Original Article

Ultrasound Elastography Using Empirical Mode Decomposition Analysis

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ABSTRACT

Ultrasound elastography is a non-invasive method which images the elasticity of soft-tissues. To make an image, pre and after a small compression, ultrasound radio frequency (RF) signals are acquired and the time delays between them are estimated. The first differentiation of displacement estimations is called elastogram. In this study, we are going to make an elastogram using the processing method named empirical mode decomposition (EMD). EMD is an analytic technique which decomposes a complicated signal to a collection of simple signals called intrinsic mode functions (IMFs). The idea of paper is using these IMFs instead of primary RF signals. To implement the algorithms two different datasets selected. The first one was data from a sandwich structure of normal and cooked tissue. The second dataset consisted of around 180 frames acquired from a malignant breast tumor. For displacement estimating, two different methods, cross-correlation and wavelet transform, were used too and for evaluating the quality, two conventional parameters, signal-to-noise ratio (SNR) and contrast-to-noise ratio (CNR) calculated for each image. Results show that in both methods after using EMD the quality improves. In first dataset and cross correlation technique CNR and SNR improve about 16 dB and 9 dB respectively. In same dataset by using wavelet technique, the parameters show 14 dB and 10 dB improvement respectively. In second dataset (breast tumor data) CNR and SNR in cross correlation method improve 18 dB and 7 dB and in wavelet technique improve 17 dB and 6 dB respectively.

Key words: *Elastogram, elastography, empirical mode decomposition, intrinsic mode function*

INTRODUCTION

Ultrasound elastography is a non-invasive imaging method which introduced about two decade ago to image the elasticity of soft tissues. Lots of cancers cause stiff masses that aren't recognized simply by conventional ultrasound. Hence, the elastography has attracted attentions as a diagnostic technique especially about diseases that lead to pathological changes.

Researches on elastography can be categorized in some general groups:

The first group is the detection and recognition of tumors. Malignant tumors are usually stiffer than benign. Kumar in[1] attempted a quantitative analysis of the improvement in classification accuracy when ultrasound elastography is combined with echography. The main focus of this study is to quantify the improvement in diagnosis of tumors by combining the ultrasound B mode imaging with elastography. Quantification is based on the textural parameters measured from the ultrasound B mode image and strain measured from the elastogram. They concluded that an increase in the classification accuracy was achieved following the inclusion of the average strain parameter as an additional input to the classifier.

In another work,[2] the axial-shear strain elastogram (ASSE) was studied to decrease the unnecessary breast tumor biopsies. They hypothesized that ASSEs contain novel and independent features that may be useful for the noninvasive classification of breast tumors as benign or malignant. They showed that the feature from the ASSE, "the normalized area of the axial-shear strain region" contains valuable information useful for more accurate classification of breast cancer.

Luo *et al.* in[3] have worked on ultrasound elastography feasibility as a screening tool to reduce the number of fine needle aspiration (FNA) biopsies being performed on

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benign thyroid nodules. The diastolic strain variation is used to differentiate malignant nodules from benign. They showed the number of FNA biopsies can be reduced by 53%.

The second group of researches is on monitoring. In[4] a computationally efficient method for monitoring the progress of high-intensity focused ultrasound (HIFU) treatment is presented. The method utilizes the phase change before and after applying static compression. Both simulation and experimental results confirm that the phase change is a good and sensitive indicator of tissue stiffness which cannot be assessed with conventional B-mode imaging modalities. Rubert *et al*. in[5] evaluated the *in vivo* implementation of the electrode displacement technique in liver tissue during microwave and radio frequency (RF) ablation procedures. The results show that although principal axis measurements may be appropriate for determining cross sectional areas of spherical or cylindrical lesions, they are not generally feasible for most RF or microwave ablated lesions. Comparison of the ablated areas between gross pathology and strain images were then performed using contour delineation which resulted in good agreement between strain and pathological measurements.

Third category of studies is on measuring the parameters. Farron *et al*. in[6] developed and evaluated the use of an RF elastography algorithm for estimating the strain along tendinous fibers during a muscular twitch contraction. Experiments were performed on the tibialis anterior, a superficial dorsiflexor of the ankle, undergoing twitch contractions and strain estimations were compared with the timing and magnitude of strains determined from visual analysis of B-mode images.

