Inter-scale wavelet analysis for speckle reduction in thyroid ultrasound images

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Abstract

A wavelet-based method for speckle suppression in ultrasound images of the thyroid gland is introduced. The classification of image pixels as speckle or part of important image structures is accomplished within the framework of back-propagation tracking and singularity detection of wavelet transform modulus maxima, derived from inter-scale analysis. A comparative study with other de-speckling techniques, employing quantitative indices, demonstrated that our method achieved superior speckle reduction performance and edge preservation properties. Moreover, a questionnaire regarding qualitative imaging parameters, emanating from various visual observations, was employed by two experienced physicians in order to evaluate the algorithm’s speckle suppression efficiency.

Keywords: Thyroid nodules; Ultrasound images; Speckle reduction; Local maxima; Coarse to fine; Singularity detection

1. Introduction

Nowadays, contemporary ultrasound (US) systems have gained the medical community’s confidence among other imaging modalities such as computed tomography, magnetic resonance, γ-camera. US systems have accomplished an excellent trade off between image quality, low cost, portability and lack of any form of radiation. Ultrasonography is employed by many medical specialities, such as Ob/Gyn, Pathology, Cardiology and Endocrinology. In the latter, ultrasonic scanning of the thyroid gland constitutes an important procedure in assessing the thyroid malignancy risk factor. High resolution ultrasonography can detect several characteristics that can be employed as criteria in the differentiation between malignant and benign nodules. Such criteria include margin, shape, echo structure, echogenicity and the presence of calcifications [1]. Accurate estimation of thyroid malignancy risk factor by US may be regarded as a crucial factor in the reduction of unnecessary surgical interventions.

Despite the profound advantages of ultrasonography, US images carry a granular pattern, so called speckle, which constitutes a major image quality degradation factor. Speckle pattern is created when an ultrasonic wave with uniform intensity is incident either on a rough surface or on tissue particles that are spaced at less than the axial resolving distance of the US system. In that case, the reflection beam profile will not have a uniform intensity. Instead it will be composed of many regions with strong and weak intensities. This complex intensity profile arises because sound is reflected in many different directions from the rough surface or from the small scatterers, thus leading US waves that have travelled different scan lines to interfere constructively and destructively towards the ultrasonic transducer. The intensity fluctuations within a uniform anatomic area, caused by the above phenomenon, constitute speckle. The resulting degraded by speckle US image does not correspond to the actual tissue microstructure. In fact, speckle noise deteriorates image quality, fine details and edge definition. Speckle also tends to mask the presence of low-contrast lesions, therefore reducing the physician’s ability for accurate interpretation. Moreover, it constitutes a limiting factor in the performance of quantitative procedures such as segmentation and pattern recognition algorithms. Hence, effective speckle suppression is considered of
value as a pre-processing step towards an efficient segmentation [2] as well as an efficient tool for improving US image quality and possibly the diagnostic potential of medical ultrasound imaging.

A variety of speckle reduction techniques have been implemented in the past two decades. Part of them reduce speckle by acquiring the radio frequency (RF) pulse echo signals from the US devices directly after log compression and time gain compensation (TGC) and before scan conversion [3]. However, access to raw RF data [4] in our US scanner was not possible due to software unavailability by the manufacturer.

In the early years of computer image processing speckle removal in US images was achieved via simple averaging, median filtering and Wiener filtering. Simple averaging not only failed to eliminate speckle but introduced blurring and edge loss in areas where anatomical boundaries prevail. Median filtering enhances edges and speckle indiscriminately, while Wiener filter manages to remove considerable amounts of speckle but also tends to over-smooth the boundaries of important image features. Various adaptive filters based on local statistics, such as mean and variance, have been implemented for noise reduction not solely in medical imaging but for image denoising in general. As the computing technology boosted during the 1990s, along with the processors speed and power, new and more complicated filters were introduced. They were employed mainly in time domain such as the adaptive speckle suppression by Karaman et al. [5], the symmetrical speckle reduction filter by Huang et al. [6] and the diffusion stick model by Xiao et al. [7].

