REVIEW IN IMAGES ENHANCEMENT MEDICAL USING CURVELET TRANSFORM AND VECTOR INFORMATION

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ABSTRACT

The use of medical imaging for the purposes of medical monitoring and diagnosis has seen tremendous growth in recent years, which has resulted in a rising need for suitable data storage and accessibility. The primary goal of image enhancement is to generate a processed image that is suitable for a specific application. This can be accomplished by acquiring the image in the highest resolution possible or by using a variety of techniques to extract the important information while ignoring the irrelevant information. Image processing can then be performed on the processed image. Image enhancement techniques are used in medical imaging to increase the quality of the visual representation of an image by reducing the amount of noise present and sharpening the features. This study examines the Curvelet transform-based approach for increasing medical image quality. The contribution of the proposed review two steps are advised for optimizing the images. The first step is the optimization step utilizing the Curvelet transform, which featured a series of image-preparation processors. Curvelet's ability to extract complete spectrum information from an image with varying edge orientations makes it valuable for assessing data about wave propagation. In light of this, the curvelet transform is considered an excellent filter for improving and denoising images, and it is intended to deal with components in several orientations and scales. The primary objective of this treatment is to boost visibility and eliminate noise, which is superior to conventional techniques of enhancement in which the enhancement step is performed by discrete curvelet transform through wrapping.

The contribution of the proposed review the usual vector is the second step of this review approach. The vector image is distributed randomly to each pixel in images that are unclear and noisy. This procedure eliminates the unpredictability in the previously computed directions and makes them regular, producing more precise results and enhancing image clarity, particularly at the image's edges. By comparing the results of the proposed technique of improvement to the results of existing improvement methods, it was determined that the proposed approach yields superior performance and is more efficient. The efficiency and efficacy of the suggested technique may be determined based on the results of the trials, which demonstrated that the method performs very well and yields accurate and precise results.

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1. INTRODUCTION

The principal goal of enhancing the image is to produce a processed image that suitable for a specific application, to make the image capable of processing and analysing by computer,by obtaining the image in best resolution or extract the important information and ignore the unimportant information by using various methods[1]. Image enhancement provides processing of poor quality images which helps to extract the important information from selected image. It improves the perception of information in images for human viewers.[2] Image enhancement

techniques, such as noise reduction and detail sharpening, are often used in medical imaging in order to provide a more accurate and understandable visual representation of the image. In imaging modalities such as magnetic resonance imaging MRI(Magnetic Resonance Imaging, ultrasound, and x-ray, medical image enhancement is a helpful way for seeing anatomic areas. In order to have a deeper comprehension of the many strategies for enhancing images, we may classify them into one of two primary categories: spatial domain approaches or frequency domain methods. Using a method based on the spatial domain may make it possible to increase image quality by directly modifying pixels [3].

Image quality may be increased using the spatial domain approach, which involves directly changing image pixels to get the desired effect [4]. This contains examples of a wide array of methodologies and settings. The spatial domain is the term used to refer to the collection of discrete image components, often known as pixels."spatial domain techniques"are procedures that act directly on these pixels, and they have a specific name [5]Frequency Domain Method (also known as the FDRM) The Fourier transform, the discrete wavelet transform (DWT), and the discrete cosine transform are the three unique mathematical tools that are used in the frequency domain method, which is a common and efficient strategy (DCT). Image enhancement in the frequency domain involves calculating the Fourier transform of the image, multiplying the result by a filter, and then taking the inverse transform to obtain the improved image [6]. This is in contrast to image enhancement in the spatial domain, which involves convolving the image in order to improve it. Curvelet was well-suited for evaluating wave propagation data [7] due to its ability to extract complete spectrum information of an image with varying image edge orientations. Since this is the case, it has been concluded that the curvelet transform is a great filter for both improving and denoising the image.The discrete curvelet transform by wrapping FDCTW (Fast Discrete Curvelet Transform via Wrapping FDCTW) is a powerful tool for enhancing images by enhancing vision and removing noise.

2. RELATED WORKS

Authors of [8] include Athar A. Ein-Ashoka, Hamdy M. Kelash, Osama S. Faragallah, and Hala S. El-Sayed. introduced a theoretical framework for improving Infrared photographs. The Fast Discrete Curvelet Transform with homomorphic filtering is used in the suggested technique (FDCT). Based on combining the benefits of FDCT for modeling curves and clarifying features on it with Homomorphic filtering, an effective approach for improving the look of IR images, this method is able to provide impressive results. We also study how the FDCT coefficients affect the Infrared images. When employing just the first and final FDCT coefficients, the approach yields satisfactory results in terms of objective and subjective assessments.

