image processing as well as compared with other approaches for image decomposition, denoising and image compression.

Keywords- Digital image processing, SEM, 2D-DWT.

1. Introduction

Understanding the characteristics and behavior of distinct materials across arrange of scientific and engineering areas depends critically on material characterization. Accurate characterization makes it easier to analyze material composition, shape, and structure, which propels developments in industries like semiconductor production, nanotechnology, and materials research (Joshi et al., 2022; Joshi et al., 2023). Images obtained using cutting-edge imaging methods, such as scanning electron microscopy (SEM) and atomic force microscopy (AFM), are crucial sources of data for material investigation in this situation (Rades et al., 2014). SEM and AFM images, however, frequently have inherent flaws such noise, blurring, uneven illumination, and low contrast. These innate restrictions may make it difficult to accurately understand important characteristics, perform quantitative analysis, and generally characterize materials effectively (Buhr et al., 2009; Rades et al., 2014). Therefore, the use of picture enhancing techniques becomes crucial. The term "image enhancement" refers to a group of algorithms and methodologies used to improve the visual appeal and readability of images while maintaining or adding pertinent data. Image optimization techniques are essential for SEM and AFM image optimization in the field of material characterization, allowing researchers to precisely measure material properties and extract relevant features (Maksumov et al., 2004; Sheppard et al., 2004). Noise reduction is a primary goal of picture enhancement for material characterization. Electronic noise, thermal noise, and shot noise are some of the noise sources that can affect SEM and AFM images and obfuscate minute structural features. The most common tool for image processing is the Fourier transform. But Fourier transform is not suitable for processing sudden changes which are the most important part of the image to study. By applying Short Term Fourier Transform (STFT) approach, which allows for the visualization of many aspects of a signal, this issue is resolved. Heisenberg's Uncertainty Principle, however, stipulates that when the signal's resolution is enhanced in the time domain by zooming in on various regions, the resolution degrades in the frequency domain. Therefore, we need to apply a new class of functions that are properly confined in time and frequency in order to accurately assess signals and images that contain sudden changes (Singh and Dixit, 2015; Kimothi et al., 2023). In order to successfully suppress noise artifacts and improve visual clarity and authenticity, researchers can use denoising methods like wavelet denoising or adaptive filters.

Another important component of image enhancement is contrasting improvement. Poor innate distinction is typically present in SEM and AFM images making it difficult to distinguish between various material components or detect minute differences in surface properties. To change image intensities and improve the visibility of important features, contrast enhancement algorithms, such as histogram equalization, adaptive contrast stretching, or local enhancement approaches, can be used (Tian et al., 2023). These methods enable more precise characterization by successfully highlighting changes in material composition, surface topography, or flaws.

Particularly for image analysis and representation, the 2D-DWT has shown to be a potential tool. Wavelet transformations provide a multi-resolution analysis by breaking down an image into several frequency bands and spatial scales, in contrast to conventional Fourier-based approaches, which simply rely on frequency components to deconstruct an image (Demirel and Anbarjafari, 2011; Abdoli et al., 2019). This characteristic enables the extraction of pertinent characteristics and the preservation of small details, allowing for the effective portrayal of images. The capacity of 2D-DWT modification to capture both local and global aspects of an image is one of its main features. Wavelets multi-resolution capability enables the simultaneous examination of several image details from coarse to fine scales. To performing denoising processing at various degrees of image details, produce superior noise reduction with keeping key image structures, this technique has significant capability (Maksumov et al., 2004). The 2D-DWT also has a wide range of uses for image compression. Compared to other conventional approaches, image data can be efficiently represented with fewer coefficients by taking advantage of wavelets' energy compaction property. As a result, there is notable compression ratios achieved while still preserving excellent reconstructed images. Wavelets have been used to compress images in a number of standards, including JPEG2000, where they have proven to perform better than older compression methods (Othman and Zeebaree, 2020). The 2D wavelet transformation is essential for object recognition and image segmentation as well as denoising and compression. Accurate segmentation is made possible by the multi-resolution analysis, which identifies picture regions with various textures and structures. Wavelet-based features also offer reliable representations for object recognition, allowing for the differentiation of items based on their particular frequency characteristics.