Next group of researches is on improving the quality of elastography images. In[7] a two dimensional (2-D) strain imaging technique based on minimizing a cost function using dynamic programming introduced. Furthermore there are researches that present new methods for strain estimating.

Making an elastogram with a simply distinguishable stiffer area is the challenge of almost all techniques that have been presented up to now. It means that improving the image contrast can be one of the main goals of each method. In this study, achieving this goal is attempted.

With a glimpse on the works are done in elastography domain and especially in the field of signal processing, an explicit point is found out. Almost in all methods presented in papers, for strain estimating, the original pre and post compression RF signals without any changes are used. In this paper, we are going to use intrinsic mode functions (IMFs) obtained from RF signals in the estimation process.

ACQUIRING ELASTOGRAM USING EMPIRICAL MODE DECOMPOSITION (EMD) METHOD

EMD Algorithm

EMD is a relatively new form of time series decomposition that without leaving the time domain, breaks down a complicated signal into a collection of simpler signals called IMF.[8]

The process is useful for analyzing natural signals, which are most often non-linear and non-stationary. An IMF is a function that satisfies two conditions: (1) In the whole data set, the number of extrema and the number of zero crossings must either be equal or differ at most by one; and (2) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. The way that extracts IMFs, designated as the sifting process, is described as follows.

By virtue of the IMF definition, the decomposition method can simply use the envelopes defined by the local maxima and minima separately. Once the extrema identified, all the local maxima are connected by a cubic-spline interpolation as the upper envelope. The procedure is repeated for the local minima to produce the lower envelope. Then their mean is designated as m_1, the difference between the data and m_1 will be the first component, h_1, i.e.,

$$X(t) - h_1 = m_1 \tag{1}$$

If h_1 satisfies the requirements of an IMF, it is selected as the first extracted component of signal else h_1 itself regarded as a signal and the explained process implemented on it.

$$h_1 - m_{11} = h_{11} \tag{2}$$

Sifting procedure repeats k times, until h_{1k} chosen as first IMF, that is

$$h_{1(k-1)} - m_{1k} = h_{1k} \tag{3}$$

$$c_1 = h_{1k} \tag{4}$$

To guarantee that the IMF components retain its two requirements, a criterion is determined for the sifting process to stop. This can be accomplished by limiting the size of the standard deviation (SD), computed from the two consecutive sifting results as

$$SD = \sum_{t=0}^{T} [\frac{\left|(h_{1(k-1)}(t) - h_{1k}(t))\right|^2}{h_{1(k-1)}^2(t)}] \tag{5}$$

A typical value for SD can be set between 0.2 and 0.3.[8]

After specifying c_1 as the first component of signal, it is separated from primary signal and now the sifting process executes for rest r_1

$$X(t) - c_1 = r_1 \quad (6)$$

The sifting process can be stopped by any of the following predetermined criteria: Either when the component, c_n, or the residue, r_n, becomes so small that it is less than the predetermined value of substantial consequence, or when the residue, r_n, becomes a monotonic function from which no more IMF can be extracted. Finally, the signal can be explained as:

$$X(t) = \sum_{i=1}^{n} c_i + r_n \quad (7)$$

In Figure 1 an example of a signal and its IMFs are shown.

The various advantages and differences of EMD with wavelet or Fast Fourier Transform (FFT) based analysis is listed below in the Table 1. The table shows that EMD is indeed a powerful tool for analyzing data from non-linear

