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Research Article

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Estimation of Displacement Tissues in Breast Ultrasound Ultrasound Elastography

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Abstract

Displacement estimation in ultrasound imaging is a topic of crucial research in diagnosis of diseases related to tissue stiffness that to analyze expression differences between normal and tumor cells of various tissue.

In this work, we investigate a new clinical application of the monogenic signal method. The new case report focuses on the study of breast organ of which the estimated displacement is done by monogenic signal method.

This method has proven effective in the case of heart and thyroid organs but it is never applied to estimate breast tissue displacement. In this context, we adopt this technique for breast case study analyzing, that to be used as a future application in estimation of breast tissue elasticity.

Our proposed method is used that to excerpt ultrasound breast image features such as local orientation and phase using pre and post compression image, image features are used to estimate analytically the displacement fields.

By Adapting this model on breast organ, we show that it has proven effective sub pixel accuracy in breast tissues, it gives better values in term of standard deviation, better contrast to noise ratio (CNR)and much faster than Block Matching (BM) method.

Keywords

Breast static elastography; Displacement estimation; Monogenic signal; Motion estimation

Introduction

One of the oldest concepts in medicine is the principle of palpation. This method is still used today in order to achieve a subjective evaluation of tissue stiffness, particularly the development of pathological breast phenomena is often correlated with changes in motion of tissue, and can be indicators of histological diagnosis and diseases, such as cancer, cysts or other breast illnesses [1].

However, palpation performed by doctors has limited effectiveness, since it provides superficial information and gives only anomalies with relatively large size, which unfortunately already indicates an advanced stage of the disease. In addition, palpate a patient's body does not allow access to specific quantitative information about tissue [2].

In this context, access to the elastic properties of the tissues can provide information on the healthy or pathological state of the tissues, which offers more information than analysis technique of palpation, its purpose is to provide local information about tissue rigidity, that is presents a major interest in clinical diagnosis.

The conception of a new imaging technique for accessing this mechanical information was therefore required. This is now done thanks to recent developments in the medical field.

Imaging the mechanical properties of tissue in ultrasound elastography has become the subject of increasing interest during the past two decades [3]. It came to conventional ultrasound as complement result allowing to access to mechanical properties of tissue. It is an imaging modality of tissue elasticity, or more precisely of the elastic behavior of the tissue which are under compression [4]. This method is based on the theory of the mechanics of elastic tissue backgrounds, widely used to detect tumors and cysts in biological tissues.

From this basis, we interest of displacement estimation in ultrasound imaging, the one of medical applications for this technique is elastography, this is a very active field of research and it is motivated in diagnostic aid that can provide tissues deformation [5].

In this paper, an application to static elastography is presented. A small compression is applied to breast tissues directly with the ultrasound probe; the displacement or deformation of breast tissue can inform us about the elastic properties of tissues.

To start the displacement estimation, we used a B-mode image as indicated in the literature that a great number of ultrasound elastography development use Radio Frequency (RF) data [6,7] to generate displacement fields. But commercial ultrasound machines do not always contain RF data, in this way access to B-mode images is more obtainable [8]. Therefore, using B-mode images alternately of RF data can improve elastography techniques in commercial machines.

There are numerous techniques of displacement estimation that can be used with B-mode images to estimate the displacement tissues. Such as differential methods, which use the spatial-temporal gradients of the image brightness. In order to have a differential estimation, it is necessary to answer the hypothesis of the pixels luminous intensity preservation during all the displacements. However, this condition is not fulfilled in elastography, because of the variability of the intensity of the pixels all along the compression axis. This shows that differential methods are not perfect for estimating tissue displacements in static ultrasound elastography.

Then, the researchers has developed techniques based on the statistical approach, these techniques seek the resemblance between the images by exploiting their contents. On a defined local or whole region, we can apply estimation methods based on Markovian or Bayesian approaches, these approaches select the moving pixels for a local or global estimate, therefore all the regions that who are not involved in displacements will be eliminated. Although these

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techniques are widespread, they are not suitable for estimating complex displacements in elastography.