In the settings of SEM and AFM image augmentation and denoising techniques are of utmost importance. Several crucial techniques go into the application of image enhancement and denoising in SEM and AFM. Gaussian filtering, median filtering, and wavelet denoising are three noise reduction techniques that are good at controlling different types of noise, increasing small details, and guaranteeing that the collected images accurately represent the sample structures. Image enhancement uses edge detection methods to highlight feature borders and edges, highlighting regions of interest and facilitating segmentation tasks. Additionally, by effectively removing artifacts like stains, scratches, and sensor-induced abnormalities, these techniques ensure that image quality is not jeopardized. Patterns and textures within SEM and AFM pictures are also highlighted by image enhancement techniques designed for texture analysis, providing insights into the surface properties and characteristics. When wavelet-based techniques are used for multiscale analysis, image details at different sizes can be independently enhanced or denoised, achieving a balance between fine-scale detailed information and large-scale structural context. The improvement of SEM and AFM images not only makes these visuals ideal for careful study, interpretation, and communication but also enables researchers to get significant insights from complex material, samples, and surface structures. This review primarily focuses on the utility of the 2D-DWT on SEM and AFM images. The authors examine the advantages of 2D-DWT over the other alternative approaches for image decomposition, denoising and image compression respectively.

2. Materials and Methods

2.1 Dataset used

To study the impact of wavelet, transform on morphology analysis, we have taken a test SEM image of Ni-P-CNF nano-composite plated on mild-steel substrate (gradeAISI1040) through electroless plating (Ram et al., 2023). The SEM image consists of Ni-P matrix with low enormity of CNF particles as long white tubes. The as-plated platings revealed mostly amorphous structure and whereas heated platings were transformed from amorphous to crystalline structures. Wavelet transform on the SEM image can be employed to get several decomposed images stressed only those frequencies above the threshold coefficient (Bora and Joshi, 2023). With this, one will be able to analyze different aspect of an image, in this case cracks or in the structure or crystal structure efficiently.

2.2 Morphology Analysis

2.2.1 Root Mean Square Roughness

The most widely used surface roughness metric is root-mean-square roughness. It is determined by taking the square root of the mean of the squares of the differences from the mean.

$$RMS = \sum_{n=1}^{N} \left[\frac{(x_n - \bar{x})^2}{N}\right]^{\frac{1}{2}}.$$

where, x_i represents the maximum pixel value of selected peak, $\bar{x}$ represents the average peak value of the surface profile, and N is the number of data points. The average peak value of the surface profile of image matrices is given as,

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_\mathrm{i}.$$

Due to its analytical convenience and capacity to represent the surface roughness as a single number, RMS roughness is particularly appealing. RMS roughness is essentially described in terms of statistics in the same way as the standard deviation. Because of this, the RMS roughness would also be subject to the same assumptions about data that is independent samples as were placed on the standard deviation (Falsafi et al., 2020; Ismail et al., 2022). This means that in order to understand the value of RMS roughness, we must first confirm that the data are unbiased and identically (uniformly) distributed across all surfaces. There are several approaches to verify this supposition. One method is to create a plot of the data distribution and contrast it with the normal distribution curve. Another straight forward statistical metric is the average (or arithmetic) roughness. It is characterized by:

$$R_a = \frac{1}{N}\sum_{n=1}^{N}|x_i - \bar{x}|.$$

The RMS roughness and the average roughness measures will be inaccurate if a surface has a character with any significant departures from the average height. RMS roughness assessments will take into account the huge peaks and valleys, which can result in a value that is substantially higher than the average roughness. Calculating the averaged peak-to-valley height difference in this situation is helpful.

$$R_i = \frac{1}{N}\sum_{k=1}^{M}(x_{max} - x_{min})k.$$

A surface profile's RMS slope, skewness, and kurtosis would likewise be determined using scattering theory. As all of these measurements are restricted to heights, drawing a final judgment based solely on them may not be adequate and can result in a wrong assessment of surface properties.