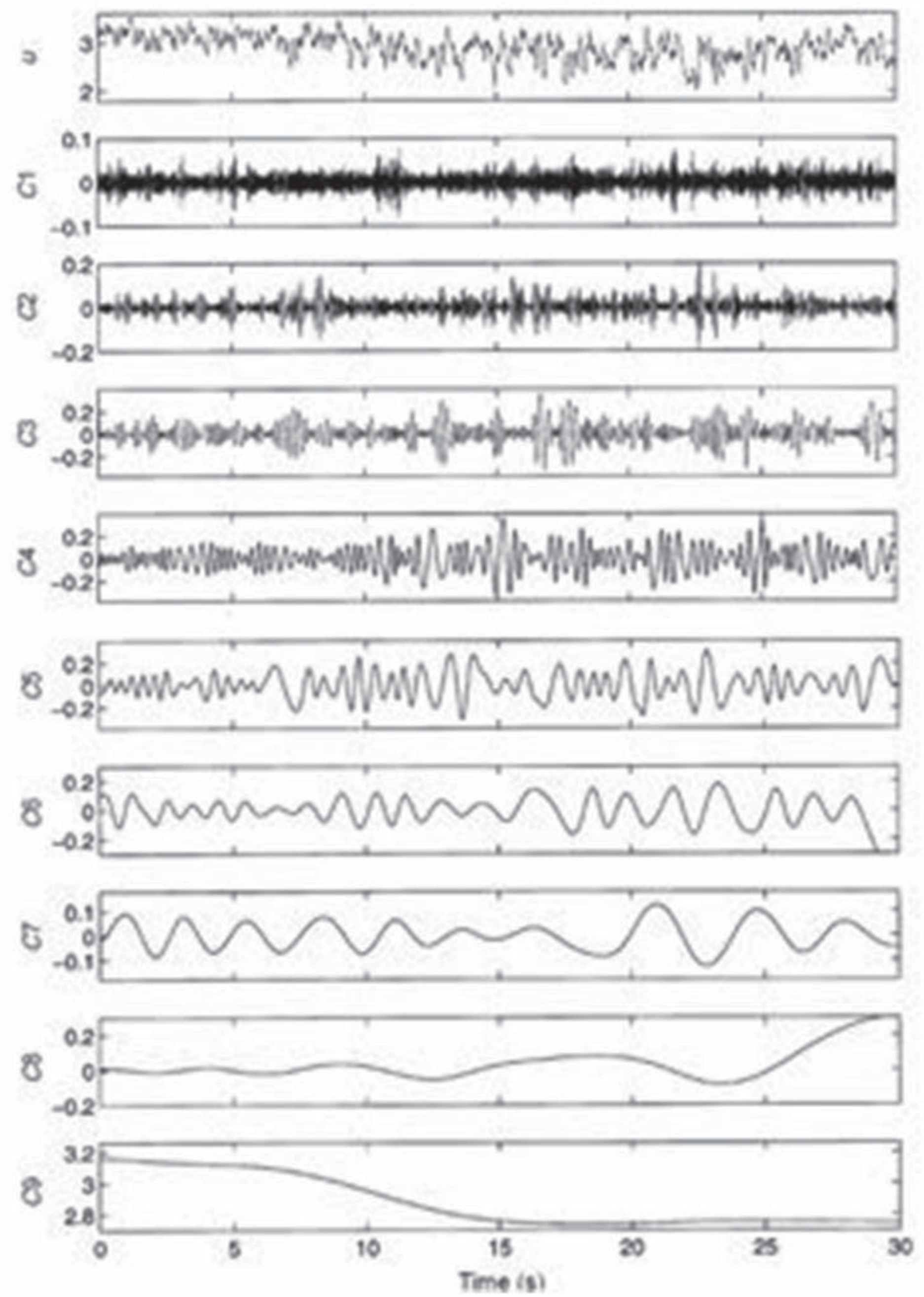

Figure 1: A signal and its intrinsic mode functions

Table 1: Differences of EMD with wavelet and FFT

Feature	Fourier	Wavelet	EMD
Basis	A priori	A priori	Adaptive
Frequency	Convolution Global Uncertainty	Convolution Regional Uncertainty	Differentiation Local Certainty
Presentation	Energy-frequency	Energy-time-frequency	Energy-time
Suitable for analysing which type of signals			
Non-linear	No	No	Yes
Non-stationary	No	Yes	Yes
Feature extraction	No	Discrete: No Continues: Yes	Yes
Theoretical base	Theory complete	Theory complete	Empirical

EMD – Empirical mode decomposition; FFT – Fast fourier transform

and non-stationary processes: It is based on adaptive basis; the frequency is derived by differentiation rather than convolution; therefore it is not limited by the uncertainty principle.

Data Acquisition

To implement the idea of paper, two datasets are used. In first data a sandwich structure of cooked and normal tissue provided where the cooked tissue becomes stiffer than normal one. To do this, two pieces of pork tissue were obtained. One of the pieces was placed in boiling water (100°C) for 30 min. The other piece was kept normal. Both pieces of tissues (normal and coagulated) were kept in degassed de-ionized water at 5°C for 24 h. A transverse cut was made through the normal tissue and consequently two pieces of normal tissue were obtained with thicknesses half of the thickness of the original normal tissue. The coagulated tissue is further sandwiched [Figure 2] between the two normal pieces of tissues. Extensive amount of coupling gel was poured in between each layer in order to minimize the reflection of the ultrasound waves propagating through this sandwich.