Karaman’s method introduced a non-linear adaptive filter employing some local statistics such as the ratio of $\sigma^2/m$ where $\sigma$, $m$ are the local variance and mean inside a moving window with pre-specified dimensions. The filter was transformed into a mean filter or a median depending on an estimated homogeneity criterion inside the window. Huang divided his filtering strategy based on the slope facet model in two stages: firstly he introduced two criteria in the region growing process to approximate the largest despeckling window within an $11 \times 11$ matrix. The first is the widely used variance to mean criterion and the second is the gradient criterion. In the second stage after the major removal of speckle he used only the gradient criterion for the final noise elimination. In both stages the filter acts generally as a common mean filter.

Xiao exhibits an interesting oriented filter with 24 asymmetrical diffusion sticks inside a symmetric moving matrix. Through a variation function applied in every stick, the algorithm smooths the sticks with high homogeneity and penalizes smoothing within heterogeneous regions. The smoothing function comprised the weighted sum of averages along each stick. For optimization of the results the whole filtering process is done iteratively. The empirical choice of some parameters such as window size, weight calculation, homogeneity criterion or various thresholds employed of the above mentioned methods degraded their generalization ability thus made them US machine and anatomical region depended.

Throughout the last decade a new approach in US images denoising emerged based on the wavelet transform. Some of the wavelet-based proposed methods for US image despeckling, the multiscale non-linear processing method by Hao et al. [8], and the Bayesian wavelet method by Achim et al. [9]. Hao combined a non-linear adaptive filter and the wavelet transform shrinkage. Initially, he divided the image via the adaptive-weighted median filter in two parts that approximate signal and noise. These two parts are decomposed through the wavelet transform and a modification of Donoho’s soft thresholding [10] is used to remove speckle. The final denoised image is the sum of the two reconstructed image parts, into which the original image was split in the first stage. This method mainly adopts the denoising thresholding procedure presented by Donoho in which all thresholds are calculated empirically and in an ad hoc manner without taking into account the special statistical properties of speckle.

Achim in his attempt to overcome the limitations arising from empirical thresholding of wavelet coefficients employed a Bayesian approach for signal extraction and speckle suppression. The log-transformed US image was decomposed in different frequency scales via the wavelet transform. In each scale a Bayesian estimator is used, based on symmetric alpha stable distribution of the wavelet decomposition, to differentiate the signal coefficients from the noise coefficients.

Besides US images, speckle dominates Synthetic Aperture Radar (SAR) images as well, introducing difficulties on their correct interpretation. Various attempts are made in the wavelet domain in order to efficiently reduce the resulting granular pattern. Sveinsson and Benediktsson [11] via orthogonal wavelet transform applied soft thresholding on the wavelet coefficients to reduce the presence of speckle. The aforementioned wavelet-based approach used the logarithmic transform to convert the multiplicative model of speckle into additive model with signal-independent noise before performing the speckle reduction method. After that, an exponential transform is applied to convert the denoised image to its original format. The fact that the mean of the log transformed speckle noise is not zero, whereas additive white Gaussian noise (AWGN) is considered with zero mean from the above methods, led to the need of a correction step regarding the mean bias in the processing stages, to avoid distortion in the despeckled image [12].

Several recent studies avoid the log transform and directly apply the wavelet transform onto the SAR images. Foucher et al. [13] in order to discriminate reflectivity coefficients from speckle coefficients implemented a Bayesian analysis based on the Pearson system for probability density function (pdf) approximation of the wavelet coefficients.

An efficient discrimination between speckle noise and reflected signal in US or SAR images either in time or wavelet domain is still under discussion in the scientific society. As already mentioned an accurate despeckling algorithm is very important in the decision making process especially in US images of the thyroid gland. Often, thyroid nodules, which play the most important role in estimating the malignancy risk factor, are of low contrast in a noisy background. Likewise the presence of various structures inside the nodules comprises a critical factor for a proper interpretation of the US image. The dominating speckle noise in all US images can lead to misleading analysis thus obstructing the physician’s diagnosis.
A wavelet-based method is introduced in this paper for efficient speckle suppression in sonographic images of the thyroid gland while important edges and boundaries are preserved. The proposed wavelet approach avoids both log and exponential transform, considering the fully developed speckle as additive signal-dependent noise with zero mean. The proposed method throughout the wavelet transform has the capacity to combine the information at different frequency bands and accurately measure the local regularity of image features. The inter-scale information is acquired by means of a coarse to fine connectivity of the wavelet transform modulus maxima (WTMM). Two structures, represented by the modulus maxima, in two consecutive scales belong to the same anatomic area if the pair ‘position and angle’ pixel of the maximum wavelet coefficient value in the upper scale is also approximately present in the lower scale. The decay across scales of wavelet transform maxima is related to local regularity of these structures and is assessed by the Lipschitz exponent $\alpha$ [14]. The purpose of the present article is to employ the knowledge given from the evolution of the wavelet transform maxima across scales to discriminate image singularities from speckle singularities.