2.3 Image Enhancement

2.3.1 Power Spectral Density

The frequency content as well as the distribution of power of a picture is defined while utilizing Power Spectral Density (PSD) for image analysis. The image is preprocessed to make sure it is ready for analysis. To reduce noise or highlight certain aspects of an image, this may require resizing, cropping, or applying filters. The image is then transformed from the spatial domain to the frequency domain using the Fourier Transform (FT). The FT formula is given as:

$$F(u,v) = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)e^{j2\pi\left(\frac{ux}{M}+\frac{vy}{N}\right)}.$$

where, $F(u,v)$ represents the FT coefficients at frequency (u,v), $f(x,y)$ is the pixel intensity of the image at location(x,y), M and N are the dimensions of the image, and j is the imaginary unit.

Because the Fast FT is a more effective algorithm to compute than the FT, it is preferable to the FT. Using "divide-and-conquer" strategies, the computational complexity is decreased from O(N2) to O(NlogN) (Tang et al., 2022). The FT coefficients' squared magnitude is used to calculate the Power Spectrum. The distribution of power across various frequencies is depicted in the image by the Power Spectrum:

$$PSD(u,v) = |F(u,v)|^2.$$

where, $PSD(u,v)$ is the Power Spectral Density at frequency(u,v), and $|F(u,v)|$ represents the magnitude of the FT coefficients at frequency (u,v).Plot the PSD as a 2D intensity map or a 3D surface plot to visualize it. Each point's intensity on the map corresponds to the strength or energy present at a particular frequency. To obtain pertinent information about the image, the PSD is examined. Identifying dominating frequencies or frequency ranges, spot- ting periodic patterns or textures, or measuring the energy distribution across various frequency components can all be done in this manner. The features that are pertinent to the particular image analysis task are subsequently extracted from the PSD (Wang et al., 2021). This may entail employing image processing techniques to segment or filter the PSD or computing statistical metrics from the PSD, such as mean or standard deviation. The image is then classified or decided upon using these features.

2.3.2 Histogram Equivalence

Due to its straight forward operation and efficiency, histogram equalization is a widely used method for contrast enhancement in a range of applications. In the framework of image processing, the histogram is the operation that displays the occurrences of each intensity value in the image. The histogram typically consists of a graph that counts the total number of pixels in an image at every distinct intensity value that can be observed in that image. An 8-bit grayscale image contains 256 distinct intensities; thus, a histogram will show the 256 integers that indicate the distribution of pixels among those values (Abdoli et al., 2019). A well-known technique for improving images is histogram alteration, particularly histogram equalization. As a result, “spreading” rather than “flattening” is a preferable way to explain histogram equalization and each pixel receives a new intensity value based on its previous intensity level. Three steps are taken while applying the histogram equalization to an image. The histogram of the grayscale image, which shows the frequency of occurrence of each intensity level, is calculated first in the procedure. After that, the cumulative sum of the histogram values is used to produce the cumulative distribution function (CDF). Each intensity level in the image is represented by cumulative probability. The CDF measurements are then divided by the total number of pixels in the image, allowing them to cover the whole range of pixel intensities (usually 0 to 255 for 8-bit images). The equalized image will make use of the entire spectrum of intensities due to normalization.

The following step entails utilizing the normalized CDF to translate the original image’s intensity values to new values. Every pixel in the original image is converted to its new value. Finally, the equalized image is created by substituting each initial pixel with its matching new pixel value produced from the mapping stage. This mapping stretches the intensity values of the image, emphasizing. The equalized image’s histogram becomes uniform in shape, enhancing contrast and enhancing visual quality (Stark, 2000; Mayathevar et al., 2020). Histogram equalization is a popular and simple method for improving photographs, and it works especially well for pictures with poor contrast or uneven illumination. However, it also has some disadvantages that must be taken into account. Histogram equalization occasionally results in over-enhancement of the image, producing results that are artificial and abnormal looking. This happens when the contrast is overly extended, bringing out additional noise and fine details. Additionally, it makes an overall adjustment to the entire image without taking local image properties into account. Global histogram equalization might not be the best technique in photos with variable lighting or regions of interest. In severe circumstances, histogram equalization might result in truncated values for intensity and incorruption of some image data. When the intensity values are mapped outside of the output image’s range (0 to 255 for 8-bit pictures), clipping can happen. Particularly for high-resolution photos, computing the histogram, CDF, and mapping the intensity values can be computationally demanding (Abdoli et al., 2019; Diniz, 2020). This expense might become a restriction for real-time applications or massive image processing.