The tissue sandwich was placed on a scale. A SonixRP (UltraSonix, 12-14 avenue, Carnot batiment, Carnot plazza, Massy, France) scanner and a linear transducer array (L14-5/38) were used to image the tissue sandwich. It was imaged at the center frequency of 4 MHz and sampling frequency of 40 MHz. The linear probe was pressed on the sandwich to generate pressure. This dataset was provided in Advanced Biomedical Ultrasound Imaging and Therapy Laboratory, Ryerson University in Canada. For second dataset, the data from[9] was used. In this data a ramp- and-hold stress stimulus was used to initiate a creep-recovery method for imaging breast lesions. A patient lied on her side while a linear transducer array from an Antares™ System is manually pressed into the skin surface, scanning in the anterior-posterior direction during

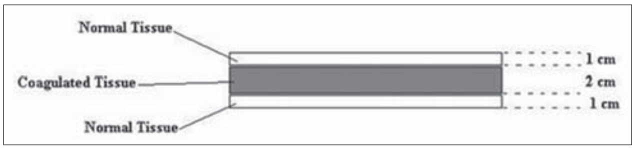

Figure 2: Sandwich structure of cooked and normal tissue

a time period of approximately 15 s. A set of malignant and a set of benign patient data acquired. Both sets are from biopsy-verified studies and both presented with non-palpable tumors initially detected by mammography. Both sets provide 183 RF frames in total and are recorded at a rate of 17 frames/s. In this paper, we just used data from malignant lesion.

Strain Estimation Techniques

To estimate the displacement, two techniques are used: Cross correlation and continues wavelet transform. In cross correlation algorithm a frame before and a frame after compression are chosen and corresponding A-lines are windowed and corresponding segments are cross correlated, then the lag which is corresponds to the peak correlation coefficient is considered as the time delay of that segment, then the time delay is converted to displacement. To implement this method the windows with a size of about 100 samples and 70% overlapping considered and a polynomial interpolation to find the subsample location of the correlation peak was used.

In wavelet algorithm, corresponding A-lines from pre and post compression frames were segmented and then each segment is continues wavelet transformed. The result of transformation is a 2-D matrix of scale versus time. Now for finding the time delay between segments their matrixes move on each other until in an instance of time that the maximum correlation happens. That time is selected as the time delay between those segments.[10]

In both methods, after estimating the displacements, a 2-D median filter is used to increase the signal-to-noise ratio (SNR).

The Idea of Using IMFs

At the first step, using EMD, pre and post compression signals is decomposed to their IMFs, then in the process of displacement estimating these IMFs are used instead of original signals. Regarding the first IMF of pre compression signal and the first IMF of post compression signal a displacement matrix is estimated. Differentiating this matrix resulting in the elastogram from the first IMFs. Similarly, for each IMF a displacement matrix and elastograms are obtained. Final elastograms is made by averaging these elastograms. Two ways of averaging is possible, before differentiating and after it.

Averaging before differentiating means that first obtain a displacement matrix from each IMF and average them then differentiate from the averaged displacement matrix to get the final elastogram. Averaging after differentiating means that different from each displacement matrix to get one elastogram from each IMF and then averaging these elastograms. Figure 3 shows a schematic of displacement matrix. In this matrix, the number of columns is equal to the number of A-lines of RF data frame and the number of rows is equal to the number of windows which is placed on each line.

Evaluating the Elastograms

To evaluate the generated elastograms two conventional parameters were used. Elastographic SNR and contrast-to-noise ratio (CNR) are the most common criterion for evaluating elastographic images and define as follows:[11]

$$CNR = \frac{C}{N} = \frac{2(\bar{s}_b - \bar{s}_t)^2}{\sigma_b^2 + \sigma_t^2} \tag{8}$$

