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Literature Review of Wavelet-Based Image Filtering Methods

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Abstract: Noise is a random signal that corrupts the quality of an image. For many decades, eliminating it or reducing its intensity in the image has been a major concern for many scientists. To this end, several studies on image processing (with the aim of eliminating or reducing the intensity of noise) have been carried out. Although a multitude of filtering methods emerged from these studies, numerous works have shown the effectiveness of the wavelet transform in image filtering. Thus, several wavelet-based methods (for image filtering purposes) have been illustrated in the literature. Some methods involve performing wavelet decomposition followed by thresholding and other methods involve combining wavelet decomposition with various filtering methods. This combination can have two or more methods. After filtering, the effectiveness of the filter can be evaluated. It is measured in terms of qualitative and/or quantitative parameters. Indeed, a filtering method is said to be efficient when the PSNR parameter (parameter most used in the literature) obtained has a minimum value of 30dB. This article presents a literature review of wavelet-based image filtering methods. Emphasis is placed on works presenting a better PSNR value (wavelet type, combination carried out, mother wavelet, decomposition number). In the end, this article gives a panoramic view of the choices of tools to use by a reader who would like to get involved in image filtering.
Keywords: Image filtering, wavelet decomposition, image processing, PSNR

I. INTRODUCTION

According to D. Lingrand [1], image processing refers to all the techniques used to improve an image and extract information deemed relevant. It can be applied in several fields such as robotics, remote sensing, security and medical imaging. Among the techniques used in image processing, we have filtering, compression, restoration and segmentation. Image filtering, which is our center of interest, is an essential step in the image analysis process. In fact, it makes it possible to eliminate or reduce the noise (or spurious information) present in an image. This facilitates its interpretation and therefore decision-making, which is a very important step whatever the field of study. In order to find a method to improve the quality of an image, and thus facilitate rapid and efficient decision-making, this work reviews various image filtering methods. The study summarized in this article highlights the different image filtering methods based on wavelets. Indeed, numerous studies on image processing have proven that the wavelet transform makes it possible to easily determine singularities in the image. Among other things, it makes it possible to effectively filter images while preserving both their structures and their textures [2], [3], [4]. Furthermore, in the context of image denoising, using a wavelet-based method can achieve better results thanks to properties such as multi-resolution and multi-scale [5]. Additionally, wavelet-based methods have shown better results compared to other filtering methods in denoising ultrasound images of the heart [6]. This article aims to provide the reader with a deeper and more comprehensive knowledge of the wavelet transform applied to image filtering. The rest of the document is structured as follows: Section I emphasizes the concepts and types of noise encountered in images; Section II deals with the wavelet transform; Section III presents the different metrics for evaluating the performance of filtering methods; Section IV illustrates the state of the art of different wavelet-based image filtering methods and Section V presents the discussion. The work ends with a conclusion and future directions.

II. NOISE IN IMAGES

A. Definition of Noise

Noise is defined differently from one author to another. The work of [7]–[11] allows us to define it as being a signal appearing randomly in the image and altering the quality of the latter.

B. Sources of Noise

Due to its random nature, noise can have various origins. The acquisition phase [12] and the effect of environmental conditions during the image transmission process [8] can be the cause of noise in the images.

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C. Types of Noise

The removal of noise in the image has been the subject of several studies from which it appears that to eliminate noise in an image, it is necessary to identify the type of noise in order to apply the algorithm or method to the image. deemed more effective; that is to say whose performance is quite satisfactory. For this purpose, several types of noise could be identified. The table below summarizes the different types of noise encountered in the literature.

TABLE I
TYPES OF NOISE

Type of noise	Description
Gaussian noise	For A. K. Boyat and B. K. Joshi [11], Gaussian noise is produced by the sensor and is linked to the low brightness of the latter. It disrupts the gray values in the image. In a book in [13], Gaussian noise mainly taints digital images.
Speckle noise	Also called granularity noise or task noise, speckle noise reduces the power of perception of details and fine structures of the imaged scene. it appears superficially in the image and is visible in imaging systems such as laser, radar, ultrasound, etc. Its fundamental properties have been the subject of studies by several authors such as in [14] and [15]. According to [16], task noise is modeled by random values which are multiplied by the pixel values. It therefore belongs to the multiplicative noise model.
Salt of pepper noise	According to [16], salt and pepper noise results in black and white points distributed with a certain density in the image. This noise is visible in data transmission
Noise of poison	From [15], noise of poison (also called photon noise) is due to the statistical nature of electromagnetic waves such as X-rays, visible light and Gamma rays. It is also called quantum or shot noise.