Then, we find the spatio-temporal approaches, these methods have been used for a long time in estimating displacements, using a sequence of several images, these approaches use the temporal repetition of the similar intensities of the pixels between the images. Two spatio-temporal estimation techniques have been considered: Lagrangian technique and Eulerian technique. As the name of the method indicates, it is based on a strategy of development in space and time. As for the spatial approach, the shape parameterization is applied while providing the form of local displacements to be analyzed. As for the temporal approach, it is assumed that the pixel displacement is proportionally linear as a function of time, these methods give good results, and however, they are very expensive in computation time.

Other techniques based on two-dimensional translation of the tissues, in order to provide the tissue displacements which have arisen as a result of compression applied to the breast. In this perspective, the use of two-dimensional translation-based information is unsatisfactory.

In this work we launched a new clinical case of breast organ using the monogenic signal method, integrating a DOG Filter that to confirm that this method can meet the conditions of ultrasound elastography and surpasses the performance of other used techniques [9].

The results of clinical and *in vitro* studies are presented to assess the proposed method. We show that the monogenic signal method can be applied to the case of breast and improves clinical diagnosis. The performances of our proposed method are compared with Block Matching (BM) method, we show also that it is more accurate, better CNR and much faster than BM method.

The paper proceeds as follows: The monogenic signal theory and the analytical estimation algorithm is resumed and presented in section 2.

Section 3 shows the results on soft biological phantom designed for elastography and clinical breast images, we address also the comparison between the results obtained with our method and those obtained with BM method.

Section 4 shows the discussion of results.

Concluding remarks are left to Section 5.

Displacement Estimation Based on Monogenic Signal Method

Image filtering

Speckle is due to multiple coherent reflections from the ambience around the target, it is a multiplicative noise that degrades the visual evaluation in ultrasound imaging [10], so filtering of B-mode image is a very essential step before going to estimate the displacement of breast tissue. We may apply a band pass filter to B-mode images, the objective of using the band pass filter is to preserve detail of desired signal and reduce the speckle noise [11].

In this context, to preserve the details in image, the main characteristics of the image must be selected in a window function of band pass filtering characteristics.

From the band pass filters family, the Difference of Gaussian (DoG) is adopted in our work.

Thus, we can reduce the noise frequency and only locate the desired frequency in the Gaussian window. The filtered image is modeled by the following structure:

$$P=I(x,y)_{*}f(x,y) \tag{1}$$

Where I(x,y) is the image to be processed, (x,y) is the two-dimensional coordinates of image and f(x,y) is the band pass filter, "*" is a convolution operator. The frequency response of selected filter is shown by the following expression

$$F(u_1,u_2)=\frac{1}{2\Pi\sigma_1^{\,2}}e^{\left(-\frac{u_1^2+u_2^2}{2\sigma_1^{\,2}}\right)}-\frac{1}{2\Pi\sigma_2^{\,2}}e^{\left(-\frac{u_1^2+u_2^2}{2\sigma_2^{\,2}}\right)} \tag{2}$$

(u1, u2) is the frequency variable and σ1 and σ2 are the widths of the Gaussian kernels.

We set the following parameters σ_1=1 and σ_1=4 with the aim to reduce a noise in the image.

Monogenic signal method

Our strategy focuses on the use of properties of the monogenic signal extracted from image, In this part, we explain how some properties of monogenic signal has been exploited to realize a platform for estimating of breast deformation tissue.

We may apply two odd filters (Riesz transform) [12], that the Riesz transform is used in the case of two dimensions or arbitrarily higher dimensions, with an objective to compute the monogenic signal. The frequency response in the Fourier domain is:

$$H_1(u_1,u_2)=\frac{u_1}{\sqrt{u_1^2+u_2^2}};H_2(u_1,u_2)=\frac{u_2}{\sqrt{u_1^2+u_2^2}} \tag{3}$$

H1, H2 are the frequency responses of h1 and h2. The monogenic signal has the following format:

$$I_M(x,y) = p(x,y)+ i_{q1}(x,y)+ j_{q2}(x,y) \tag{4}$$

Where p(x,y)is the filtered image by using the DoG, (i,j) are two imaginary components of a quaternion.