$$SNR = \frac{\bar{s}}{\sigma} \tag{9}$$

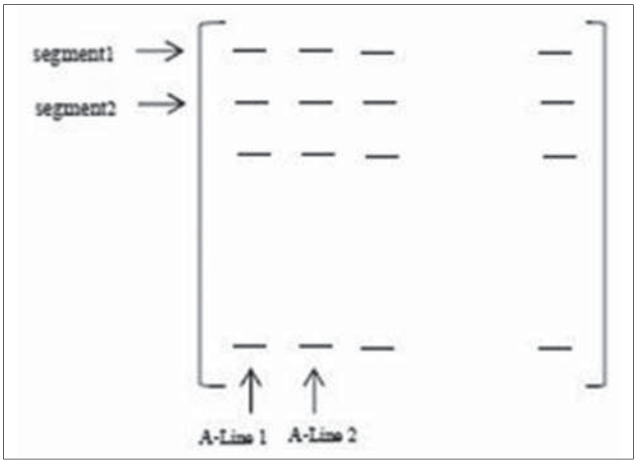

Figure 3: Schematic of displacement matrix

Where $\bar{s}_b$ and $\bar{s}_t$ 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 $\bar{s}$ and σ are the spatial average and standard deviation of estimated values from one window in the strain image, respectively. In order to get a more confident evaluation for each image, 3 windows in the target area and 6 windows in the background area are considered. In this way, 18 SNR and CNR values obtained for each elastogram and then they are averaged.

RESULTS

As mentioned before two techniques of strain estimating were used in this paper. In this section, first results of the cross correlation and then the results of the wavelet method will be presented.

In Figure 4a, the B-mode image obtained from cooked and uncooked tissue sandwich structure is shown. Figure 4b also shows the primary elastogram obtained from RF signals or in the other word "before EMD" elastogram.

In Figure 5, the elastograms obtained after using EMD is observed. Figure 5a shows the elastogram which is made by averaging the elastograms produced by each IMF and Figure 5b shows the elastogram which is made by averaging the displacement matrix produced from each IMF and then averaged displacement matrixes is differentiated.

It can be seen that both elastograms in this figure in comparison with the primary elastogram in Figure 3 show considerable improvement and the cooked part of tissue in the middle of the image is better distinguishable. Furthermore, as it will be brought in follow, the Figure 5b in comparison with Figure 5a has better SNR and CNR, it means that when the averaging is done among displacement matrixes and then averaged matrix is differentiated, the destructive effects of differentiating is reduced.

As shown in Figure 6, the images are made from second dataset, the malignant tumor. The B-mode image, primary elastogram or before EMD elastogram and two elastograms

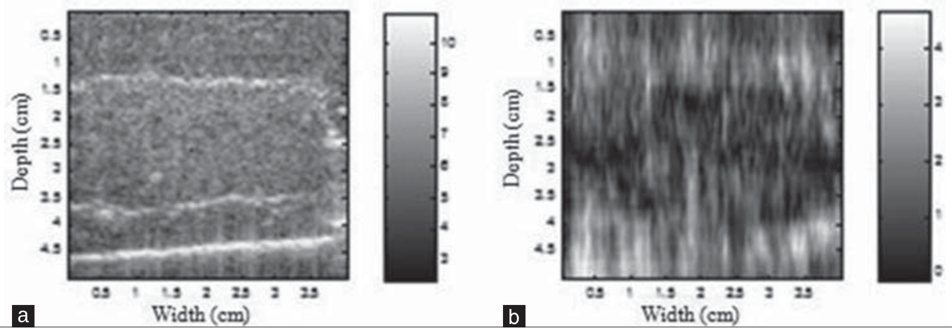

Figure 4: (a) B-mode image and (b) Before empirical mode decomposition elastogram obtained from cooked and uncooked tissue using the cross-correlation technique

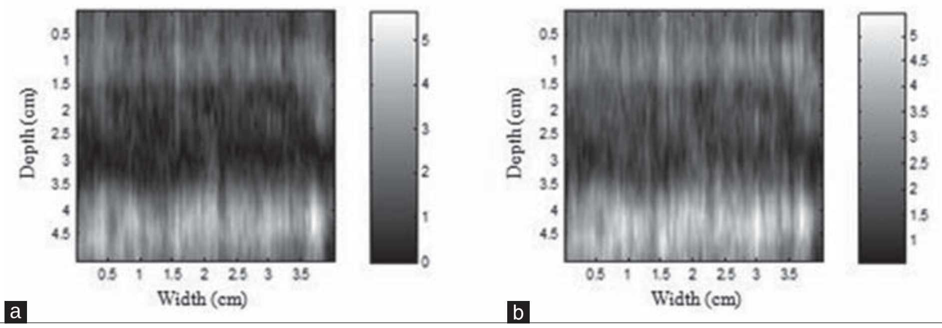

Figure 5: (a) Elastograms which is made by averaging of elastograms produced by each intrinsic mode function (IMF) (b) Elastograms which is made by averaging of displacement matrixes obtained from each IMF and then differentiating the averaged matrix