Approximate digital implementations of two novel mathematical transformations, the ridgelet transform and the curvelet transform, are described by Jean-Luc Starck, Emmanuel J. Candès, and David L. Donoho in [9]. Our solutions are low-complexity and easy to implement, and they provide accurate reconstruction and resistance to perturbations. Computing an approximation of the digital Radon transform in the Fourier domain is a key instrument. We provide a straightforward interpolation in Fourier space, one that converts Cartesian samples into those on a rectopolar grid—a pseudo-polar sampling set based on a concentric square's topology. Though our interpolation isn't very refined, the visual performance is above average. To the Radon transform, we apply our ridge let transformation, which uses wavelets with compact support in the frequency domain and a specific overcomplete wavelet pyramid. Using the ridge let transform as a building block, we construct the curvelet sub bands using a filter bank of à torus wavelet filters, making our curvelet transform both efficient and effective. Throughout, our guiding principle is that transformations should be overcomplete rather than critically sampled. We use these digital transformations to remove the white noise from certain reference images. This study shows that, in comparison to "state of the art" wavelet-based approaches like thresholding of decimated or undecimated wavelet transformations and tree-based Bayesian posterior mean methods, simply thresholding the curvelet coefficients achieves extremely similar results. Additionally, the curvelet reconstructions provide visibly crisper images and, in particular, superior quality recovery of edges and weak linear and curvilinear features than wavelet-based reconstructions. Curvelet and ridgelet transformations have theoretical support that implies they can outperform wavelet techniques for several image reconstruction tasks. An promising concordance is found between the presented empirical findings.

Reham R. Mostafa, Hazem M. Al-Bakri, and Abdullah M. Hammouche, Create a novel technique for improving the contrast of gray images using the Fast Discrete Curvelet Transform and the Unequally Spaced Fast Fourier Transform (FDCT-USFFT). This transformation type gives back a table of curvelet coefficients that may be searched for in terms of scale parameters, orientation, and position. It is possible to improve an image's contrast by adjusting the FDCT-USFFT coefficients. According to the obtained data, the suggested solution outperformed its two main competitors, histogram equalization and contrast enhancement based on the wavelet transform.Edge enhancement of low contrast medical images, such as breast ultrasound (US) images, is proposed in [11] by Sirikan

Chucherd and Annupan Rodtook. Vector analysis of the gradient vector field computed from the image's edge map forms the basis of the vector projection method (PRO). For each window, it calculates a summed projection of all vectors inside that window. The PRO then calculates the gap between the projection's extremes. These distances are sorted by the clustering method into boundary and non-border categories.

3. CURVELET TRANSFORM

Within the realm of image processing, the curvelet transform has seen an abundance of use. The disadvantage of the wavelet is remedied by the use of a method that was devised by Candes and Donoho in 1999 [12]. [12] [Cances and Donoho] By transforming wavelets into curvelets, one of the limitations of the wavelet has been removed. Curvelet has a wide variety of uses, and the medical image is only one of them. The curvelet transform is an extension of the wavelet transform that has a higher dimension and has the ability to represent images at numerous scales and angles. The curvelet transform is one of a kind when it comes to multi-scale geometric transformations. The transform [13] consists of a multi-scale pyramid with many directions present at each length scale.

However, the two-dimensional (2D) wavelet transform that is often employed is a separable extension of the one-dimensional (1D) wavelet transform. The 1D wavelet transform does not function very well in capturing the image's geometric edges because of its isotropy [14]. In the beginning, the goal was to make this a better representation of curves and edges than wavelet. As a result of the fact that curvelet is an extension of wavelet, there is a connection between the sub-bands of curvelet and wavelet. The components of the curvelet transform have a position, an orientation, and a scale, while the elements of the wavelet transform have just location and scale parameters [15].

Curvelets are an efficient kind of modeling that not only takes into account a multiscale time-frequency local partition, but also makes use of the direction of geometric feature direction. This transform was developed to depict edges and other singularities along curves in a manner that is far more effective than that of conventional transforms, making use of a great deal fewer coefficients while maintaining an equivalent level of accuracy [13]. The continuous curvelet transform and the fast discrete curvelet transform are both examples of the two generations of the curvelet transform that have been produced.

3.1. CONTINUOUS CURVELET TRANSFORM

It first generation includes special partitioning and ridgelet transform which is done on blocks of data. These constructions (partitioning and ridgelet transform) is redundant and make the curvelet transform works slowly[13]. The ridgelet-based curvelet transform may be used for a variety of purposes, such as image denoising, decomposition, texture classification, deconvolution, astronomical imaging, and contrast enhancement. The ridgelet-based curvelet transform, on the other hand, is ineffective since it is dependent on the ridgelet transform and uses equations that are difficult to comprehend.