$q_1(x,y)$ and $q_2(x,y)$ represent the result of image filtered with DoG filter convolved with Riesz Transform, the inverse Fourier transforms of H1 and H2 is denoted by h1, h2, as shown below;

$$q_1(x,y)= p(x,y) * h_1(x,y) \tag{5}$$

$$q_2(x,y)= p(x,y) * h_2(x,y) \tag{6}$$

The monogenic signal computes the image features [13]: local orientation (θ) and Phase (φ), from which one can find the instantaneous frequency (f). The following equations give expression to each of its information in a pixel: we as shown below.

$$\theta(x)=\arctan\left(\frac{q_2(x)}{q_1(x)}\right) \tag{7}$$

$$\varphi(x)=\arctan\left(\frac{|q(x)|}{p(x)}\right) \tag{8}$$

$$f=sign\left(\frac{\delta\varphi}{\delta_x}\right)\times\sqrt{\left(\frac{\delta\varphi}{\delta_x}\right)^2+\left(\frac{\delta\varphi}{\delta_y}\right)^2} \tag{9}$$

From the filter responses, monogenic phase, orientation and frequency are obtained. According to this, to estimate the displacement, we combine the orientation vector and the phase, a phase vector can be created, this resulted in the availability of structural information of the signal in the axial and lateral directions. (A phase vector (r) is denoted in bold characters):

$$r = (\varphi.\cos(\theta), \varphi.\sin(\theta)) \quad (10)$$

Displacement estimation using differences of monogenic phases

Displacement can be formulated along axial displacement (d_x) and lateral displacement (d_y) using two phase vectors **r1**and **r2** as follows

$$r2(x,y)=r1(x-d_x, y-d_y) \text{ With } d= [d_x, d_y] \quad (11)$$

We can use a Taylor series expansion of the first order, if we set:

$$n = [\cos(\theta), \sin(\theta)]^T \quad (12)$$

That it will give us:

$$r2 \approx r1 - n.n^T.f.d \quad (13)$$

Displacement can be computed using Taylor series expansion; however in practice the summation between the neighboring blocks to estimate the displacement maintains a constant deformation in the region (N).

The assumption is made that all the pixels of the block have a constant displacement; an analytical estimation of displacement can be obtained:

$$\hat{d} = \left(\sum_N \left[n.n^T.f\right]\right)^{-1} . \sum_N [r1 - r2] \quad (14)$$

Displacement estimation algorithm

The use of a database containing RF signals as described in literature [8] is not always provided on commercial ultrasound devices; however, the use of a data base containing B-mode images is more available. Thus, the use of B-mode images to generate the deformation of the breast tissue can be integrated as an additional module for commercial machines.

Getting the two B-mode images, we proceed after to filter them, and then the monogenic signal is computed for each image.

Some breast tissues deform slightly [14] and it does not indicate a large displacement, in this case, the pixel value changes with little variation, so we compute a mean orientation (θ), mean frequency (f) and phase difference (Δφ), we have:

$$\theta(x) = \frac{\theta_1(x) + \theta_2(x)}{2} \quad (15)$$

$$f(x) = \frac{f_1(x) + f_2(x)}{2} \quad (16)$$

$$\Delta\varphi(x) = \varphi_1(x) + \varphi_2(x) \quad (17)$$

The extracted features such as mean orientation, frequency and phase difference will be integrated into analytical equation of estimation, to give a block displacement. Once the displacement is estimated, we can interpolate it by a classical bilinear interpolation, in order to obtain a displacement field.

Results

In this section, all results have been verified and validated by two radiologists, doctors selected images before and after compression, they manually selected tumor areas and healthy areas, and they assessed the results of the proposed method as a good estimation of breast tissue deformation.

Soft biological phantom designed for elastography

We present in this section a simulation result coded with the Matlab software (The MathWorks, software Matlab, Pentium 4, 3.2 GHz), two models of phantom elasticity are used in our test validation sold by the company CIRS, the first phantom contains 10 mm and 20 mm diameter spheres of varying hardness relative to the background material. The sphere is located at depths of 15 mm and 35 mm respectively and will appear almost isoechogenic to the background using standard B-mode imaging.