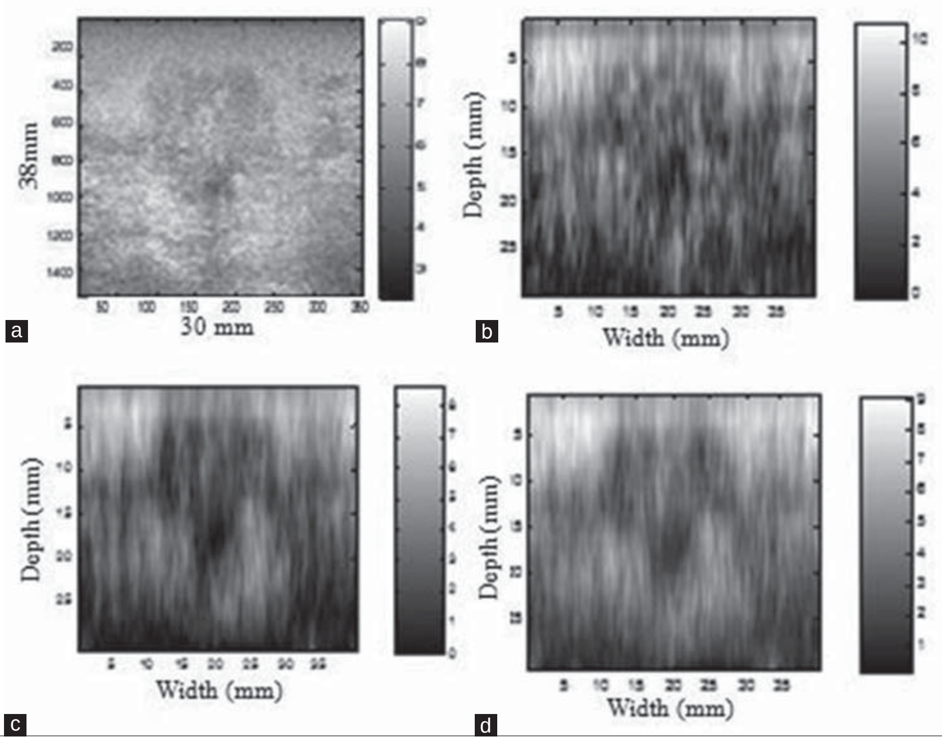

Figure 6: (a) B-mode image of malignant tumor (b) Elastogram produced before using empirical mode decomposition (c) Elastogram that is made by averaging the elastograms produced from each intrinsic mode function (d) elastogram that is made by averaging displacement matrixes and then differentiating

made by averaging of elastograms and displacement matrixes are observable.

As it's observed in Figure 6b, finding the margins of tumor in primary elastogram is very difficult and maybe without looking at sonography image [Figure 6a] is impossible. However as Figure 6c and d show in both elastograms produced after using EMD the area of the tumor can be recognized more easily. In this dataset likewise, the elastogram made by differentiating after averaging yields higher SNR and CNR.

As hinted before for getting SNR and CNR, for each image the mean value of 18 CNRs and SNRs is calculated. These 18 values resulted from 6 windows in the background area and 3 windows in the target area. Figure 7 represents these windows for both dataset elastograms.

In cross correlation method for cooked and normal tissue datasets, CNR and SNR for elastogram formed from original RF signals (before using EMD) are 21.31 and 14.21 respectively. These parameters after using EMD will improve to 35.09 and 18.32 respectively for elastogram made by averaged strain matrixes and 37.86 and 23.73 respectively for elastogram made by averaged displacement matrixes.

In a malignant tumor dataset, CNR and SNR for primary elastogram are 11.98 and 9.49 respectively. After using EMD these values improve to 28.86 and 12.21 for elastogram made by averaged strain matrixes and 30.03 and 16.82 respectively for elastogram made by averaged displacement matrixes.