2.3.3 Wavelet Transform

An extensive representation of signals and images in both the time and frequency domains can be obtained using the mathematical tool known as wavelet transformation. By utilizing a collection of wavelet-based functions, which have favorable characteristics for capturing features at various scales, it provides a localized analysis. A wavelet is fundamentally a waveform with specific properties that make it appropriate for signal and picture analysis. Wavelets are dynamically flexible to represent signals with variable frequencies and temporal durations, in contrast to conventional Fourier transform-based approaches that use a fixed set of basic functions.

The wavelet function can capture localized characteristics and transients in the data since it is often localized in both time and frequency. Two key characteristics localization in the time as well as frequency domains and quick oscillation and decay defines the wavelet function. These features make wavelets ideal for storing both transient and steady-state components of a signal or image, allowing them to simultaneously offer excellent time and frequency localization (Chun-Lin, 2010; Rades et al., 2014; Mustafa et al. 2019). The wavelet transforms driven by breaking down a signal or image into a collection of coefficients that represent its various frequency components at various scales. The detailed flow of the image processing algorithm through 2D-DWT is shown in the Figure 1. Convoluting the signal or image with a family of wavelet functions, which are scaled and translated variations of the original wavelet, results in this decomposition. At each level of the transformation, a set of approximation and detail coefficients are produced as a result of a series of filtering procedures.

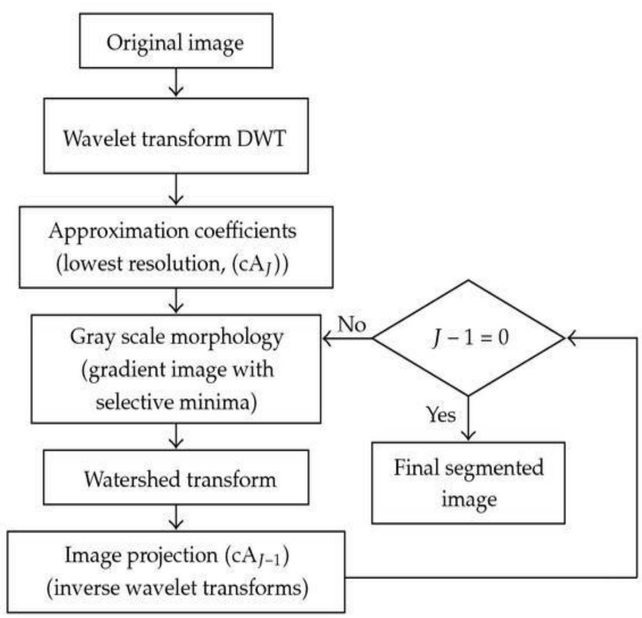

Figure 1. Algorithm for image processing by 2D-DWT.

An initial approximation of the signal or image with low-frequency components serves as the basis for the decomposition process. The specifics of the prior approximation are systematically examined to capture higher-frequency components at subsequent levels of decomposition. The procedure keeps on until the necessary level of decomposition is reached or a certain criterion is satisfied. When using a DWT transformation, the original signal or image is reconstructed by synthesizing approximation and detail coefficients. The global and local characteristics of original dataset are preserved in the reconstructed signal by properly mixing the coefficients at various scales. Wavelet transformation adaptability is based on its effectiveness in carrying out both forward and inverse transformations, which makes it easier to analyze, process, and compress signals and images (Jakhar et al., 2023). The wavelet transform decomposition and reconstruction processes enable multi-resolution analysis, allowing distinct frequency components to be examined and controlled independently, resulting in a more adaptable and potent tool for signal and image processing.