The paper is organized as follows: in Section 2 the speckle model adopted by this study is presented. In Section 3 we describe the proposed strategy based on the inter-scale wavelet analysis for characterizing an image’s variation from Lipschitz exponents employing the local regularity of US image. In Section 4 the quantitative results regarding the speckle removal efficiency and edge preserving are compared to that of current speckle suppressing methods. Moreover 63 US images of the thyroid gland are subjected to review by 2 experienced observers via questionnaire for qualitative evaluation of the proposed despeckling process. In Section 5 we conclude the methods and results of this research. The primary steps of the proposed method are illustrated in Fig. 1.

2. Speckle model

The speckle model employed in the despeckling strategies in time domain [5–7] considers the envelope detected RF signal having a Rayleigh distribution, thus speckle can be considered as multiplicative noise. However, due to US device’s undergoing signal processing stages, the finally formatted US image speckle is no longer multiplicative and can be thought as Gaussian additive noise independent of the noise-free signal. Most wavelet-based methods, adapted for additive Gaussian white noise, applied a logarithmic transform in the speckle image and approximated speckle as additive noise.

The proposed method adopted Foucher’s et al. [13] approach, by omitting the log-transform to avoid the mean bias correction problem and decomposing the multiplicative speckle model into an additive signal dependent noise model.

The multiplicative speckle model at pixel position $[x,y]$ is expressed in the following form:

$$I(x, y) = f(x, y) \cdot r(x, y)$$  \hspace{1cm} (1)

where $f(x,y)$ is an unknown 2d function, such as the original image to be recovered without noise. $I(x,y)$ is the corrupted with noise formatted US image, and $r(x,y)$ a random variable that represents speckle. We consider speckle as fully developed (large number of small scatterers in each resolution cell) whose magnitude follows the Rayleigh pdf [15]:

$$p_r(r) = \frac{\pi r^2}{2} \exp \left(-\frac{\pi r^2}{4}\right), \quad r \geq 0$$  \hspace{1cm} (2)

Its mean and variance are [17]:

$$E(r) = 1, \quad \text{var}(r) = \frac{4}{\pi} - 1$$  \hspace{1cm} (3)

We convert the multiplicative model into an additive model:

$$I(x, y) = f(x, y) + f(x, y)[r(x, y) - 1] = f(x, y) + N_\sigma(x, y)$$  \hspace{1cm} (4)

where $[r(x, y) - 1]$ is a random variable with zero mean and variance $\sigma^2$. $N_\sigma(x,y)$ represents an additive signal dependent noise term, which is proportional to the signal to be estimated.

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**Fig. 1.** Block diagram of the proposed wavelet-based algorithm for speckle suppression.
3. Inter-scale wavelet analysis

3.1. Dyadic wavelet transform

Employing wavelet theory, the correlation of the inter-scale edge information may be applied to characterize different types of edges. Wavelet analysis was performed by means of the Dyadic Wavelet Transform (DWT) introduced by Mallat and Zong [16] for characterization of signals from multiscale edges. DWT is based on a wavelet function $\psi(x)$ with compact support, which is the first order derivative of cubic spline function. The wavelet decomposition across scales of the original image was implemented with a filter bank algorithm, so called ‘algorithme a trous’ (algorithm with holes). The proposed transform is in fact a fast biorthogonal discrete wavelet transform, in which the size of the decomposed subband images is the same as that of the original image thus making the transform highly redundant.