III. THE WAVELET TRANSFORM

A. Wavelet Transform Theory

The wavelet transform is a sophisticated tool used for signal analysis. Thanks to the satisfactory results it offers for classical signals, its performances have been tested on the image signal by [2]–[4]. From [17] and [18], a wavelet is an oscillating function (which explains the word "wave") with zero mean, having a certain degree of regularity and whose support is finite (which explains the word “wavelet”, which means small wave). Furthermore, the wavelet transform is a function that decomposes the input signal into a series of wavelet functions ψ(t) that derive from a parent function ψ(t) given by dilation and translation operations. Its equation translates into:

$$C_{a,b} = \int_{-\infty}^{+\infty} x(t)\psi(t)dt \tag{1}$$

Where $C_{a,b}$ represents the wavelet coefficients; $x(t)$ represents the signal to be decomposed and $\psi(t)$ represents the mother wavelet used.

B. Multiresolution Analysis

Using wavelets amounts to implementing multi-resolution analysis; that is to say carrying out a series of decompositions of the image followed by its reconstruction. We can thus have several levels of decomposition of the image and choose the level which presents the most satisfactory result. It should be noted that at each level of decomposition we can see four essential elements: The horizontal details HL, vertical LH, diagonal HH as well as the “approximate” image LL. The image is reconstructed from certain coefficients deemed relevant. These coefficients can undergo certain processing (contrast improvement, smoothing, modification of contours, etc.) before reconstructing the image. The approximation obtained is a smoothed version of the initial image, but it may still contain noise; the filtering operation is repeated on the approximation image in order to access an even lower resolution, and so on until a satisfactory result is obtained.

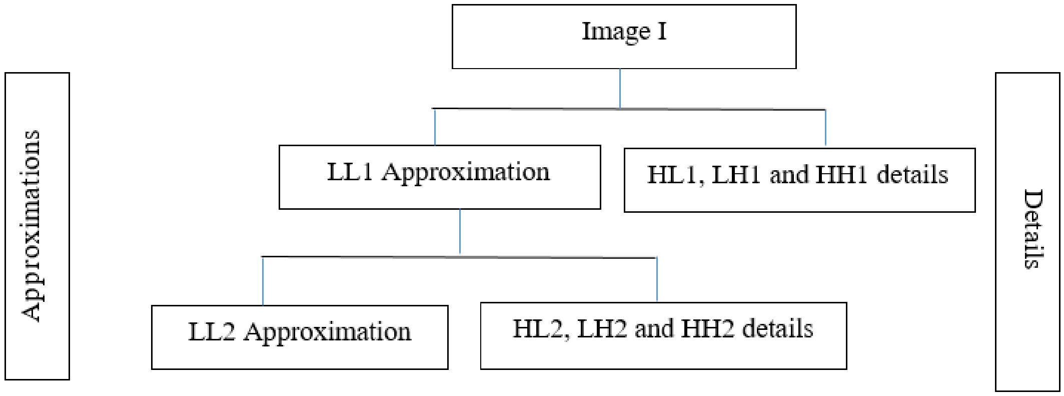

Fig. 1 A Representation of multiresolution analysis on two levels

In the remainder of this study, we describe the types of wavelet transform most used in the literature for image filtering.

C. Types of Wavelet transform

1) *The Discrete Wavelet Transform:* It is a mathematical tool as mentioned by [19] effective and useful to decompose the signal [8]. It is widely used in various fields of image processing [20]. It allows the signal to be analyzed in both the time and frequency domains. The wavelet transform implements the principle of multiresolution which consists of breaking the image into four sub-bands. This decomposition thus makes it possible to treat each sub-band individually. When the different sub-bands have been analyzed, a reconstruction of the image must be carried out. The performance of the discrete wavelet transform appreciated by many authors has led to its use in the context of image denoising.
2) *The dual-density dual-tree discrete wavelet transform:* According to [21], the double-density dual-tree wavelet transform is a transform that combines the characteristics of the dual-tree discrete wavelet transform and that of the dual-tree discrete wavelet transform. density. Its filter bank structure is composed of two iterated over-sampled filter banks operating in parallel. In each filter bank, the synthesis filters are the time-reversed versions of the analysis filters [22]. After one level of decomposition, we obtain nine (more detailed) sub-bands. This is why, thanks to this transform, we can obtain images of excellent quality [23]. However, complicated wavelet transforms are not always the best performing (compared to real discrete wavelet transforms); and it is not always true that more redundancy equals higher image denoising performance [22].
3) *Non-decimated wavelet transform:* The non-decimated wavelet transform is a shift-invariant transform which unlike the classical wavelet transform eliminates undersampling and oversampling. It is therefore more suitable for identifying stationary and non-stationary behaviors in signals [24]. With this transform, the number of pixels involved in the calculation of a coefficient increases more slowly and thus the relationship between frequency and spatial information more precise. Ideally, this means that noise removal is only done where it actually appears without affecting neighboring pixels [25]. However, it has been underused in the literature; this is why an article in [24] presented its advantages. Although very little used in the literature compared to the classic discrete wavelet transform, the performance of the non-decimated wavelet transform has been evaluated by some authors with regard to image denoising.
4) *The complex double-tree wavelet transform:* According to [26], the complex double-tree wavelet transform was first introduced by Kingsbury in 1998. Unlike the classical form of the wavelet transform (DWT-Discrete Wavelet Transform), the transform complex wavelet is almost invariant and requires relatively few calculations. Its use requires two separate filter banks to calculate the complex values: a filter bank for the real part and another filter bank for the imaginary part. In the 2D case, the complex wavelet transform requires six wavelet filters to extract information in six analysis directions: ±15°, ±45° and ±75° [27].