Wavelet transformation is extended to two-dimensional data, such as photographs, by the 2D-DWT. Applying a sequence of high-pass and low-pass filters in both horizontal and vertical dimensions is what the 2D-DWT mathematically entails. Typically, a quadrature mirror filter (QMF) bank is used to implement the filters. Approximation coefficients (LL), horizontal detail coefficients (HL), vertical detail coefficients (LH), and diagonal detail coefficients (HH) are the four sets of coefficients that are produced by this decomposition procedure (Pimpalkhute et al., 2021). Let us consider an input image of size N×N. The 2D-DWT decomposes the image into four components LL, LH, HL, and HH and formulae are given by:

$$LL_{(k,l)} = \sum_{m=0}^{\frac{N}{2}-1} \sum_{n=0}^{\frac{N}{2}-1} x(2m, 2n) h(k-m) h(l-n).$$

$$LH_{(k,l)} = \sum_{m=0}^{\frac{N}{2}-1} \sum_{n=0}^{\frac{N}{2}-1} x(2m, 2n+1) g(k-m) h(l-n).$$

$$HL_{(k,l)} = \sum_{m=0}^{\frac{N}{2}-1} \sum_{n=0}^{\frac{N}{2}-1} x(2m+1, 2n) h(k-m) g(l-n).$$

$$HH_{(k,l)} = \sum_{m=0}^{\frac{N}{2}-1} \sum_{n=0}^{\frac{N}{2}-1} x(2m+1, 2n+1) g(k-m) g(l-n).$$

where,
(k,l)-represents the coordinates of the output coefficients in the transformed domain.
$x(m,n)$-represents the pixel values of the input image.
h and g-represent the scaling and wavelet filters, respectively.
$\frac{N}{2}$- represents the reduced size of the transformed domain due to down sampling.

The time-frequency localization features of the transform depend on the wavelet filters selected (Othman and Zeebaree, 2020). Different frequency bands and spatial characteristics of the image at various scales are represented by the resultant coefficients (LL, LH, HL, HH). The LH, HL, and HH components, meanwhile, stand in for the horizontal, vertical, and diagonal high-frequency features, respectively, while the LL component denotes the low-frequency approximation. Few layers of decomposition can be obtained by iteratively applying the 2D-DWT to the LL component to produce a multi-resolution representation of the image. This supports many images processing tasks, including denoising, compression, and feature extraction, as well as the study and manipulation of multiple scales of image features.

2.3.4 Denoising by 2D Discrete Wavelet Transformation

In this part, we have applied a 3-level discrete wavelet transform to a noisy SEM picture while maintaining a threshold on the frequency domain of the image high frequency (detail) components. Here, we have introduced some noise (Gaussian) on purpose to the example image and are attempting to remove it with the 2D Discrete Wavelet Transform (DWT). All detail coefficient thresholds are first estimated. We obtain the denoised matrices for all the detail components in each level after applying the threshold to all levels. To recreate the image, we employ these matrices as the coefficients of an inverse discrete wavelet transformation. Currently, the image has been denoised (Wahab and O'Haver, 2020). A specific example provided below. The 2D DWT divides a 2D signal or image into coefficients at various scales for approximation (LL), horizontal detail (LH), vertical detail (HL), and diagonal detail (HH). The following can be used to express the 2D DWT's general formula:

$$C_{[i,j]} = \sum_{m=0}^{m-1} \sum_{n=0}^{n-1} h_{[m-i]} h_{[n-j]}.$$

where, $C_{[i,j]}$ represents the wavelet coefficient at position (i,j),$x[m,n]$denotestheinputsignal or image at position (m,n), and $h_{[m-i]}$ and $h_{[n-j]}$ represent the wavelet filters in the horizontal and vertical directions, respectively. To distinguish between the noise and signal components, threshold is applied to the wavelet coefficients. The thresholding equation's general form is as follows:

$$C_{denoised[i,j]} = S\left(C_{[i,j]}\right)\left(\left|C_{[i,j]}\right|\right) > T.$$

where, $C_{denoised[i,j]}$ represents the denoised wavelet coefficient at position (i,j), $\left|C_{[i,j]}\right|$ denotesthe magnitude of the wavelet coefficient, T represents the threshold value, and $S(C_{[i,j]})$ is the threshold function applied to the coefficient. The threshold function can be chosen as either the soft threshold or hard threshold function.