In order to create the ridgelet-basedd curvelet transform, the radon transform and the wavelet transform were merged. The initial phase in this curvelet approach involves disassembling the input image into a number of sub-bands, followed by the partitioning of each of the bands that are produced into a number of blocks for ridgelet analysis. The ridgelet transformation may be realized by the use of the radon and one-dimensional wavelet transformations [16]. A function that is defined on the plane can be mapped onto a function that is defined on the (two-dimensional) space of lines in the plane using an integral transform that is known as the radon transform. This means that the value of the function at a given line is equal to the line integral that the function has across that line. In 1917, Johann Radon[17] was the first person to mention the transfor.

The overlapping of windows is done in order to avoid blocking effects from occurring as part of the spatial partitioning that happens during the ridgelet transform. This results in a significant amount of redundant work being done. In addition to this, it takes a very long time to finish, which renders it unfeasible for conducting an analysis of the textural properties of a big data set. The variable width and length of Curvelets, which suggest a greater level of anisotropy [16], contrasts with the fixed length of Ridgelets, which is proportional to the size of the image. The curvelet transform is simply an extension of the ridgelet transform when it comes to doing multi-scale analysis. As a result, the first thing we are going to do is have a conversation about what ridgelet transforms are. Wavelet and curvelet representations are shown in Figure 1., which demonstrates their use for edge information collection (1).
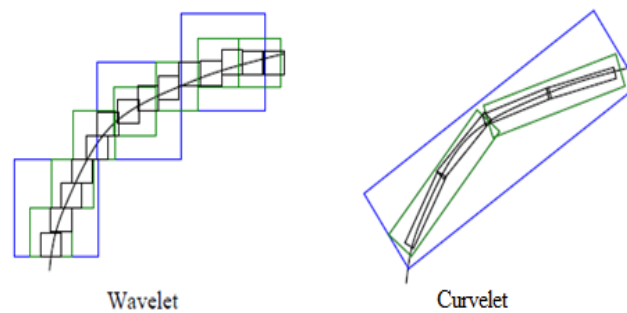
Figure 1. Edge Representation Using Wavelet and Curvelet

Figure 2. shows the components of the sampling in the frequency plane in continuous-time curvelet transform. In the frequency domain, Curvelets are supported near a 'parabolic' wedge. The shaded area represents such a generic wedge.
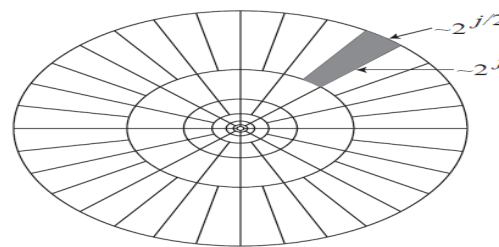

Figure 2. Continuous Curvelet Transform

3.2. Fast Discrete Curvelet Transform

In the Fast Discrete Curvelet Transform, there are two methods to obtain the curvelet coefficients:
1) USFFT (Unequal Space Fast Fourier Transform) method.
2) Wrapping method.

A. Unequal Space Fast Fourier Transform (USFFT)

USFFT transform finds the curvelet coefficients by using Fourier on the image. The Fourier sampling used in USFFT are sampling irregularly. This method has the same output of wrapping curvelet but the wrapping is faster. Curvelet via wrapping will be used for this work[15].

B. Fast Discrete Curvelet Transform via Wrapping (FDCTW)

Because this transform uses the quick Fourier transform, which has less processing complexity than the sophisticated ridgelet transform[16], it was utilized in the process of enhancing medical images. Fast Discrete Curvelet Transform (FFT) is an improvement over the previous generation of Curvelet Transform (Fast Fourier Transform). In the Fourier transform (FFT), the image is converted into a Fourier representation. The Curvelet Transform's convolution in the spatial domain is transformed into a Fourier domain product. Each orientation and scale coefficient is ranked higher than the previous one. The curvelet has a trapezoidal wedge for a frequency response. Wedge wrapping is accomplished by amassing coefficients of rectangles from adjacent parallelograms. Wedge wrapping is an application of the "wrapping based Curvelet Transform" [15]. FDCTW has faster computation time than the USFFT technique[18].The reason of fast computation of this technique is consider to two reasons,first, it doesn't use the ridgelet transform so, it reduces the amount of redundancy in transform and makes the speed higher[19]. Second, the low computation time is also become of using a series of translation and wraparound technique[20].