In practice, in addition to the type of wavelet transform, it is necessary to define the mother wavelet to use. For this purpose, there are numerous mother wavelets used in image filtering. The following lines summarize the mother wavelets most used in image filtering.

D. Mother Wavelet

1) *Haar Wavelet:* Created in 1910 by the Hungarian mathematician as mentioned in [28], the Haar wavelet is the first mother wavelet but also the simplest. Its basis is obtained from a multi-resolution analysis consisting of piecewise constant functions. The Haar wavelet has the smallest support among all orthogonal wavelets [29]. It represents a very interesting tool thanks to its approximation precision and especially the speed of its transformation. For this purpose, it can be very effective for image processing [30]. The Haar system is an orthonormal system in the interval [0,1] whose scaling function is defined by

$$\phi(t) = \begin{Bmatrix} 1, if \le t \le 1 \\ 0, else \end{Bmatrix} \tag{2}$$

The mother wavelet is obtained using the following function:

$$\psi(t) = \begin{Bmatrix} 1, if\ 0 \prec t \le 1/2 \\ -1, if\ 1/2 \prec t \le 1 \\ 0, else \end{Bmatrix} \tag{3}$$

2) *Daubechies wavelet:* Proposed by Ingrid Daubechies, the Daubechies wavelet is an orthogonal wavelet with minimal compact support of size [-r+1, r] (for a given number of zero moments r), and defining a discrete wavelet transform. Furthermore, the regularity of this wavelet increases with r. the support of the scaling function ϕ is [0, 2r-1] [29]. Most often and in practice, the Daubechies wavelet is written dbN where db represents Daubechies and N the order, with N varying from 1 to 10 [28]. The main characteristic of the Daubechies wavelet is the availability of a maximum number of vanishing moments for a predefined support length. The Daubechies wavelet can be evaluated using the following parent and scaling functions:

$$\psi(t) = \sqrt{2}\sum_{m=0}^{2r-1}(-1)^m h_{2r-1-m}\phi(2t-m) \tag{4}$$

Where $h_0, h_1, h_2, \ldots h_{2r-1}$ are the constant coefficients of the *h* filter

$$\psi(t) = \sqrt{2}\sum_{m=0}^{2r-1} h_m \phi(2t-m) \tag{5}$$

3) *Meyer Wavelet*: From [31], we note that Meyer wavelets are orthogonal wavelets and have a symmetric scaling wavelet function. They have an infinite number of supports.
4) *Coifflet Wavelet*: The coifflet wavelets were constructed by Ingrid Daubechies at the request of Ronald Coiffman. They are more symmetrical than the Daubechies wavelet and have a support of size 3r-1 instead of 2r-1 like that of Daubechies [31]. In practice, the coifflet wavelets can be written as coifN where N denotes the vanishing moment [28]. The main characteristic of coifflet wavelets is to have the largest number of vanishing moment for the scale and wavelet function for any given support width [32]. The scaling function ϕ associated with the coifflet wavelet verifies the equation below given by [33]:

$$\int_{-\infty}^{+\infty}\phi(t)dt = 1 \ \ and \ \int_{-\infty}^{+\infty} t^k\phi(t)dt = 0 \ \ for \ \ 1 \le k < N \tag{6}$$

5) *Biorthogonal Wavelet*: They are symmetric in nature. They are invertible but can be orthogonal in nature or not. In practice it can be written in the form biorN where N represents the order [28]. Using biorthogonal wavelets presents a very advantageous advantage because this amounts to using two wavelets: one for decomposition and one for reconstruction. They are not based like other wavelets on a vanishing moment. As for orthogonal wavelets, the scaling function and the mother wavelet are represented by the recursive relation below given by [32]:

$$\psi(t) = \sqrt{2}\sum_m g_m\phi(2t-k) \tag{7}$$

$$\phi(t) = \sqrt{2}\sum_m h_m\phi(2t-m) \tag{8}$$

6) *Symlet Wavelet*: Symlet wavelets are the least symmetric Daubechies wavelets. Their construction is similar to that of Daubechies but their symmetry is stronger than that of Daubechies [31]. Symlets wavelets are constructed in such a way as to have the least asymmetric analyzing functions possible. These are wavelets having a minimum support equal to [-r+1, r] with r zero moments [33]. In practice, symlet wavelet functions denoted symN where N denotes the order and ranges from 2 to 8 [34].

IV. PERFORMANCE METRICS

Performance metrics are parameters that allow you to evaluate a filtering method or algorithm. The table below summarizes the different metrics encountered in the literature.