Let $\theta(x,y)$ be a symmetrical smoothing function approximating the Gaussian. The two-dimensional Dyadic Wavelet Transform of a function $f(x,y) \in L^2(\mathbb{R}^2)$ is the set of functions $(W^1_{2^j} f(x,y), W^2_{2^j} f(x,y))$, which are, respectively, the partial derivative along the horizontal and vertical orientation of the convolution of $f(x,y)$ with the smoothing function $\theta(x,y)$ dilated along a dyadic sequence $(2^j)_{j \in \mathbb{Z}}$. The DWT is given by:

$$\begin{pmatrix} W^1_{2^j} f(x,y) \\ W^2_{2^j} f(x,y) \end{pmatrix} = f \ast \begin{pmatrix} \psi^1_{2^j} \\ \psi^2_{2^j} \end{pmatrix} = 2^j \begin{pmatrix} \partial_x (f \times \theta_{2^j})(x,y) \\ \partial_y (f \times \theta_{2^j})(x,y) \end{pmatrix}$$

where $\psi^1(x,y)$ and $\psi^2(x,y)$ are the analyzing wavelets and $j$ the dyadic scale.

We performed the dyadic wavelet transform using Mallat’s filters. These filters are suitable for fast implementation of discrete algorithms and they offer exact reconstruction. At a dyadic scale $j$ the dilation of the discrete filters is obtained by inserting $(2^j - 1)$ zeros (holes) between each of the coefficients of the corresponding filters. The redundant wavelet transform presented in this paper is in fact shift-invariant and it is widely used for pattern recognition, feature extraction and edge detection purposes.

The wavelet coefficients comprise the intensity profile of an image’s local variations for a given scale. They can be considered as a classification map in which any kind of change (abrupt or smooth) exist in an image can be localized on a particular scale. The latter conclusion indicates the importance of an accurate selection of the dyadic scale $j$ in which the image will be decomposed. The choice of that scale is in fact a trade off between the suppression of wavelet coefficients characterizing image’s irregularities and the blurring effect caused by the dilation of the smoothing function. In small scales the wavelet coefficients mostly characterize high frequency events mainly caused by noise. In bigger scales low frequency events are detected such as smooth image variations.

3.2. Gradient vector

Eq. (5) indicates that the above set of functions can be viewed as the two components of the gradient vector of $f(x,y)$ smoothed by $\theta(x,y)$ at each scale $2^j$:

$$\begin{pmatrix} W^1_{2^j} f(x,y) \\ W^2_{2^j} f(x,y) \end{pmatrix} = 2^j \cdot \nabla(f \times \theta_{2^j})(x,y)$$

The modulus-angle representation of the gradient vector is given by:

$$M_{2^j} f(x,y) = \sqrt{|W^1_{2^j} f(x,y)|^2 + |W^2_{2^j} f(x,y)|^2}$$

and

$$A_{2^j} f(x,y) = \arctan \frac{W^1_{2^j} f(x,y)}{W^2_{2^j} f(x,y)}$$

3.3. Modulus maxima

The sharper variation points of $f \times \theta_{2^j}(x,y)$ at a scale $2^j$ correspond to edges, are obtained from the local maxima of $M_{2^j} f(x,y)$ along the gradient direction given by $A_{2^j} f(x,y)$. The gradient direction values $A_{2^j} f(x,y)$ were constricted to the following values:

$$\{0, \frac{\pi}{4}, \frac{\pi}{2}, \frac{3\pi}{4}, \pi, \frac{2\pi}{3}, \frac{3\pi}{2}, \frac{5\pi}{3}, \frac{3\pi}{2}, \frac{5\pi}{2} \}$$

At each scale $2^j$ of the Dyadic Wavelet Transform, the point $(x,y)$ where the modulus of the gradient vector $M_{2^j} f(x,y)$ is maximum compared with its neighbour’s locally positioned in the direction specified by $A_{2^j} f(x,y)$, is called modulus maxima. Each time such a point is detected, the position of the resultant local maxima is recorded as well together with the values of the modulus $M_{2^j} f(x,y)$ and angle $A_{2^j} f(x,y)$ at the corresponding locations.