2.3.4.1 Soft Threshold

Soft threshold is a technique that preserves coefficients above the threshold while reducing or attenuating values below it. A shrinkage effect is introduced, wherein the magnitude of the coefficients below the threshold is somewhat diminished. Soft threshold reduces or suppresses small or noisy coefficients, which has the effect of denoising. It contributes to noise reduction while maintaining crucial signal components, resulting in a smoother representation of the signal or image (Huimin et al., 2012).

2.3.4.2 Hard Threshold

Hard threshold is an approach that effectively removes or eliminates coefficients below the threshold value from the signal or image by setting them to zero. It makes a binary choice, tossing out coefficients below the threshold and holding onto coefficients above the threshold.

$$S\left(C_{[i,j]}\right) = 0 \qquad \left(\left|C_{[i,j]}\right|\right) < T.$$

$$S\left(C_{[i,j]}\right) = C_{[i,j]}\left(\left|C_{[i,j]}\right|\right) > T.$$

2.3.5 Image Reconstruction (Inverse 2D DWT):

The denoised signal or image is reconstructed from the modified wavelet coefficients using the inverse 2-DDWT,

$$x_{denoised[m,n]} = \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} C_{denoised[i,j]} h[m-i] h[n-j].$$

where, $x_{denoised[m,n]}$ represents the denoised signal or image at position(m,n), $C_{denoised[i,j]}$ denotes the modified wavelet coefficient at position(i,j), and $h[m-i]$ and $h[n-j]$ are the inverse wavelet filters in the horizontal and vertical directions, respectively.

2D-DWT makes it easier to divide a signal or image into wavelet coefficients, which are then threshold to separate signal from noise (Unni, 2014). The denoised signal or image is then rebuilt using the changed wavelet coefficients by the inverse 2D-DWT, producing a clearer more precise portrayal while retaining the key features.

2.3.6 Image Compressions

SEM images frequently have enormous file sizes due to their high resolution and plenty of data. These files can be greatly compressed to minimize their size, which makes it simpler to keep track of the enormous numbers of SEM images. Additionally, reduced photos enable quicker data transfer, facilitating effective sharing and teamwork. The original quality of SEM pictures can be maintained by using lossless compression techniques, which guarantees that crucial features and structural details are not lost during storage or transmission. Compressed images can also aid image analysis procedures because they are easier to modify computationally. 2D-DWT analysis wavelet functions with various positions and sizes of image. High energy compression and de-correlation are characteristics of DWT (Yin et al., 2022). Wavelet-based image coders do not suffer from issues like blocking artifacts, and distortion brought on by aliasing is completely removed by the design of the right filters. Wavelets were ideal for image compression because of these characteristics. Comparable to other linear transforms, DWT lower the entropy of a picture, meaning that the wavelet coefficient matrix is more effectively encoded because it has lower entropy than the image itself. The 2-D DWT enables effective localization in frequency and space, and fast O (nLog n) method of execution are available (Kumar et al., 2022). A set of waveforms are used in the wavelet decomposition of a picture to denote the high frequencies. After the signal has been decomposed, a threshold is selected for each level from 1 to N, and the detail coefficients are then subjected to harsh threshold. Finally, wavelet reconstruction is obtained utilizing the initial level N approximation coefficients and the modified level 1 through level N detail coefficients (Chang and Girod, 2007; Keshri et al., 2022). While the low frequencies or smooth sections of an image (scaling function) relate to estimated coefficients, the intricate sections of an image (wavelet function) correlate to the intricate sections of an image, which clearly reveal the Vertical, Horizontal, and Diagonal details of the picture. The value less than these features can be regarded insignificant enough to be turned to zero is referred to as threshold. If the high frequency coefficients are very small, they can be reduced to zero without appreciably affecting the image (Mishra et al., 2020; Keshri et al., 2022). Compression can be obtained increases with the bottom level (i.e., zero). The scarcity of the signal's wavelet domain representation has a direct impact on a wavelet basis's capacity for compression. In order to achieve compression, the conventional signal component must be accurately approximated using a minimal number of approximation coefficients at a selected level and certain detail coefficients.

3. Results and Discussions

The SEM image under the experiment consists of Ni-P-CNF nano-composite plating heated at 4000C changes from amorphous to crystalline structure examined in following different wavelet tests.