TABLE III
PERFORMANCE METRICS

Metrics	Description	Formula
MSE	The MSE represents the mean square error between the processed image and the original image. It is calculated pixel by pixel by adding the difference to the square of the entire pixel and dividing it by the total number of pixels. A low MSE value indicates the resulting image is close to the original image.	$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j)-D(i,j)]^2$ m and n are the dimensions of the image $I(i,j)$ is the pixel intensity of the original image $D(i,j)$ is the pixel intensity of the denoised image
RMSE	This is the square root of the MSE. A low RMSE value should be obtained for better filtering	$RMSE = \sqrt{MSE}$
SSIM	SSIM is a quality metric based on the human visual system. It is used to estimate the similarity between two images and represents a reference for measuring the quality of an image. It is based on the calculation of three terms namely luminance, contrast and structure. Its range of values is between 0 and 1. A value of the structural similarity index close to 1 indicates better image quality and better preservation of the structure of the latter.	$SSIM(x,y) = \frac{2\mu_x\mu_y + (k_1L)^2}{\mu_x^2+\mu_y^2+(k_1L)^2} * \frac{\sigma_{xy}+(k_2L)^2}{\sigma_x^2+\sigma_y^2+(k_2L)^2}$ μ_x represents the average of x μ_y represents the average of y σ_x represents the variance of x σ_y represents the variance of y L is the dynamic of the pixel values, i.e. 255 for images coded on 8 bits $k_1 = 0.01$ and $k_2 = 0.03$ by default
UQI	The UQI Universal Quality Index is a measure used to assess distortions between two images by combining three factors: contrast distortions, luminance distortions and correlation loss. Its values vary between -1 and 1. For similar images, the best Universal Quality Index value is 1.	$UQI = \alpha \cdot \tau \cdot c = \frac{\sigma_{od}}{\sigma_o\sigma_d} \cdot \frac{2\mu_o\mu_d}{\mu_o^2+\mu_o^2} \cdot \frac{2\sigma_o\sigma_d}{\sigma_o^2+\sigma_d^2}$ α is the correlation coefficient which defines the relationship between the original image and the denoised image; τ is the parameter which makes it possible to measure the similarity of the average luminance between the original image and the denoised image and c is the parameter that measures the contrast similarity between the original image and the denoised image. μ_o represents the average of o (original image); μ_d represents the average of d (denoised image) and σ_o represents the variance of o σ_d represents the variance of d
FSIM	This is the magnitude of the gradient of an image. It is used to measure the degree of similarity and quality between noisy and denoised images.	$FSIM = \frac{\sum_{x\in\omega} S_L \cdot PC_m(x)}{\sum_{x\in\omega} PC_m(x)}$ ω means the entire spatial domain of the image ; $S_L(x)$ represents the similarity at each location X and PC_m represents phase congruence
SNR	The SNR parameter is a basic metric used to measure noise level. It is also used to visualize the effectiveness of noise reduction as it mainly compares the desired signal level and the background noise. It is a measure of distortion especially in homogeneous regions for low speckle intensity, the SNR value is high therefore the SNR value should be high for a good quality image.	$SNR = 10\log_{10}\left(\frac{\sigma_o^2}{\sigma_e^2}\right)$ σ_o represents the noise variance of the original image and σ_e represents the error variance (between the original image and the denoised image)