Wavelet transform was the second strain estimator method that EMD idea was implemented on it. Again two datasets considered and images before and after using EMD were made. Figure 8 shows results of this technique. In Figure 8a-c elastograms from normal and cooked data and Figure 8d-f obtained elastograms from a malignant tumor are shown.

As it is seen, in this method likewise, the first dataset, the cooked part in the middle of the image is better distinguishable. But in second dataset it is almost impossible to find the tumor area in primary elastograms but in "after EMD" elastograms this area becomes distinguishable and the margins simply recognizable.

Calculations of CNR and SNR for cooked and normal tissue are 20.32 and 12.43 respectively for before EMD elastogram. These parameters after using EMD will become 33.21 and 15.59 respectively for averaged strain matrixes and 35.05 and 22.90 respectively for elastogram made by differentiating of averaged displacement matrixes.

In a malignant tumor dataset CNR and SNR for primary elastogram are 6.73 and 9.26 respectively. After using EMD these values improve to 21.69 and 10.44 respectively for elastogram made by averaging the strain matrixes and 24.40 and 16.25 respectively for elastogram made by differentiating of averaged displacement matrixes.

In[12] the normalized cross-correlation, sum squared difference and sum absolute difference are used as three techniques for strain estimating. For these methods they has reported the CNR, 16.4, 16 and 16.1 respectively. It is seen that using the method which is described in this paper, we will have about 19 dB improvements in CNR for cross correlation method.

DISCUSSION

Improving the elastogram quality has been ever one of the important researchers' challenges. In this paper using a relatively new processing method called EMD and by making changes in the process of displacement estimating, attempt is made to get better quality elastograms. The main idea is that instead of directly using RF signals for displacement estimating, the pre and post compression signals decompose

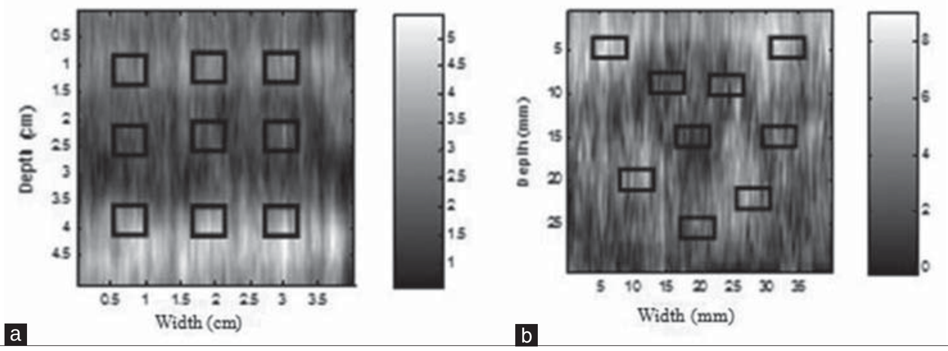

Figure 7: Windows on background and target area for (a) Cooked and uncooked dataset (b) Malignant tumor dataset

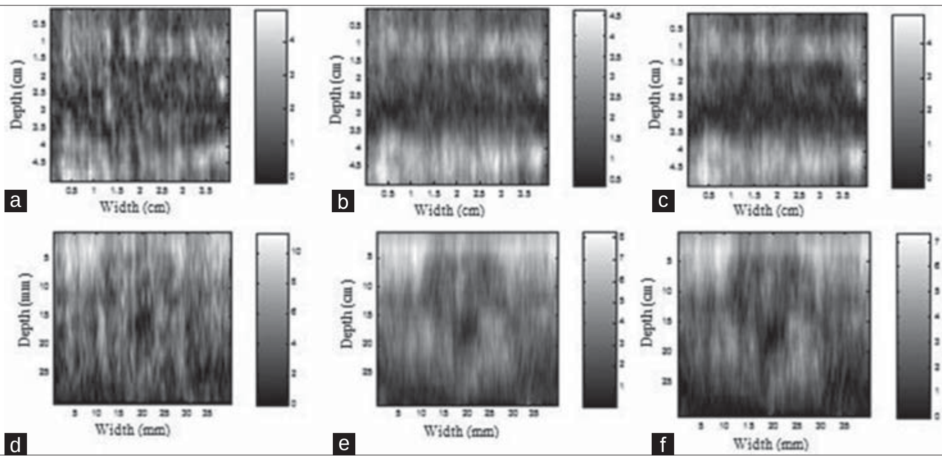

Figure 8: Wavelet method: Elastograms from first dataset (a) Before empirical mode decomposition (EMD) elastogram (b) After EMD elastogram: averaging of strain images (c) After EMD elastogram: Differentiating of averaged displacement matrixes, Elastograms obtained from second dataset d) Before EMD elastogram (e) After EMD elastogram: Averaging of strain images (f) After EMD elastogram: differentiating of averaged displacement images