Curvelet[21] may be used to preserve image details along fixed axes and keep spatial attributes within predetermined bounds. The Fast Discrete Curvelet Transform by Wrapping is an octahedral pyramid with varying orientations and locations at a low frequency [22]. The input 2D image is in the form of a Cartesian array, and the Fast Discrete Curvelet Transform through Wrapping (FDCTW) method uses this to do the transform. A raster point P at (i,j) is shown in Figure.3.
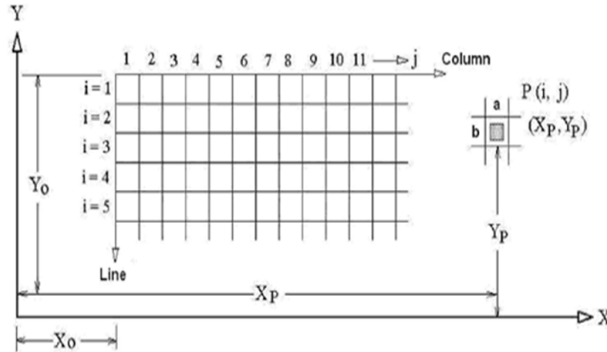

Figure 3 Raster to Cartesian Array

The Cartesian system has (X_p, Y_p) coordinates which are computed in equations(1)and(2) follows:-

$$X_p = X_0 + (j-1).a + \frac{a}{2} = X_0 + \left(j - \frac{1}{2}\right).a \qquad (1)$$

$$Y_p = Y_0 + (i-1).b + \frac{b}{2} = Y_0 + \left(i - \frac{1}{2}\right).b \qquad (2)$$

Where X_0, Y_0 are the coordinates of the origin of raster system a is the width of raster cell and b is the height of raster cell. These digital transformations are linear and take as input Cartesian arrays of the form $f[n1, n2]$, and values $0 \le t_1, t_2 < n$.

Where n is the image size, usually its square shape, $n1, n2$ represent the coordinate in a Cartesian array which, allow the output ,Where the steps of Fast Discrete Curvelet Transform via wrapping be as following:-
1.Take the two dimensions Fast Fourier Transform (2DFFT) for the input image, and obtain the fourier samples $\widehat{f}(x, y)$ equation (3) explain it, Which Divide FFT into collection of Digital Corona (wedges) Tiles.

$$\widehat{f}[x, y] = \frac{1}{n^2} \sum_{n1, n2=0}^{n-1} f[n_1, n_2] e^{-i2\pi(n_1 x + n_2 y)/n} \quad (3)$$

Where$-n/2 \le n_1, n_2 < n/2$ and $f[n_1, n_2]$input 2D image in cartesianarray,and$\widehat{f}[x, y]$ denote the 2D discrete Fourier transform. This curvelet has a trapezoidal wedge for a frequency response. Figure 4. displays the digital curvelet tiling of space and frequency .
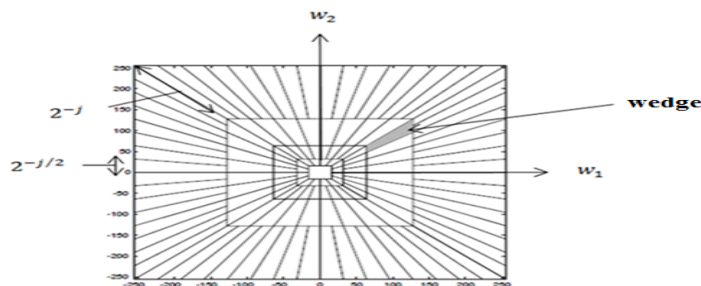

Figure 4. Digital Curvelet Tiling of Space and Frequency

2.For each corona tile translate to the origin, i.e. for each scale j and angle l pair (j, l) generate the product, defined in equation(4)as following :-

$$d(x,y) = U_{j,l}(x,y)\hat{f}(x,y) \qquad (4)$$

Where, $U_{j,l}(x, y)$ is the Cartesian window, the Cartesian window U_j is defined in equation(5)as following :-

$$U_j(w) = W_j(w)V_j(w) \qquad (5)$$
$$w = (w_1, w_2), w_1 > 0, w \in R^2$$

Where W_j radial window, V_j angular window defined in equations (6) ,(7). These are both smooth , nonnegative and real valued, with W_j take positive real arguments and a V_j taking real arguments [15],(w) mean frequency domain variable and $j \geq 0$.