The second phantom contains sets of stepped cylinders that vary in diameter from 1.6 mm to 16.7 mm. The stepped cylinders in each set are located at depths of 3 cm and 6 cm. Each set has a different hardness relative to the background material and will appear almost isoechogenic to the background using standard B-mode imaging.

In the software parameterization, we used the linear transducer features with which the phantom was originally acquired: 7.5 MHz center frequency, 60 MHz sampling frequency, 512 physical elements of size 5 mm - 0.2 mm (height and width, respectively), with 128 active elements.

Two B-mode images (pre-compression and post compression image) are loaded while the pressure was applying by the probe. As shown in Figures 1 and 2, the proposed algorithm was tested on pair of ultrasound B-mode images (Before and after compression image) from two phantoms to estimate the displacement field. Band pass filter parameters are fixed to σ1=1 and σ2=4. The results were validated by two radiologists.

In order to quantitatively compare the efficiency and robustness of our proposed method, The phase-based technique is compared to

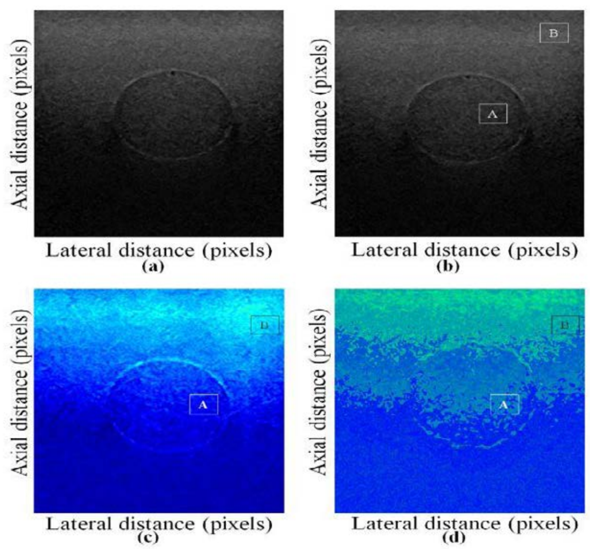

Figure 1: Two B-mode images (pre-compression and post compression image).

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BM method using standard deviation (in pixels) of the errors between estimated and B-mode post compression image (as shown in the Table 1), CNR comparison (as shown in Table 2) and time compute (as presented in Figure 3).

On these motion phantom results, a CNR is computed as follows:

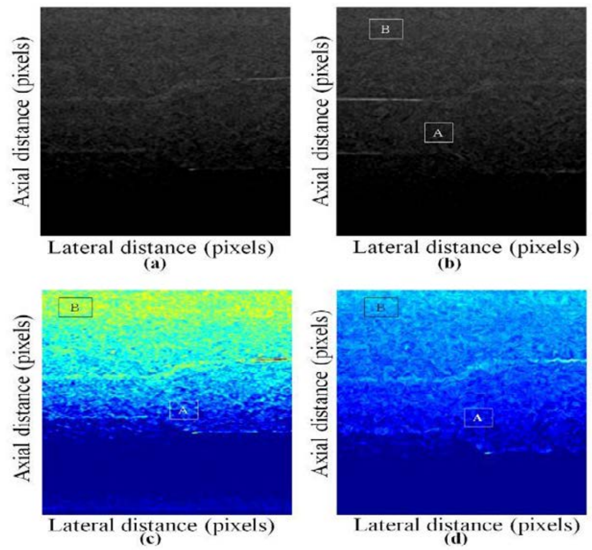

Figure 2: Two B-mode images (pre-compression and post compression image).

Table 1: Comparison of the standard deviation for the proposed and BM method.

	Proposed method	BM method
Standard deviation First phantom	0.07	30.48
Standard deviation Second phantom	15.96	20.25

Table 2: Comparison of CNR for the proposed and BM method.