3.1 2-Level Decomposition of SEM of Image

The 2D-DWT individually applies the wavelet decomposition and reconstruction operations to each pixel intensity value in gray scale images. As a result, the image is represented at several resolutions, with the detail coefficients storing high-frequency aspects and the approximate coefficients expressing the low-frequency components. More levels of insight can be obtained by further decomposing the coefficients. Red (R), Green (G) and Blue (B) channels in RGB image scan each treated as a distinct gray scale image by applying the 2D-DWT independently. This makes it possible to analyze color and texture features separately, giving a detailed representation of the image's frequency and spatial properties. At each decomposition level, they are built to capture various frequency components. Decomposition of SEM image is shown in Figure 2 at different resolution. The wavelet transform characteristics are determined by the low-pass (images-b, c, d,e) and high pass filters (images-f, g and h).

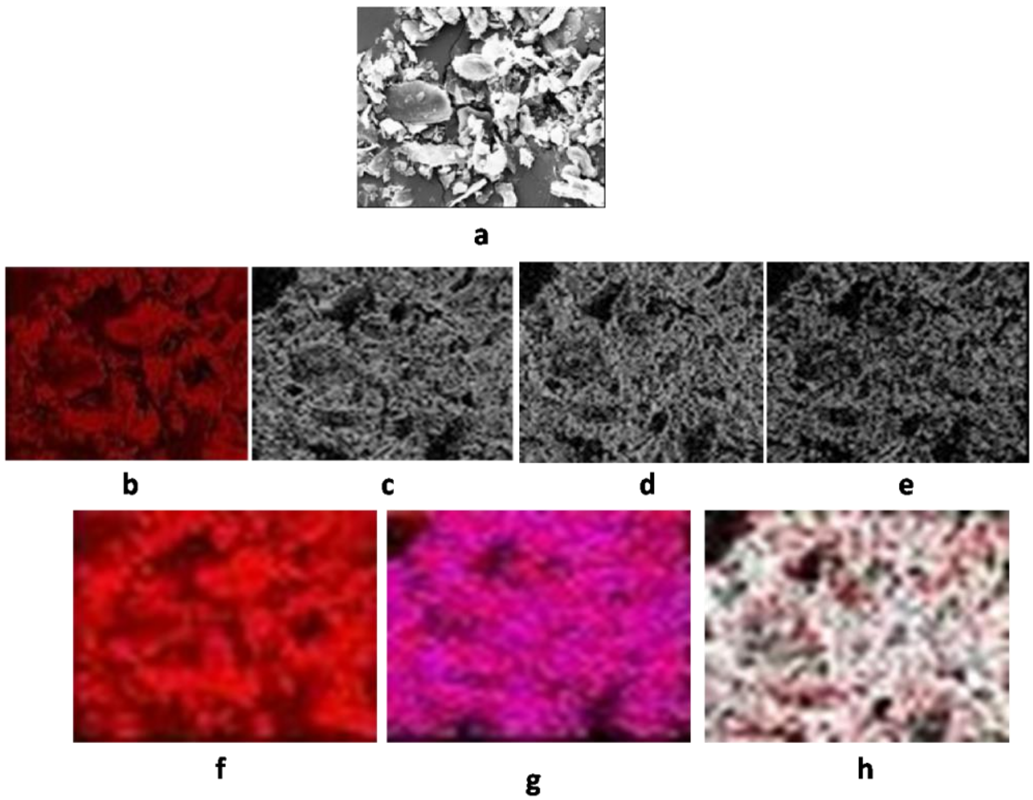

Figure 2. 2-level decomposition of SEM of image (a) Original image (adopted from (Ram et al., 2023)), (b,c,d,e) Low-pass filtered, and (f,g,h) high-pass filtered image at different resolution.

3.2 Denoising of Image

The soft threshold function reduces the magnitude of coefficients below the threshold by a certain amount, while the hard threshold function sets coefficients below the threshold to zero (Pimpalkhute et al., 2021; Jakhar et al., 2023). In Figure 3, noise is added intentionally to the test image to test the efficacy of the 2D-DWT to denoise an image. Here, the added noise is of Gaussian nature and Gaussian wavelets algorithm is used for denoising.