$$W_j(w) = \sqrt{\Phi_{j+1}^2(w) - \Phi_j^2(w)} \qquad (6)$$
$$V_j(w) = V\left(2^{[j/2]} w_2/w_1\right) \qquad (7)$$

Where the Φ is the outcome (product) of low pass 1D window defined in equation(8), and w_1 and w_2 are coordinates of low pass one dimensional window [23] .

$$\Phi(w_1, w_2) = \Phi(2^{-j}w_1)\Phi(2^{-j}w_2) \qquad (8)$$
$$\{(w_1, w_2): 2^j \leq w_1, w_2 \leq 2^{j+1}, 2^{j/2} \leq w_2/w_1 \leq 2^{-j/2}\}$$

And $0 \leq \Phi \leq 1$.

Using the window U_j is insulates frequencies near the wedge(corona). The rotation matrix (Shear matrix S_θ) can also be used to maintain symmetry around the origin point, and rotation by $\pm \pi/2$ radiance because the curvelet is obtained by applying shifts and rotation to curvelet $\varphi_{j,l,k}^d$ in the frequency domain[24]. The Cartesian window U_j defined in equations(9)as following:

$$U_{j,l}(w) = W_j(w)V_j(S_\theta w) \qquad (9)$$

Where S_θ is the shear matrix defined as following :

$$S_\theta = \begin{pmatrix} 1 & 0 \\ -tan\theta & 1 \end{pmatrix}$$

Instead of the polar tilted network in continues curvelet, the discrete curvelet use Cartesian (regular rectangular network). The n_1, n_2 after apply Fourier transform will exceed allowed by IFFT because that the response of the frequency for Fourier is divided the image into wedges by drawing concentric squares and radial lines , each wedge is trapezoidal shape , that IFFT can't deal whit it so it use rectangular network for wedges so, $U_{j,l}$ supported in a parallel region[25].

3.Figure 5. explains them and the following equation (10) defines them: Wrap the parallelogram-shaped tile's support around a rectangle centered at the origin.

$$\hat{f}_{j,l}(x,y) = W(U_{j,l}, \hat{f})(x,y \qquad (10)$$

The wedge is wrapping to be rectangle about the origin with sides of length $L_{1,j} \times L_{2,j}$ where $0 \leq x < L_{1,j}$, $0 \leq y < L_{2,j}$.
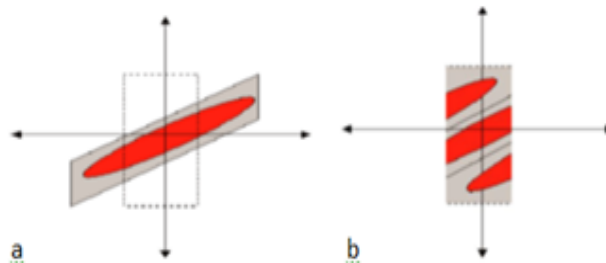

Figure 5. (a) Support of Wedge before Wrapping
(b) Support of Wedge after Wrapping in Curvelet.

4. Take the Inverse Fast Fourier Transform (IFFT) for each $\hat{f}_{j,l}$, defined in equations(11)as following:

$$f[n_1, n_2] = \sum_{x,y=0}^{n-1} \hat{f}\,[x,y]e^{i2\pi(n_1 x + n_2 y)/n} \quad (11)$$

To simplify periodization[1][2], place the localizedFourier samples in a rectangular region where IFFT may be performed in place of interpolation.

5. Collect the discrete coefficient CD by including the curvelet array in the set of curvelet coefficients (j,l,k). After completing the calculation specified by the following equations(12), the wrapping curvelet coefficients are determined through inverse FFT of the spectral product:

$$C^D(j,l,k) = \sum f[n_1, n_2]\varphi_{j,l,k}^d\,[x,y] \qquad (12)$$

$\varphi_{j,l,k[x,y]}^d$ the digital curvelet function C^D its mean Curvelet coefficient indigital and j scale parameter $j = 0,1 \ldots$, l angle parameter $l = (-\pi/4, \pi/4)$ and k position parameter $k = (k_1, k_2), k_1, k_2 \in Z$.

4. Images Enhancement Using Fast Discrete Curvelet Transform via Wrapping (FDCT-Wrap)

Enhancement in curvelet is used to improve the vision and strip undesirable noise to mend contrast and to discovery more details in an image[26], This technique aims to improve the visibility of a image, particularly a medical image, so that it may be better used for analysis, edge detection, and feature extraction[27]. To enhancement the image FDCTW can be used Rather than a line or point singularities the medical images often times contain curves singularities[28]. Curvelet is used to capture the feature and texture pattern in the frequency domain from the image[8]. The discontinuity in the edge is considered a problem that approximated better in curvelet [29].