3.4. Lipschitz regularity

The aim of the present study is to efficiently characterize the image’s singularities, via an inter-scale wavelet analysis, in order to discriminate speckle-noise from signal. The classification of singularities depends upon their local regularity. This regularity is quantified by Lipschitz exponents [14]. A function $f(x,y)$ is said to be Lipschitz $\alpha$, $0 \leq \alpha \leq 1$, at $(x_0,y_0)$ if there exists $K>0$ such that for all points $(x, y) \in \mathbb{R}^2$,

$$|f(x,y) - f(x_0, y_0)| \leq K(|x-x_0|^{\alpha} + |y-y_0|^{\alpha})$$

If there exists a constant $K>0$ such that Eq. (9) is satisfied for any $(x_0,y_0) \in \Omega$, then $f$ is uniformly Lipschitz $\alpha$ over $\Omega$. The larger the $\alpha$, the more regular is the function. The Lipschitz regularity of a function $f(x,y)$ is related to the asymptotic decay from coarse to fine scales of its wavelet transform along horizontal and vertical directions $|W^1 f(u, v, s)|$ and $|W^2 f(u, v, s)|$ in the corresponding neighbourhood. This decay is controlled by the wavelet transform local maximum value $Mf(u, v, s)$ [17].
A function \( f(x,y) \) is uniformly Lipschitz \( \alpha \), \( 0 \leq \alpha \leq 1 \) inside a bounded domain of \( \mathbb{R}^2 \) if and only if there exists a constant \( A > 0 \) such that for all \( (u, v) \) inside this domain and for any dyadic scale \( s \) relation 10 holds:

\[
|Mf(u, v, s)| \leq A2^{\alpha s + 1}
\]  

By measuring from Eq. (10) the Lipschitz exponent \( \alpha \) through the computation of the decay slope of \( \log_2|Mf(u, v, s)| \) we derive an estimate of the Lipschitz regularity along the edge.

3.5. Detection of singularities

All singularities of \( f(x,y) \) can be located by following the wavelet transform modulus maxima up to the finer scale. The terms coarse and fine are relative. Conventionally, coarse scales are referred to bigger dyadic scales \( (2^j, 2^{j+1}) \), whereas fine scales are referred to smaller dyadic scales \( (2^j, 2^{j+2}) \). The main objective of that inter-scale analysis is to isolate different structures exist in the image, beginning at a coarse scale and adaptively decrease the scale to gather the necessary details. If an edge appears in a coarser level \( 2^j \), it should also appear in finer level \( 2^{j+1} \). The latter can be rephrased that any wavelet transform modulus maximum at a coarse scale belongs to a connected inter-scale chain that is never interrupted when the scale decreases [17], which in turn means that any structure – represented by the corresponding maxima – is located in a coarse scale can also be found in a finer scale with an approximate position and angle value.

Mallat and Hwang [14] Mallat and Zhong [16] implements the maxima chaining procedure starting from a scale \( 2^j \) and considers that it propagates to coarser scale \( 2^{j+1} \) having similar position and angle values. In this study the forming of maxima chains in the scale-space domain is made with a back-propagation approach starting the inter-scale connectivity from the coarser scale \( (2^{j+3}) \) computed and complete it at the finer scale \( (2^j) \) available. With this approach the computational complexity of the implemented algorithm is reduced even more since we employ the inter-scale exhaustive search with the smaller possible number of local maxima (as the scale increases the number of local maxima decreases).

Before we apply this back-propagation tracking of modulus maxima in wavelet space, the majority of some false maxima at the coarser scale \( (2^j) \) – that either are not suppressed by the smoothing function or created by numerical errors in regions where the wavelet transform is close to zero – are removed through a simple 70th percentile thresholding (all maxima values below the 70% of the maximum modulus value are discarded) [18]. The chaining of modulus maxima, after the thresholding procedure, across scales employs a two-folded inter-scale investigation based on the parameter pair: position–angle. Two modulus maxima at two successive scales \( (X_k, Y_k, M_k, A_k)2^j \), \( (X_k, Y_k, M_k, A_k)2^{j-1} \) are chained if they have a close position in the image plane \( (X_k, Y_k) \) and similar angle value \( (A_k) \). If a single coarse local maximum computed to back-propagate in more than one finer local maxima, only the one having the largest maximum \( (M_k) \) is considered to belong to the maxima chain.