EPI	The edge preservation index is a parameter generally used to ensure that a certain operation performed on an image preserves the edges of that image. Indeed, when the contours are well preserved the EPI parameter will have a value close to 1	$EPI = \frac{\sum_{x=1}^{M-1}\sum_{y=1}^{N-1}(\Delta n_o(x,y)-\Delta n_o^{'})-(\Delta n_d(x,y)-\Delta n_d^{'})}{\sum_{x=1}^{M-1}\sum_{y=1}^{N-1}(\Delta n_o(x,y)-\Delta n_o^{'})^2\left(\Delta n_d(x,y)-\Delta n_d^{'}\right)^2}$ $\Delta n_o(x,y)$ and $\Delta n_d(x,y)$ represent the contour images of the original image $n_o(x,y)$ and the denoised image $n_d(x,y)$; $\Delta n_o^{'}$ et $\Delta n_d^{'}$ are the average intensities of Δn_o et Δn_d respectively
ENL	ENL is a metric used to evaluate the suppression of speckle noise in homogeneous regions of the image. It is derived by taking the ratio between the mean square and the variance of a homogeneous region. A good speckle reduction filter is obtained when the value of the ENL parameter is high.	$ENL = \frac{\mu_{RI}^2}{\sigma_{RI}^2}$ μ_{RI}^2 and σ_{RI}^2 represent respectively the mean and the standard deviation of the region of interest (RI) of the image
SMPI	This parameter is used to accurately measure speckle denoising performance. In addition, the denoising performance is high when the SMPI value is low.	$SMPI = Q \cdot \frac{\sigma_d}{\sigma_o} = 1 + \lvert mean(o) - mean(d)\rvert \cdot \frac{\sigma_d}{\sigma_o}$ o and d are respectively the original image and the denoised image σ_d and σ_o are respectively the standard deviation of the denoised image and the standard deviation of the original image
CoC	The correlation coefficient is a parameter which makes it possible to measure the degree of similarity between two images (the reference image and the denoised image of the speckle). Its values vary between 0 and 1. For different images its value is 0 and for similar images it is 1	$CoC = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(X_{i,j}-\overline{X}_{i,j}\right)\left(X_{i,j}^{'}-\overline{X}_{i,j}^{'}\right)}{\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(X_{i,j}-\overline{X}_{i,j}\right)^2\sum_{i=1}^{M}\sum_{j=1}^{N}\left(X_{i,j}^{'}-\overline{X}_{i,j}^{'}\right)^2}}$ $\overline{X}$ and $\overline{X}^{'}$ are respectively the averages of the original and denoised images
SSI	The SSI parameter also called speckle suppression index is a parameter used to indicate the amount of speckle removed in an image. When its value is less than 1, the filter used is said to be effective	$SSI = \frac{\sigma_d}{mean(d)} \cdot \frac{mean(o)}{\sigma_o}$ o and d are respectively the original image and the denoised (filtered) image σ_d and σ_o are respectively the standard deviation of the denoised image and the standard deviation of the original image $mean(o)$ and $mean(d)$ are respectively the average of the original image and the average of the denoised image.
PSNR	PSNR is one of the most used techniques to evaluate the amount of noise that corrupts an image. It allows you to estimate the quality of a reconstructed image compared to the original	$PSNR = 20log_{10}\left(\frac{M^2}{MSE}\right) = 20log_{10}(M) - 20log_{10}(MSE)$ M represents the maximum number of pixels in the image and MSE represents the mean square error
Processing time	Processing or calculation time is expressed in terms of microprocessor processing time. This parameter is expressed in seconds. It is calculated from the start to the end of the program. The lower it is, the less complex the algorithm and the better it is.	
The visual appearance	It is a qualitative parameter which allows us to visually assess the ultrasound images resulting from filtering.	
The opinion of an expert in the field	It is a qualitative parameter that allows an expert in the field to give his opinion regarding the results of the image filtering carried out.	

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V. WAVELET-BASED IMAGE FILTERING METHODS: STATE OF THE ART

In this section, we set out to review the different image filtering methods. We have summarized them in the table below. Related works are compared in terms of methods, wavelet types, mother wavelets, decomposition number, performance metrics, type and number of test images, noise variance, and noise type.

TABLE III

WAVELET-BASED IMAGE FILTERING METHODS: STATE OF THE ART

References	*Method(s) used*	*Types of wavelets*	*Mother wavelets*	*Number of decomposition*	*Performance Metrics*	*Type / Number of test images*	*Noise Variance*
[34]	Combination of discrete wavelet transform and mean and median filters	Discrete wavelet transform	Haar, Daubechies, Biorthogonal, Coiflet and Symlet	No indication	PSNR and MSE	IRM /1	0.01 ,0.02, 0.04, 0.0, 0.08
[23]	Dual-tree, dual-density discrete wavelet transform combined with soft thresholding	Dual-tree, dual-density discrete wavelet transform	Daubechies	No indication	PSNR and RMSE	Standards (Lena, Peppers and Mandrill) and ultrasound / 4	15
[35]	Combination of discrete wavelet transform and cascade clustering and pyramid transform	Discrete wavelet transform	No indication	1	PSNR, SSIM, UQI, FSIM, EPI, treatment time and opinions of medical experts	24	2,3,4,0.2,0.4,0.6, 0.8
[36]	Discrete wavelet transform combined with soft and hard thresholding	Discrete wavelet transform	Haar, db4, sym4 and coif4	2, 3 and 4	MSE and PSNR	CT scans / multiple from the ELCAP database	10,20,30, 50
[37]	Discrete wavelet transform associated with median and wiener filters	Discrete wavelet transform	Haar and Daubechies	No indication	PSNR and MSE	Ultrasound / 1	No indication
[38]	Undecimated wavelet transform	Undecimated wavelet transform	No indication	No indication	SNR and visual appearance	Ultrasound /2	18
[8]	Discrete wavelet transform associated with the median filter	Discrete wavelet transform	No indication	No indication	PSNR, MSE and SSIM	Médical/ 30	0.01,0.02,0.03,0.04,0.05;0.06,0.07,008,0.09, 0.1