Because Curvelet can extract full spectrum information of an image with various image edge directions, it was useful for analyzing wave propagation data [2]. Consequently, curvelet transform is thought of as an useful filter to improve and denoise the image[30].
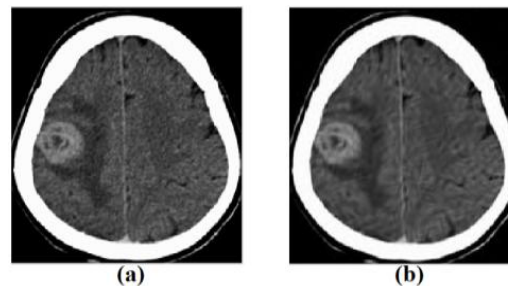

Figure 6. Application of the Enhancement Process
(a)Original image (b) Enhanced image

Where steps enhancement using Fast Discrete Curvelet Transform via Wrapping (FDCT-Wrap) to be following:-
1. Choose the image to enhancement as input.
2. Calculate the curvelet wrapping coefficients. It was explained earlier in paragraph (II.B.B). We get a set of bands , each band contains coefficients.
3. Calculate σ the noise standard deviation for each band of the

Transform using the Fast Fourier Transform, or Warp. The most used measure of variability is the standard deviation, which assesses the dispersion of a data set and its relationship to the mean. If the standard deviation is small, the data points are clustered closely around the mean (average), if it's large, the data points are widely dispersed around the mean (average), and if it's zero, the data points fall within the predicted range of the mean (average). If you know the mean and median, you may use equation(13) to get the standard deviation.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2} \quad (13)$$

Where N is the number of variables ,x_i is the variable and $\bar{x}$ the mean(average) value.

4. Multiply each (FDCTW) coefficients $W_{j,k}$ by $y_c(W_{l,k},\sigma_j)$ for each band.Where y_c is a function that define the modified value of the (FDCTW) coefficients,defined in equation(14)as following:

$$yc(x,\sigma) = \begin{cases} 1 & if \ x < c\sigma \\ \dfrac{x - c\sigma}{c\sigma}\left(\dfrac{m}{c\sigma}\right)^p + \dfrac{2c\sigma - x}{c\sigma} & if \ x < 2c\sigma \\ \left(\dfrac{m}{x}\right)^p & if \ 2c\sigma \le x < m \\ 1 & if \ x \ge m \end{cases} \quad (14)$$

The pixel value in the FDCTW scale determines the value of m, which is the value under which coefficients are amplified; p is the degree of nonlinearity; c is a normalization parameter; a value of c greater than 3guarantees that the noise will not be amplified; The value of m may be calculated using the formula m=k m, where k m=15 is the noise standard deviation. Standard values for these coefficients may be calculated using (FDCTW) as [31].

$m = 30$, $c = 3$, $p = 0.5$ and $0 < p < 1$

5. From the modified (FDCTW) coefficients reconstruct the enhanced image.

5. INFORMATION VECTOR

The information vector of the image is calculated by the following steps:

5.1 Operation Convolution between Gaussian Masks and the Image

In this procedure, the x and y axes of the gaussian operator are used to convolve each pixel of the image with a gaussian mask.

The applications of this step are described by equations (15) and (16).

$$CO_x(i,j) = -GM_y \times I(x,y) \approx \frac{\partial I(x,y)}{\partial y} \quad (15)$$

$$CO_y(i,j) = GM_x \times I(x,y) \approx -\frac{\partial I(x,y)}{\partial x} \quad (16)$$

As shown in Figure 7., the input image (x,y), GMx, and GMy stand for the gaussian weighted masks in the x-axis, and the masks were calculated using Equations (17) and (18). (7).
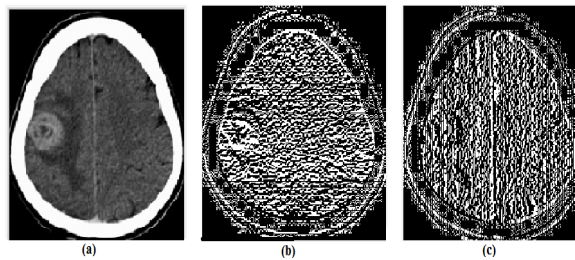

Figure 7. (a) Input image (b) Convolution in $x$direction (c) Convolution in $y$direction

$$GM_x(x,y) = \frac{1}{\sqrt{2\pi}\sigma}\left(\frac{x}{\sqrt{x^2+y^2}}\right)\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \quad (17)$$

$$GM_y(x,y) = \frac{1}{\sqrt{2\pi}\sigma}\left(\frac{y}{\sqrt{x^2+y^2}}\right)\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \quad (18)$$