The maxima matching between different scales was not an easy task. The position–angle investigation was implemented at each scale within a different neighbourhood taking into account the different size of the decomposition Mallat’s filter (different number of zeros ‘holes’ between the coefficients). The coarse information is traced within large neighbourhoods whereas the fine information in small neighbourhoods. The adaptively decreasing investigation window from coarse to fine scales avoids matching errors created either from small maxima groups that might not constitute an exact match or large maxima groups that may produce inaccurate inter-scale linking if the two successive structures are locally distorted. A square window of width \( K \) at a coarse resolution \( 2^j \) corresponds to square windows with approximate size of \( K/2 \) and \( K/4 \) at finer resolutions \( 2^{j-1} \) and \( 2^{j-2} \).

At each of the maxima chains, acquired from back-propagation tracking, the decay of the modulus maxima amplitude across scales is calculated in order to discriminate speckle singularities from image singularities. In maxima chains where the amplitude of the wavelet transform modulus maxima decreases when the scale decreases the Lipschitz regularity is positive (positive Lipschitz exponents). On the contrary, when the maxima amplitude increases when the scale decreases the Lipschitz regularity is negative (negative Lipschitz exponents). The Lipschitz regularity was calculated between those scales in which the amplitude of the decay slope was the greater. In our case was between the \( 2^3 \) and \( 2^2 \) scales. The different decay behavior of the modulus maxima is the main criterion in an accurate discrimination of image and noise singularities. Image singularities belong to regular curves with positive Lipschitz regularity that varies smoothly along these curves. Speckle singularities give rise to negative Lipschitz regularity and considered as irregular variations of the positions, angle and modulus values of the maxima.

The propagating maxima chains with positive Lipschitz regularity can be considered as an edge map that corresponds to important image structures. The despeckling procedure implemented in this article removes all wavelet coefficients at all scales that correspond to those maxima whose amplitude increase when the scale decreases or do not belong to a back-propagating maxima chain. The maxima recognized by the algorithm as speckle and as edges for all scales are presented in Fig. 2.

The remaining coefficients at all scales including the coarse image for completeness are utilized in the inverse Dyadic Wavelet Transform to obtain the speckle suppressed US image. The ability to isolate all important structures at all scales (Fig. 2, right column) via the proposed wavelet inter-scale analysis gave us the opportunity to perform the despeckling strategy (maxima removal) at all computed scales, even at the finer one \( (2^1) \), contrary to Mallat and Zhong [16] which avoids to incorporate that scale to his denoising procedure due to signal domination from noise. In our method as we can see in Fig. 2 (left column) although at the finer scale \( (2^1) \) available the human eye cannot discriminate the contours of the anatomical structures, after the back-propagation tracking and singularity detection, in the same scale these contours with approximate positions and angles became prominent.
3.6. Algorithm implementation

All the proposed method’s steps (i.e. redundant wavelet transform, multiscale edge representation, coarse to fine analysis together with the wavelet coefficient and maxima display) were all implemented in Matlab 6.5. The methods to which the proposed algorithm is compared with were also implemented and integrated with the same software packet. The computer used for processing has an AMD Athlon XP+ processor running at 1.8 GHz and 512 of RAM.

The ultrasound system used for this study was the HDI-3000 ATL digital ultrasound system with a broadband linear array with 7 MHz central frequency. The digitization of the output Video signal of the ultrasound system was made via the video card Micro PCTV (Pinnacle Systems), which is installed in a PC. US images are stored in JPEG format and their size is $768 \times 576 \times 8$.

4. Experimental results and evaluation

The effectiveness of the introduced wavelet-based de-speckling approach was tested using a tissue mimicking digital phantom and a US image of the thyroid gland. An observer evaluation study was also undertaken involving 63 US thyroid images of 63 patients via a questionnaire regarding the performance of the proposed algorithm. The proposed inter-scale wavelet analysis method was compared with three representative denoising methods: (a) Karaman’s adaptive speckle suppression filter
ASSF [5], (b) Donoho’s soft thresholding and (c) Donoho’s hard thresholding [10]. Wavelet shrinkage was implemented with Daubechies 8 mother wavelet in three decomposition scales, produced by the wavelet toolbox in matlab. The quantification of the speckle suppression performance of all methods (in both phantom and thyroid US image) was carried out by means of the speckle index (SI: mean to standard deviation), on a homogenous area with uniformly distributed echoes, and the signal-to-mean-square-error ratio ($S$/mse), introduced by Gagnon and Jouan [19], on the same homogenous area (local region of interest) and on the entire image (total).