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[39]	Combination of discrete wavelet transform and SRAD, GDGIF and WGIF filters	Discrete wavelet transform	bior, coif, db, dmey, sym, haar, and rbio	2	PSNR, SSIM, ENL, SMPI and processing time	Ultrasound/12	0.04
[40]	Discrete wavelet transform associated with soft threshold and TV(Total Variation)	Discrete wavelet transform	Db8	1	PSNR, SNR, CoC, MSE, RMSE, SSIN	Ultrasound /8	0.05
[28]	Wavelet transform associated with VisuShrink thresholding and Wiener filter	No indication	Haar, Bior, Symlet and coif	1 and 2	PSNR and MSE	Standards(cameraman and lena) / 2	5, 10
[41]	Discrete wavelet transform associated with adaptive thresholding and median filter	Discrete wavelet transform	No indication	2	PSNR	Standards(barbara and lena) / 2	0.05
[42]	Wavelet transform associated with median filter	Discrete wavelet transform	No indication	No indication	PSNR	Standard (lena) / 1	0.01, 0.05, 0.1,0.15,0.2,0.25,0.30, 0.40
[43]	Wavelet transform associated with median filter and BayesShrink thresholding	No indication	No indication	No indication	PSNR, MSE, BER and time processing	Standard(montagne)/1	15
[44]	Discrete wavelet transform associated with BayesShrink, VisuShrink and SureShrink thresholding	Discrete wavelet transform	No indication	No indication	PSNR, MSE, visual appearance and processing time	Standard(desert, koala, penguins, hydrangeas and chrysanthemum)/ 5	No indication
[22]	Dual-density dual-tree discrete wavelet transform	Dual-density dual-tree discrete wavelet transform	No indication	No indication	PSNR and MSE	Standards (lena and stonehenge) /2	10,20,30,40,50, 60,70,80,90, 100
[45]	Discrete wavelet transform associated with the SRAD filter	Discrete wavelet transform	No indication	1	PSNR, RMSE and SSI	Standards (Cameraman, House and Lena) andUltrasound /5	0.3, 0.35, 0.4
[46]	Discrete wavelet transform associated with thresholding Visushrink, Bayesshrink, Sureshrink, Smoothshrink, Neighshrink and Neighshrinksure	Discrete wavelet transform	db8	1	PSNR, CoC and EPI	Ultrasound / 2	0.02, 0.03, 0.04, 0.05, 0.06, 0.07
[47]	Complex dual-tree wavelet transform associated with bivariate shrinkage	Complex double-tree wavelet transform	No indication	No indication	PSNR and MSE	Ultrasound / 2	0.02, 0.03, 0.04

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[48]	Combination of discrete wavelet transform and 4th order PDE based on anisotropic diffusion, SRAD filter and (soft) BayesShrink thresholding	Discrete wavelet transform	No indication	1	Processing time and PSNR	Ultrasound /1	No indication
[49]	Discrete wavelet transform associated with a new thresholding function	Discrete wavelet transform	biorthogonal, daubechies, symlets, and coiflets	3	PSNR and SSI	Ultrasound/50	0.01,0.02,0.04,0.06,0.08,0.1,0.12,0.14, 0.16, 0.18, 0.2
[50]	Discrete wavelet transform associated with a new thresholding function	Discrete wavelet transform	biorthogonal, daubechies, symlets and coiflets	2	an expert's opinion, MSE, PSNR, EKI and SSIM	Ultrasound/4	0.01, 0.02, 0.03, 0.04
[51]	rationally dilated wavelet transform associated with a nonlinear bilateral filter	rationally expanded wavelet transform	No indication	4	MSE, PSNR, IQI, FSIM and SSIM	Ultrasound /5	10,20, 30
[52]	Haar wavelet associated with the fractional filter	Wavelet transform based on fractional calculation	Haar	No indication	PSNR	Standards(Lena, building, cameraman, boat)/4	10,20, 30
[53]	Discrete wavelet transform associated with the median filter based on the Raspberry Pi embedded system	Discrete wavelet transform	Haar	No indication	MSE, PSNR	Standards(Lena, Cameraman, Barbara, Pepper,)/4	10,15,20,25,50, 100
[54]	Thresholding (visushrink, bayesshrink and sureshrink) based on the discrete wavelet transform	Discrete wavelet transform	Haar, db1, db2, db3 and bio3.7	2	PSNR	Lena/1	0.01, 0.02, 0.05, 0.08, 0.1
[55]	Thresholding (Bayesshrink and Neighshrink) based on discrete wavelet transform	Discrete wavelet transform	Db4, sym4 and coif4	No indication	PSNR andMSE	Standards(Lena, barbara and house)/3	10,15,20,25,30, 35,40,45, 50
[56]	Discrete wavelet transform based on an unsupervised learning model	Discrete wavelet transform	Coif and sym	2	PSNR, SSIM and visual aspect	Standars(Barbara, house, flinstones, fingerprint and bridge)/5	10,25,50,70, 100
[57]	Wavelet thresholding associated with the pre-Gaussian filter	Discrete wavelet transform	Haar	2	PSNR	Standards(Cameraman, Lena, Astronaut and Cat)/5	0.05,0.20,0.30, 0.50

In order to make an easy and efficient comparison of the different works mentioned above, we note the authors who used the same image dataset (*cameraman* image) and the same performance metrics (PSNR). The table below illustrates this collection of information.