Where the σ is standard deviation of distribution which play a fundamental role in function behavior , in the proposed method a window in size 3×3 is used and the value σ is 0.375 therefore the values of the used masks is :-

$$GM_x = \begin{bmatrix} 0.0248 & 0 & -0.0248 \\ 0.8693 & 0 & -0.8693 \\ 0.0248 & 0 & -0.0248 \end{bmatrix}$$

$$GM_y = \begin{bmatrix} 0.0248 & 0.8693 & 0.0248 \\ 0 & 0 & 0 \\ -0.0248 & -0.8693 & -0.0248 \end{bmatrix}$$

The convolution operation is done by multiply the value of each pixel and it's eight neighbors with mask values then additional the result of the previous multiply and replace it with the pixel, and this operation is repeated on all pixels in the image, where the mask is moving in each pixel horizontally between the points.

5.2 Operation Calculate the Maximum Number of Points

This phase involves computing the maximum amount of pixels in both the vertical and horizontal directions to employ in the calculation of the vector's information (19).

$$MP = max_{i,j} \left(\sqrt{CO_x(i,j)^2 + CO_y(i,j)^2} \right) \quad (19)$$

The vector information is finally obtained in this stage using the equation below (20)

$$VI(i,j) = \frac{1}{MP} \left(CO_x(i,j)\vec{\imath} + CO_y(i,j)\vec{\jmath} \right) \quad (20)$$

Where MP, CO_x and CO_y are computed in the previous steps.

5.3 Operation Compute Average Vector

When a picture is unclear and has a lot of noise, the vector image becomes dispersed erratically throughout all of the pixels. pictures that are difficult to distinguish and have a lot of background noise, the vector image has a random distribution over all of the pixels. In order to accomplish the objective of producing a vector picture that is easier to transmit, the process known as "local average" was used. During this step of the process, the value of the corresponding vector is replaced with the local average of the eight neighboring vectors for each pixel in the picture. This is done in order to ensure that the image is consistent throughout. By incorporating the instructions into the procedure in a more consistent manner, this technique enhances the accuracy of the outcomes that were previously computed and provides more accurate forecasts of those results. In order to find out what the common vector is, a mathematical equation is employed (21).

5.3. Operation Compute Average Vector

However, the portability of the vector image has been increased through the application of the local average operation. In this operation, the value of each vector is replaced with the eight local average of the vector neighbors and for each pixel in the image. This allows the vector image to be distributed randomly across all pixels in images that are unclear and noisy. With the use of the following equation, we are able to determine the mean value of a vector: (21).

$$AV(i,j) = \frac{1}{N_P} \sum_{(i,j) \in N} \sqrt{CO_x(i,j)^2 + CO_y(i,j)^2} \quad (21)$$

The equation that is used to calculate the direction, in where NP is the total number of the pixel and its neighbors, is as follows: (22). $D(i,j) = \frac{1}{N_p} \sum_{(i,j) \in N} \tan^{-1}\left(\frac{CO_y(i,j)}{CO_x(i,j)}\right) \quad (22)$

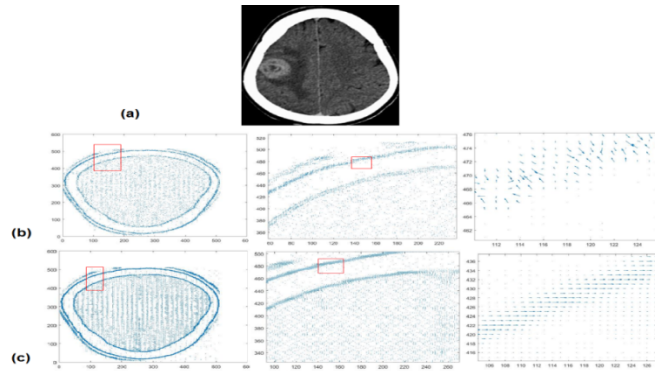Figure 8. illustrates how a vector image differs from an average vector.

Figure 8. displays the input image (a), a vector image (b), and an average vector (c).

6. RESULTS

Various medical images have been used to test and refine the process. The outcomes of this application strategy are shown in the following trials. In every single study, you'll find the same trio of images: Input image (a). (b) The end result of optimization, a crucial preliminary processing step for lowering image noise. The average vector, whose direction and magnitude you can determine, should be calculated. The vector is shown by an arrow, and its direction specifies whether the pixel should be shifted vertically or horizontally. The major benefits of this method are improved outcomes and more precise and clearer images due to the elimination of unpredictability in the previously determined directions.