$S$/mse is defined as:

$$S_{mse} = 10 \log_{10} \left( \frac{\sum_{i=1}^{K} I_i^2}{\sum_{i=1}^{K} (\hat{I}_i - I_i)^2} \right)$$  \hspace{1cm} (11)

where, $I$ is the intensity values of the speckle image, $\hat{I}$ the intensity values of the de-speckled image and $K$ is the image size. The $S$/mse index can be considered as an index of signal-to-noise within an image. High $S$/mse index values refer to efficient speckle suppression while low to inadequate performance. The $S$/mse index is expressed in dB.

The evaluation of the edge preservation capacity, both locally (area where boundaries prevail) and totally (entire image), of all methods was made by means of the parameter $\beta$, which has been introduced by Hao et al. [8] as shown in relation Eq. (12):

$$\beta = \frac{\Gamma(\Delta I - \Delta \hat{I}, \Delta I - \Delta \hat{I})}{\sqrt{\Gamma(\Delta I - \Delta \hat{I}, \Delta I - \Delta \hat{I}) \cdot \Gamma(\Delta \hat{I} - \Delta \hat{I}, \Delta \hat{I} - \Delta \hat{I})}}$$  \hspace{1cm} (12)

where $\Delta I$, $\Delta \hat{I}$ are speckle and de-speckled images, respectively, filtered by a $3 \times 3$ pixel standard approximation of the Laplacian operator, and $\Gamma$ is given by:

$$\Gamma(I_1, I_2) = \sum_{i=1}^{K} I_1^i - I_2^i$$  \hspace{1cm} (13)

In case of optimum edge preservation, $\beta$ approaches to 1. The closer the $\beta$ is to 1 the better are the edge preservation properties of each algorithm.

4.1. Tissue mimicking phantom validation

The phantom used in this study was the 403 LE model manufactured by GAMMEX. It comprises of three groups of three anechoic cystic targets (approximating thyroid nodules) with 2, 4 and 6 mm diameter positioned at 3, 8 and 14 cm, respectively. The attenuation coefficient for the tissue mimicking materials is 0.5 dB/cm/MHz whereas for the anechoic cysts is 0.05 dB/cm/MHz. Regarding the phantom image, the value of SI prior to despeckling was 6.18 and the values of SI, $S$/mse and $\beta$ after despeckling are shown in Table 1.

4.2. US image case study

All despeckling methods were also applied to an US image of the thyroid gland and their results are demonstrated in Fig. 3 and Table 2. The SI value prior to despeckling was 3.49. A more detailed description regarding despeckling and edge preservation may also be obtained by the profile signals of Fig. 4 obtained from Fig. 3.

4.3. Observer evaluation study

Sixty-three US images of the thyroid gland were included in a questionnaire that comprised seven queries concerning various visual observations regarding the proposed algorithm’s effectiveness. The image dataset was acquired following the same parameter’s protocol in the time interval from October 2003 to September 2004. The questionnaire was implemented in Microsoft Access. The seven queries were:
4. Preservation of nodules boundaries, resolvable details and anatomical structures.
5. Contrast enhancement between nodule and surrounding environment.
6. Revealing of small structures invisible in the original image.
7. Improvement of diagnostic evaluation procedure.

The study was performed by two experienced qualified radiologists specialized in ultrasonography. The reviewing of all cases was done independently on a high resolution monitor. The ranking for each query ranged from 0 to 100 with a 25-point step corresponding to fail (0), poor, good, very good and excel-

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<th>Observer B</th>
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<td>≥50</td>
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<td>Query 1</td>
<td>55 8</td>
<td>87</td>
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<tr>
<td>Query 2</td>
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lent performance (100), except query number 3 where low score refers to high effectiveness.