to their IMFs by EMD algorithm and these IMFs are used up to make an elastogram. In order to get better results, different combinations of IMFs and also the effect of high, middle and low IMFs were tested. Among all different tested conditions, whenever the combinations contained middle IMFs specially third and fourth IMFs, the SNR and CNR will improve and the resulted elastogram will have better visual quality. It means that the area that has different strain is better recognized. However, the idea that yields the best result was averaging. It means that using the first IMF of pre compression RF signal and first IMF of the post compression a displacement matrix is calculated. Similarly from each IMF of pre compression signal and its corresponding IMF from post compression signal a displacement matrix is calculated. Now two works can be done. One is differentiate from each displacement matrix to make an elastogram from each IMF and then averaging these elastograms to make the final one. Second is averaging the displacement matrixes and differentiating of averaged matrix to make final elastogram. To implement these ideas two estimating techniques, cross-correlation and wavelet transform and also two different datasets were selected. Calculations of CNR and SNR and also visual comparison of resulted elastograms show that in both techniques and both datasets after using EMD the results will improve. To continue and complement this work it is suggested to choose other estimating methods to implement the idea for them. For example angular strain estimation[13] or method that estimates the displacement from phase change[4] are interesting to test the idea on them. It is recommended to select other datasets that their stiffer area is smaller. One of the best datasets to achieve this goal is data that is acquired from HIFU lesions. In the other word, it is interesting to know is the idea helpful for HIFU monitoring or not.

CONCLUSION

It was shown that using EMD analysis for strain estimating can resulted in getting better elastograms and leading an improvement in values of CNR and SNR parameters.

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BIOGRAPHIES

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Jahan Tavakkoli obtained a BSc degree in Electrical Engineering and a MSc degree in Biomedical Engineering, both from Sharif University of Tech., Tehran, Iran. He obtained a PhD degree with the highest honors in Biomedical Physics from University of Lyon-1, and research laboratory of INSERM, Unit 556, Lyon, France, in 1997. He also completed a post-doctoral fellowship in Biomedical Engineering at University of Toronto, Toronto, Canada, in 1998. He has over 20 years of professional experience in both academia and industry in biomedical applications of ultrasound in therapy and imaging, and in ultrasound modeling and simulation. He has been holding R and D positions in several leading high-tech medical device companies including: Focus Surgery Inc., Indianapolis, IN; Visualsonics Inc., Toronto, Canada; and Guided Therapy Systems LLC, Mesa, AZ. He is currently an Assistant Professor in Dept. of Physics, Ryerson University, Toronto, Canada, and an Affiliate Scientist in Keenan Research Center, St. Michael's Hospital, Toronto, Canada. Most of Dr. Tavakkoli's research and development projects have been funded by grants from federal and provincial funding agencies, and by medical devices industry (NIH, NSERC, ORF-RE, etc.). He is the co-founder and co-director of "Advanced Biomedical Ultrasound Imaging and Therapy Laboratory" in the Dept. of Physics of Ryerson University. Dr. Tavakkoli is an active member of several professional scientific societies including: IEEE Ultrasonics, Ferroelectrics, and Frequency Control; IEEE Engineering in Medicine and Biology; Acoustical Society of America; Canadian Acoustical Association; International Society for Therapeutic Ultrasound; and Ultrasonic Industry Association. Among other positions, he is the Associate Editor, Journal of Medical Physics; the Associate Editor, Bio-acoustics, Journal of Canadian Acoustics; and the Member of Technical Committee, Biomedical Ultrasound/Bioresponse to Vibrations, Acoustical Society of America. He has published over 80 scientific papers in peer-reviewed journals and international conferences in the areas of biomedical ultrasound therapy and imaging.

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