Experiment 1: As can be seen in Figure 9, this method was applied in order to conduct an analysis on a section of the brain image
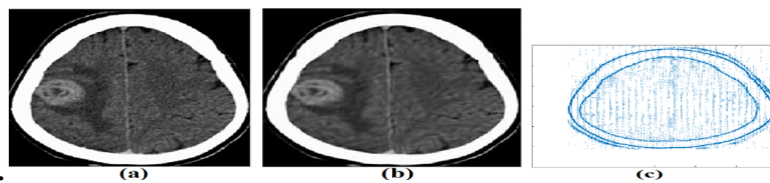

Figure 9. experiment (1) (a) The input image (b) The enhanced image (c) average vector image
Experiment 2: This time, we used the method to perform an analysis on a section of the brain image that is depicted in Figure 10.
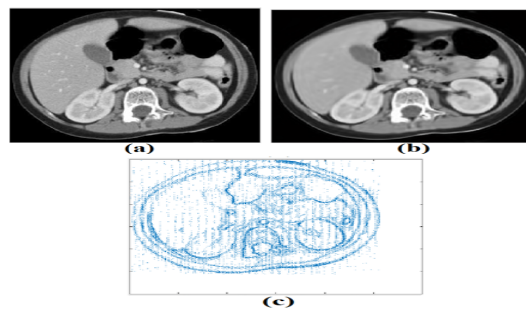

Figure 10. experiment (1) (a) The input image (b)The enhanced image (c) Average vector image.
Experiment Three: The procedure was used to analyze a portion of the brain picture that was shown in Figure 11.
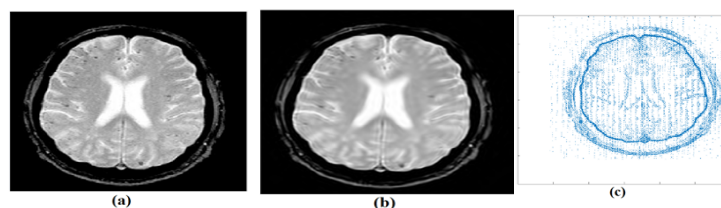
Figure 11. experiment (1) (a) The input image (b)The enhanced image (c) Average vector image.

Experiment (4): - The method was applied to a section of the kidney image as shown in Figure 12.
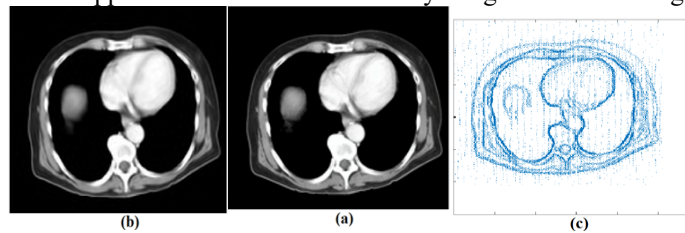

Figure 12. experiment (1) (a) The input image (b)The enhanced image (c) Average vector image.

7. CONCLUSION

The enhancement study methodology leads to the following conclusion Produce superior outcomes versus earlier techniques. Additionally, this proposed method's calculation cost is significantly cheaper than that of the other approaches. Because this study is a step in the preparation of images, it is regarded as an ideal solution for removing noise before the processing of photographs. add the accuracy rate become was excellent

 Since the study may be utilized in techniques medical images that have been impacted by sickness, such brain cancer cells, it can be used by physicians to correct abnormalities in the human body. Brain, kidney, and heart images are just some of the many forms of medical imagery the suggested approach has been tested on with great success.. The study reliance on the average vector, which makes the previously computed trends using Vector Information more regular and therefore more accurate, yields better, more precise findings and enhances the clarity of the image. In order to improve images for treatment, enhance the relevant information inside the image, and suppress irrelevant details, curvelet conversion was used. One benefit of this conversion is that it takes less time to implement and requires fewer computations.

The components are converted in many more ways than in the past on each scale. To improve readability, they work to restore contrast and minimize noise, with a focus on making medical images easier to work with for analysis, edge recognition, and feature extraction. Any image processing system benefits from this enhancement.

8. FUTURE WORKS

From future work are:

1- Make a comparison with the traditional models used now in image improvement.

2- In order to find abnormalities in the human body, doctors may find it useful to use optimization.

3. Enhanced images can be used in all image processing such as image matching and image recognition operations instead of using the original image to obtain better results.

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