The performance of the proposed method, based on both observers evaluation, was assessed by means of the percentage of cases where the algorithm is effective ($\geq 50$) in all queries (Table 3). Inter-observer agreement was determined using the weighted $\kappa$ (kappa) coefficient calculated for all qualitative parameters [20]. A kappa statistic above 0.75 was arbitrarily chosen so as to show excellent agreement, between 0.40 and 0.75 as moderate agreement and below 0.40 as poor agreement (Table 4).

Regarding query number 3 the second observer only in 4 cases observed the creation of artifacts in contrast with the first one who did not rank any of the 63 images.
5. Discussion and conclusions

Multiscale wavelet analysis is one of the most promising approaches for speckle suppression in ultrasound imaging. The proposed method attempts an optimal speckle reduction in US images of the thyroid gland, employing singularity detection on local maxima chains within a coarse to fine framework. Significant image features are represented across scales with maxima chains of positive Lipschitz regularity while speckle noise gives rise to maxima chains of negative Lipschitz regularity. The combination of the proposed back-propagation maxima tracking together with the singularity detection achieved high speckle reduction performance with remarkable edge preservation accuracy.

An important task of any multi-resolution algorithm is to optimize the detection of high resolution information. The back-propagation approach through the position–angle pair and occasionally amplitude, together with the adaptive neighbourhood size, approximates with significant proximity the coarse information even at the 2\textsuperscript{1} scale (see Fig. 2). Nevertheless the implementation of an optimized coarse to fine connection is still under investigation. Any prior information regarding potential patterns within the US image can be utilized in this research. The method is generic and can be also applied to US medical images of different anatomical structures along with other imaging modalities suffering from the presence of speckle such as synthetic aperture radar images.

The comparative study regarding the effectiveness of all methods was based on their speckle reduction and edge preservation properties. Regarding speckle reduction on the phantom image, both SI and S/mse obtained from the inter-scale analysis method were greater compared with the equivalents of the other three methods locally and totally on the phantom image (Table 1). Accordingly, regarding parameter $\beta$, the proposed algorithm exhibited greater performance.

The results of the proposed method on the thyroid US image (SI, S/mse and $\beta$) exhibited much greater scores than the other three methods (Table 2). Additionally, a closer look in Fig. 4(d) can help us observe that the inter-scale wavelet denoising method retained the boundaries of the thyroid nodule, similar to that of the original image, while at the same time the speckle suppression degree in speckle regions was high. An interesting observation made from the same figure was the tendency of Karaman’s and Donoho’s soft thresholding methods to remove completely the signal fluctuation in a homogeneous regions, thus eliminating possible small low contrast structures while failing to follow with a relative compliance the initial trend. At the same figure the spurious oscillations resulted from Donoho’s hard thresholding method are also apparent.

The results of the questionnaire given in the two specialized doctors can give us some useful conclusions regarding the adaptability and power of our method. The scores in queries 1 and 4 (>70% evaluation efficiency percentage of both observers) confirmed the results the algorithm had in speckle reduction and edge preservation. High score in query number 5 (>75% evaluation efficiency percentage of both observers) proved that a successful noise suppression without the creation of blurring actually increases the contrast of various structures in regard with the surrounding environment. An important subject introduced in this study through query number 6 (>75% evaluation efficiency percentage of both observers) is the potential of the algorithm to reveal structures that are not easily distinguishable by the human eye.

An essential issue for discussion is whether the proposed method creates any kind of artifact. One physician observed artifacts in the processed image in 4 out of 63 cases. The low score in query number 7 is predictable due to the great expertise of both observers regarding the final diagnosis. However, in less experienced physicians it could turn out as a very useful tool. The correlation results between the two observers are indicative of the algorithm’s ability. Particular attention should be given to the high correlation ($k=0.86$) of the two observers regarding the speckle suppression efficiency of our method, constituting an additional advantage of the proposed algorithm.

As a final conclusion we can say that an efficient wavelet-based speckle reduction is presented in this article. This method was based on inter-scale wavelet analysis, in which the primal aim was to isolate edges existing across scales and check their regularity. Successful speckle suppression made by the proposed algorithm can be employed as an additional step in the improvement of the overall diagnostic procedure.

References


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