	B-mode	Proposed method	BM method
CNR (First phantom)	0.10	0.29	0.14
CNR (Second phantom)	0.22	0.43	0.30

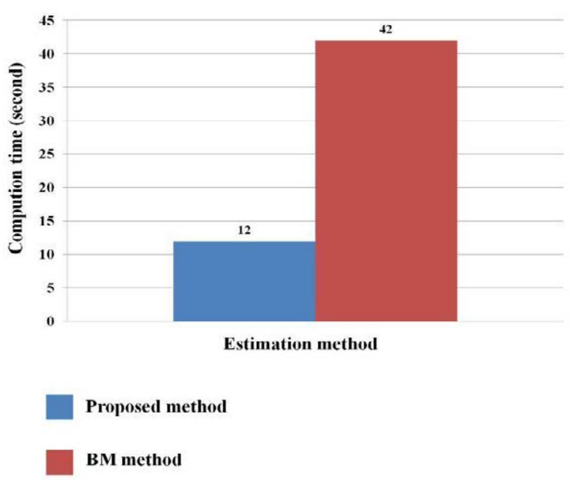

Figure 3: The runtime of monogenic signal method is about four times shorter than with BM technique.

$$CNR = \frac{Contrast}{Noise} = \sqrt{\frac{2(m_b - m_t)^2}{\sigma_b^2 + \sigma_t^2}} \qquad (18)$$

where mt and mb are the spatial strain average of the target and background, σ_b^2 and σ_t^2 are the spatial strain variance of the target and background, and are the spatial average and variance of a window in the strain image, respectively.

Areas selected by a rectangle were made by the radiologist as the region of interest (ROI) A as the target and ROI B as the background. These parameters (ROI A and ROI B) were used to calculate the CNR in the strain images.

In-vivo breast images

The process described in Section 2 is assessed here; In-vivo testing of our proposed method was performed on the sets of clinical B-mode images (pre and post compression) to 20 patients including benign and malignant breast tumors.

The radiologist applied a small compression on the breast to acquire both images (pre and post compression). Then the radiologist outlined the contours of the breast tumor.

A clinical ultrasound scanner (Logiq E9) with 7.5-MHz linear probe (GE Healthcare) is used for ultrasound acquisition.

We have presented below the results of displacement estimation methods (Figure 4).

The results of our proposed method applied to ultrasound breast image are presented in Figure 4. The tissue stiffness can be indicators to discriminate healthy tissues from breast tumors.

The parameters for the band pass filter are σ1=1 and σ2=4.

In order to evaluate the efficiency of our approach, quantitative measures as Standard deviation (as shown in the Table 3), CNR comparison (as shown in the Table 4) and time compute (as shown in Figure 5) were used in order to highlight the contribution of our method and to compare the accuracy of the two approaches.

Discussion

For studying the displacement of breast tissue, the proposed

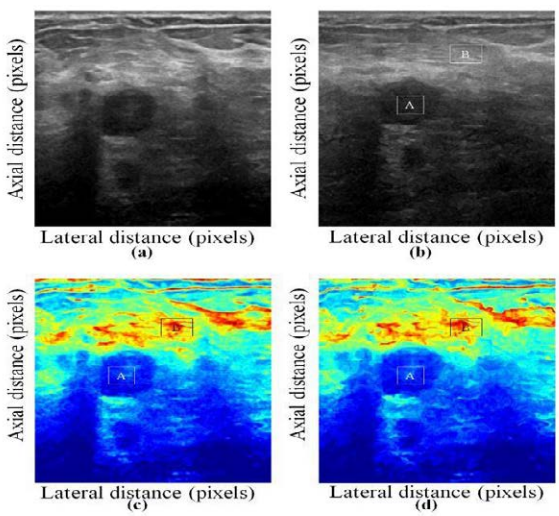

Figure 4: Results of Breast in-vivo displacement estimation images.

Table 3: *In vivo* results comparison of standard deviation for the proposed and BM method for 20 patients.