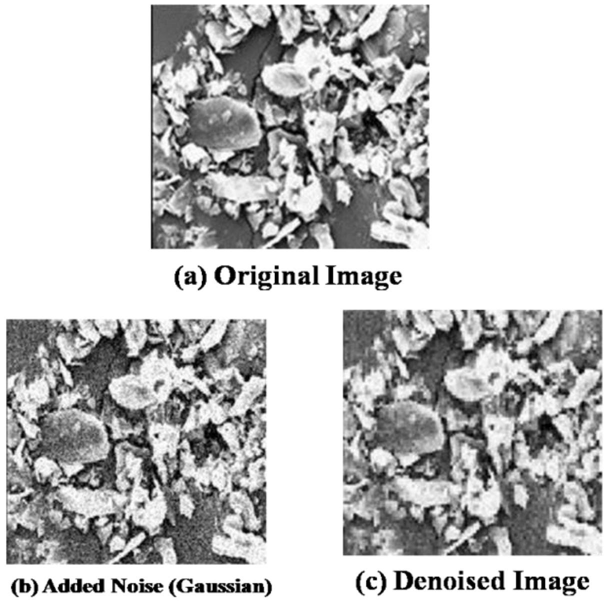

Figure 3. Denoising (Hard Threshold) of image by 2D-DWT.

3.3 Compression of Image

In the study the author has done 4-level decomposition on the SEM image of Ni-p-CNF nano-composite and applied threshold to the detail components. Sorting the wavelet coefficients and keeping the top 10%, 5%, 1%, and 0.5% biggest coefficients while threshold the rest to zero. The compression at different levels can be observed in Figure 4. Following a systematic process, the wavelet transform-based compression begins with signal decomposition using a chosen wavelet and level. Efficient compression is made possible via lowering the quantity of data needed to describe the signal while keeping essential characteristics and limiting information loss. 2D-DWT analysis wavelet functions with various positions and sizes of image can be obtained as well as high energy compression and de-correlation are characterized.

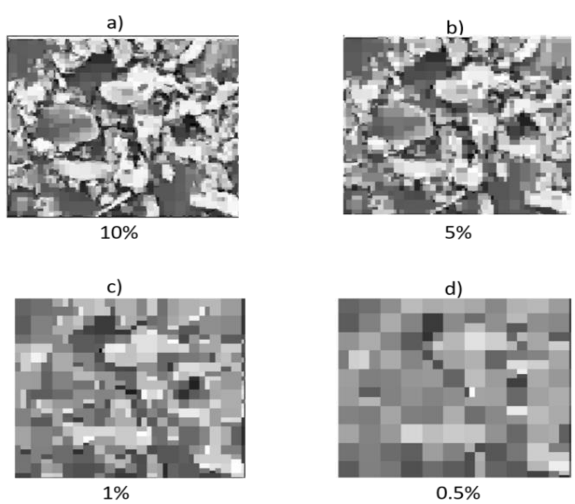

Figure 4. Image compression by 2D-DWT at different level.

The morphology reveals that the nickel and phosphorus appeared with poor dispersed of CNF nano-particles and transformations of amorphous phase into characteristic crystalline phase. DWT can be an effective method to enhance the image quality of SEM to have a better idea of the structural change that has occurred in the nanocomposite by transforming from amorphous to crystalline structure. Image enhancement functions like 2D-DWT can help in identifying defects in the materials, examine wafer cleaning methods, and surface profiling of thin films.

4. Conclusion

This study indicates that surface topography cannot be properly characterized by straightforward statistical metrics like RMS roughness, average roughness. Commonly used methods like PSD and histogram equivalence are not truly dependable. Due to the theoretical constraints of FT, PSD cannot be used to study nonstationary surface topography. Whereas, histogram equivalence can be very demanding for high-resolution images and can give over contrast images which looks artificial. In this study, we apply wavelet theory to expand our understanding of surface morphology and structures.2D DWT can be advantageous for examining specialized information because it is localized in both space and frequency. 2D-DWT is an excellent method for surface trend, discontinuity, and short periodicity detection for the host image and wavelets can be used to clean out noise and artifacts.

Conflict of Interest

The authors declare that they have no known competing financial interests that could have appeared to influence the work reported in this paper.

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