TABLE IV
WAVELET-BASED IMAGE FILTERING METHODS WITH THE SAME DATASET

References	Method(s) used	Types of wavelets	Mother wavelets	Number of decomposition	Performance Metrics (PSNR in dB)	Noise Variance/ noise type
[28]	Wavelet transform associated with VisuShrink thresholding and Wiener filter	No indication	Haar, Bior, Symlet et coif	1 and 2	27.5124	5/ Speckle noise
[39]	Combination of discrete wavelet transform and SRAD, GDGIF and WGIF filters	Discrete wavelet transform	bior, coif, db, dmey, sym, haar, et rbio	2	26.4681	0.04/ Speckle noise
[52]	Haar wavelet associated with the fractional filter	Wavelet transform based on fractional calculation	Haar	No indication	24.61	10/ Gaussian noise
[53]	Discrete wavelet transform associated with median filter based on the Raspberry Pi embedded system	Discrete wavelet transform	Haar	No indication	45.4153470	10/Gaussian noise
[45]	Discrete wavelet transform associated with the SRAD filter	Discrete wavelet transform	No indication	1	30.172	0.3/Speckle noise
[57]	Wavelet thresholding associated with the pre-Gaussian filter	Discrete wavelet transform	Haar	2	22.38	0.05/ Gaussian noise

VI. DISCUSSION

In the study on wavelet-based ultrasound image filtering methods, the authors agree on one point: the wavelet transform is a tool that can considerably improve the quality of a filter. It effectively reduces speckle noise. In addition, to further multiply the performance of the wavelet transform, the authors performed various combinations. They combined the wavelet transform with other filtering methods. Combinations of metrics were also carried out in order to effectively evaluate the performance of the filter developed. From the point of view of the wavelet type, the discrete wavelet transform is the one that has been used the most by the authors, this could be due to the fact that it is the simplest and easiest wavelet transform to implement, but also because there is a strong literature on this subject. Furthermore, some authors such as article in [22] and in [23] implemented another type of wavelet transform named dual-density dual-tree discrete wavelet transform. This choice is probably due to the fact that this transform combines the characteristics of two wavelet transforms: the dual-tree discrete wavelet transform and the dual-density discrete wavelet transform.

In addition, [47] used the complex double-tree transform for its ability to offer decomposition in six possible directions. Also, although little illustrated in the literature, the non-decimated wavelet transform was implemented by [38]. We can justify this choice by the fact that this transform has an advantage over the others: it removes noise only in the places where it is found.

From the point of view of the mother wavelet used, [28], [34], [36], [37], [39], [49], [50] tested several mother wavelets in order to detect the most effective one. Other authors like [23], [40] and [46] directly implemented the mother wavelet based on its efficiency mentioned in previous works. All these authors have chosen the Daubechies wavelet in general. As for the particularity, the db4 and db8 wavelets are the most used. This is due to the fact that they are the basis of most mother wavelets (coifflets, symlets) but also because they produce better results. As for the decomposition number, the work presented allows us to note that this number can range from 1 to 4. However, no justification for the choice of the decomposition number was mentioned by the authors. In our opinion, this choice is influenced by several parameters including the characteristics of the image and the type of wavelet transform used.

Regarding performance metrics, we noted several that we were able to group into two groups: qualitative metrics and quantitative metrics. While the authors [8], [39], [43], [22], [23], [28], [34], [36], [37], [40]–[42], [45]–[49] and [51] only use quantitative metrics of other authors like [12], [38], [44] and [50] used both qualitative and quantitative metrics. We share the order of thought of [12,38,44,50] because qualitative metrics allow on the one hand to appreciate the visual quality of the image. Indeed, the final goal of filtering being to make the image easy to analyze, it is however essential that it be visually free of noise. Knowing that the filtering process can affect the visual quality of the final image. On the other hand, this allows us to have the opinion of experts in the field because it is the final target of this study. In order to improve the visual quality of the image, some authors such as [35] after filtering proposed a method for improving the visual quality of the image. Note that filtering does not always mean that a perfect image will be obtained because this process can somewhat alter the visual quality of the image, most often a blurring effect is observed. To this end, when engaging in a filtering process, an image improvement step should be considered in order to perfect the filtering.

A. Discussion Summary

In order to objectively assess the different filtering methods encountered in the literature, we noted the works whose authors validated the results using the same image dataset and the same performance metrics. To this end, we noted that most of the work was tested using standard images such as: Lena, cameraman, barbara, house, boat and peppers. Additionally, the metric common to all is PSNR. Considering the value of this parameter as a gauge for assessing the quality of the proposed filtering method, we note that the method proposed by [53] is the best because it presents the highest value with a PSNR=45.4153470 dB. This value is obtained by using the cameraman image corrupted with Gaussian noise with a noise level of $\sigma = 10$. We therefore retain that the use of the discrete wavelet transform (with the Haar wavelet as the mother wavelet) associated with the median filter is the best combination for developing a filtering method. Considering that there are more sophisticated types of wavelets and mother wavelets than the discrete wavelet transform and the Haar wavelet, could their use not further improve the value of the PSNR parameter? Also, there are other filters more efficient than the median filter with which said wavelet transforms could be associated. Since it has been proven that the combination or association of wavelet transform with other filtering methods is the best formula to use in order to develop an effective filter.