	Proposed method	BM method
Standard deviation : Patient 1	6.12	6.90
Standard deviation : Patient 2	4.60	5.10
Standard deviation : Patient 3	3.80	4.55
Standard deviation : Patient 4	9	12.80
Standard deviation : Patient 5	5.05	6.15
Standard deviation : Patient 6	8.30	10
Standard deviation : Patient 7	4.20	7
Standard deviation : Patient 8	3.54	5.12
Standard deviation : Patient 9	4.32	6.88
Standard deviation : Patient 10	2.43	3.92
Standard deviation : Patient 11	5.13	7.16
Standard deviation : Patient 12	6.87	9
Standard deviation : Patient 13	7.54	8.32
Standard deviation : Patient 14	4.63	6.73
Standard deviation : Patient 15	2.96	5.21
Standard deviation : Patient 16	4.93	7.73
Standard deviation : Patient 17	5.66	8.21
Standard deviation : Patient 18	7.02	9.48
Standard deviation : Patient 19	6.52	8.32
Standard deviation : Patient 20	4.73	6.24

Table 4: *In vivo* results comparison of CNR for the proposed and BM method for 20 patients.

	B-mode	Proposed method	BM method
CNR : Patient 1	0.12	0.47	0.17
CNR : Patient 2	0.10	0.32	0.18
CNR : Patient 3	0.51	0.71	0.59
CNR : Patient 4	0.40	0.63	0.44
CNR : Patient 5	0.36	0.51	0.38
CNR : Patient 6	0.09	0.24	0.13
CNR : Patient 7	0.18	1	0.50
CNR : Patient 8	0.13	0.42	0.20
CNR : Patient 9	0.22	0.87	0.42
CNR : Patient 10	0.11	0.51	0.32
CNR : Patient 11	0.12	0.39	0.28
CNR : Patient 12	0.34	0.83	0.40
CNR : Patient 13	0.18	0.97	0.63
CNR : Patient 14	0.20	0.77	0.34
CNR : Patient 15	0.10	0.16	0.13
CNR : Patient 16	0.21	0.58	0.32
CNR : Patient 17	0.10	0.14	0.11
CNR : Patient 18	0.34	0.75	0.48
CNR : Patient 19	0.16	0.34	0.19
CNR : Patient 20	0.80	1.24	1

method is applied first to ultrasound B-mode images of two phantoms (that whose stiffness characteristics are the same texture of breast tissue), and to ultrasound B-mode images of breast organ of 20 patients with benign and malignant tumor.

For evaluating the overall performance of proposed method and BM technique are applied to the same images for comparison.

The results analysis of Soft biological phantoms showed that displacement estimation maps (Figures 1 and 2) with the proposed approach can improve the clinical diagnosis in displacement estimation of hard and soft areas. Compared with the monogenic signal technique, the BM method has more artifacts in strain estimation image and the lesion in phantom almost cannot be seen in the real localization in the strain images. However, the monogenic signal method can detect and localize the lesion in the real position in the strain images. This is explained by the presence of the filters contained in the proposed method that prevent the presence of noise and preserve the details in the image.

From Table 1, it is seen that the standard deviation of proposed method is lower than BM method. This is explained by the perfect sub-pixel estimation using monogenic extracted features (orientation, frequency and phase difference) and contributing to correctly follow the displacement fields. This demonstrates also that the displacement estimation result of proposed method is more accurate.

From Table 2, we notice that the CNR of our proposed method were significantly higher than those in the B-mode image and BM technique. These values showed that strain estimation with monogenic signal method can detect inclusions that can barely be seen on BM results and B-mode image; this indicated that the proposed algorithm minimized successfully the noise in image to maintain a higher level of CNR than BM technique.

The processing speeds of each method are also studied. The two methods are performed on a Pentium 4, 3.2 GHz with 4 GB RAM using MATLAB.

From Figure 3 the runtime of monogenic signal method is about four times shorter than with BM technique. This is a very important point in the evaluation process of our proposed method; this rapid response of the proposed approach is explained by the fact of the rapid extraction monogenic algorithm of images features, once the features of the images are extracted, the algorithm injects them to estimate the displacement tissue, and this explains clearly the rapidity and the excellence of this method compared to BM technique.

The computing time to perform displacement estimation depends on the size of the ultrasound B-mode images (pre and post compression). For a size of 1575×740 B-mode image, the monogenic signal model needs about 12 second to complete the estimation, while the BM model needs nearly 42 second. The proposed method needs less time to reach the displacement estimation because there is no block matching operation utilized.

The novelty of this research is not at the level of proposed approach development, but the novelty is at the feasibility of this approach in the case of breast organ that to use it as a future application, given that the proposed method is never used to estimate breast tissue displacement. The results of Breast in-vivo displacement estimation images are given in Figure 4.

For validating the estimation displacement performance of proposed method quantitatively, for each method, the standard deviation, the CNR and the time execution are computed.

From Figure 4, the results showed how the proposed approach with physiological breast tissue displacement are qualitatively consistent than BM method. Displacement estimation with the proposed method gives a good detection of tumor than BM technique, with good location and good tracing of the contours which improves the therapeutic treatment and helps doctors to evaluate the breast tissue elasticity.

It is seen from Table 3 that the standard deviation of proposed method is lower than that of BM method. Thanks to the correct

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tracking of displacement fields. This demonstrates that the displacement estimation result of the proposed method is more reliable.

Another evaluation criteria using CNR of our proposed method and BM method is calculated, a criterion often involved in the evaluation of ultrasound image processing techniques [15,16]. It is seen from Table 4 that the estimation with proposed approach gives a higher CNR than those B-mode image and BM technique. Our proposed approach helps to find the tissue displacement in the low contrast region that has similar contrast levels. This superiority can be explained by the major flexibility involved by the proposed formalism, which makes it more suitable for complex displacements (estimation in soft and rigid areas), with a good elimination of noise in the image leading to increase the CNR.

A further fundamental point concerns computational time. It is seen From Figure 5, that the computation times with monogenic signal technique are much faster than the BM approach; it was 47 second for the proposed algorithm and 322 second for BM algorithm (image size 1575×740 B-mode image). Both these values refer to MATLAB implementations executed on a desktop PC with a 4, 3.2 GHz, 4 GB RAM running Windows 7.

These results give a clear vision on the relation between the two algorithms. The increased computational burden of the monogenic technique is readily explained by its global formulation, demanding the rapid extraction of image features.

In this article we treated a new clinical case of breast, although this monogenic signal technique has been used by other modalities for other purposes, the adopted methodology has never been applied to estimate breast tissue elasticity.

The results were interesting and encouraging; the application of the proposed method to the breast will improve the elasticity evaluation of tumors and accelerate diagnosis.

As perspective, we try to improve the quantitative parameters of displacement estimation ultrasound image of the breast using the proposed approach.

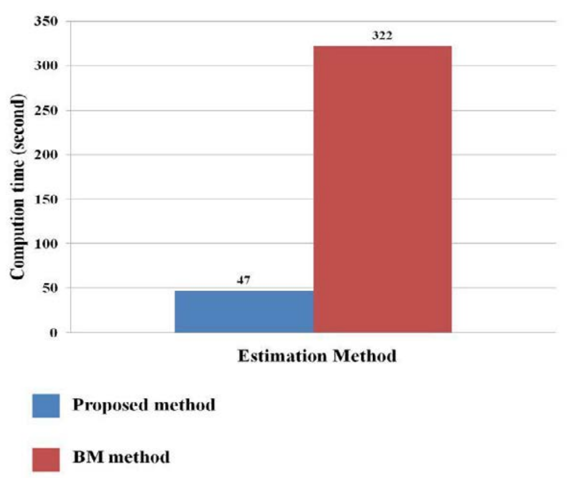

Figure 5: Computation times with monogenic signal technique are much faster than the BM approach.

Conclusion

This work implements a new clinical case for monogenic signal method, that the adopted methodology has never been applied to estimate breast tissue displacement. The new utility of proposed framework leads to facilitate the investigation of breast tissue displacement of the applied compression.

A monogenic signal method between a pair of images is presented using an analytic displacement estimator to locally control the tissues deformation.

Moreover, the implementation of monogenic signal method is discussed, using synthetic ultrasound elastography Phantom and *in vivo* B-mode breast image.

The proposed approach was shown a better accuracy, a better CNR and a short run time than BM method.

Therefore, our selected method gives encouraging results and may facilitate the breast tumors diagnosis.

Conflict of Interest

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