VII. CONCLUSIONS

In this paper, several existing works on filtering methods were compared using the quantitative PSNR metric. It appears that the best method for effective filtering is the combination of the discrete wavelet transform and the median filter. In general, it appears that a wavelet-based filtering method produces excellent results when the wavelet transform is combined with other filtering methods. This combination makes it possible to pool the advantages of the methods used but also to minimize their disadvantages. However, the result depends on certain parameters: the type of transform used, the mother wavelet, the number of decomposition and the type of combination carried out.

Thus, it is essential to choose these different parameters judiciously and effectively in order to perfect the filter developed. Ultimately, the comparisons carried out in this work on the different image filtering methods based on wavelets allow the reader to decide on the choice of the effective method to adopt when investing in image filtering. It would be interesting to set up an intelligent system that would help the reader in their decision-making.

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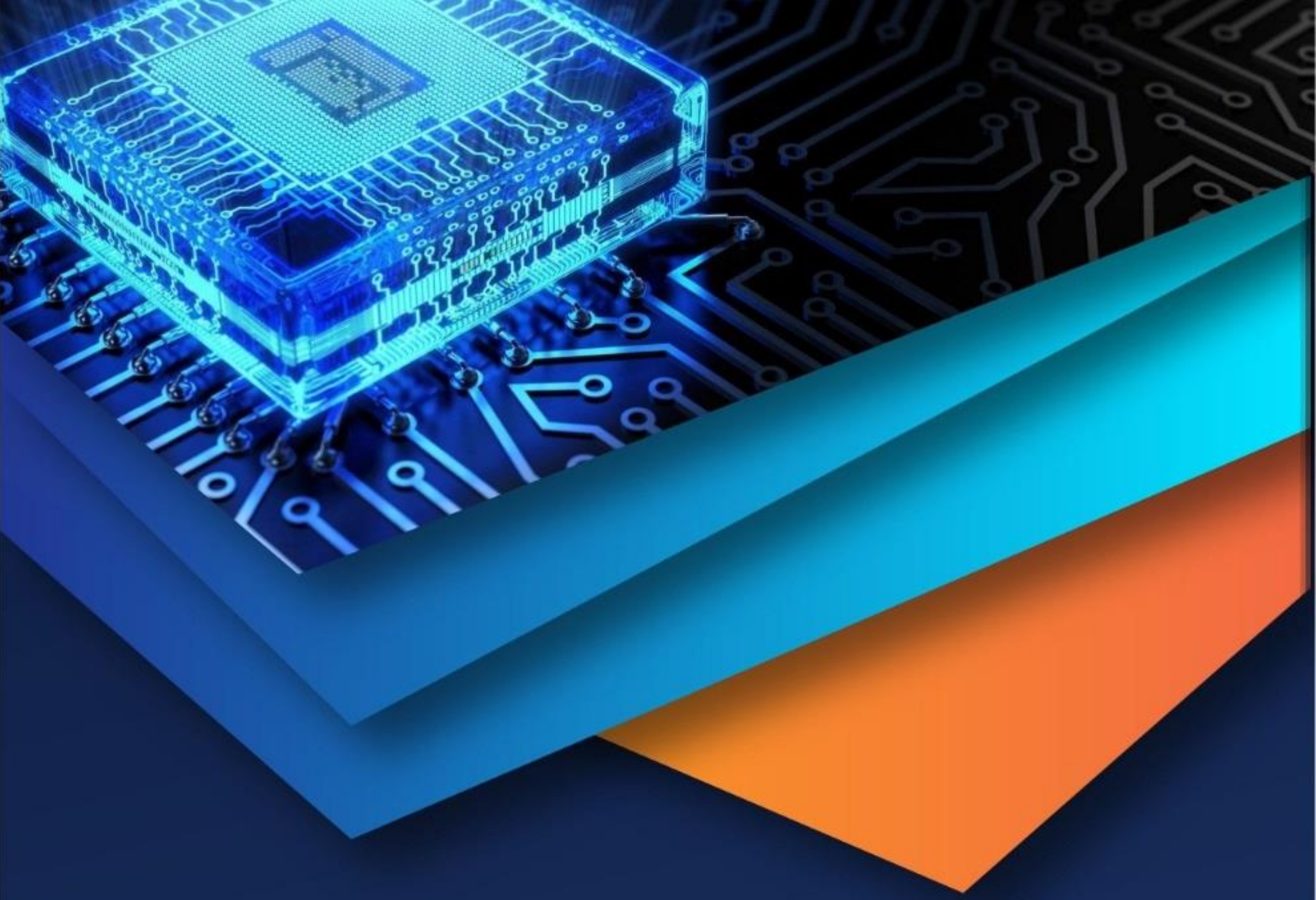

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