Original Article

High-Intensity Focused Ultrasound Lesion Detection Using Adaptive Compressive Sensing Based on Empirical Mode Decomposition

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Abstract

Background: The main goal of ultrasound therapy is to have clinical effects in the tissue without damage to the intervening and surrounding tissues. Treatments have been developed for both in vitro and in clinical applications. HIFU therapy is one of these. Non-invasive surgeries, such as HIFU, have been developed to treat tumors or to stop bleeding. In this approach, an adequate imaging method for monitoring and controlling the treatment is required. **Methods:** In this paper, an adaptive compressive sensing representation of ultrasound RF echo signals is presented based on empirical mode decomposition (EMD). According to the different numbers of intrinsic mode functions (IMFs) produced by the EMD, the ultrasound signals is adaptively compressive sampled in the source and then adaptively reconstructed in the receiver domains. In this paper, a new application of compressive sensing based on EMD (CS-EMD) in the monitoring of high-intensity focused ultrasound (HIFU) treatment is presented. Non-invasive surgeries such as HIFU have been developed for various therapeutic applications. In this technique, a suitable imaging method is necessary for monitoring of the treatment to achieve adequate treatment safety and efficacy. So far, several methods have been proposed, such as ultrasound radiofrequency (RF) signal processing techniques, and imaging methods such as X-ray, MRI, and ultrasound to monitor HIFU lesions. **Results:**In this paper, a CS-EMD method is used to detect the HIFU thermal lesion dimensions using different types of wavelet transform. The results of the processing on the real data demonstrate the potential for this technique in image-guided HIFU therapy. **Conclusions:** In this study, a new application of compressive sensing in the field of monitoring of the HIFU treatment is presented. To the best of our knowledge, so far no studies on compressive sensing have been carried out in the monitoring of the HIFU. Based on the results obtained, it was showed that the number of measurements and Intrinsic Mode Functions have the function of noise reduction. In addition, results were shown that the successful reconstruction of the compressive sensing signals can be gained using a threshold based algorithm. To this end, in this paper it was shown that by selecting an suitable number of measurements, the sparse transform, and a thresholding algorithm, we can achieve a more accurate detection of the HIFU thermal lesion size.

Keywords: *Compressive sensing, empirical mode decomposition, high-intensity focused ultrasound, radiofrequency signal, sparse representation, wavelet transform*

Introduction

Ultrasound therapy is a field with many clinical applications. The main goal of ultrasound therapy is to have clinical effects in the tissue without damage to the intervening and surrounding tissues. Treatments have been developed for both *in vitro* and in clinical applications. High-intensity focused ultrasound (HIFU) therapy is one of these. HIFU exposures create lesions of therapeutic benefit in tissue through rapid temperature elevation in the focal region. Noninvasive real-time HIFU thermal lesion detection and monitoring are keys to the success and widespread usage of this technique in clinical applications. The ideal thermal lesion detection and monitoring method must possess desired characteristics to provide accurate real-time localization of the tissue target region and to differentiate quantitatively between the areas of thermal coagulation and surrounding nontreated tissue.

The advantages of this noninvasive technique are its ability to penetrate deep tissue in the body and give the amount of heat or mechanical energy specific to the tissue. In this method, due to the presence of blood capillaries that act as heat wells and surface fat layers which divert ultrasound beams, this system requires suitable monitoring methods to solve both these problems and improve the performance

How to cite this article: Ghasemifard H, Behnam H, Tavakkoli J. High-intensity focused ultrasound lesion detection using adaptive compressive sensing based on empirical mode decomposition. J Med Signals Sens 2019;9:24-32.

Received: April, 2018. **Accepted:** October, 2018.

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DOI: 10.4103/jmss.JMSS_17_18

of the treatment.[1,2] So far, several methods have been proposed such as radiofrequency (RF) signal processing techniques and imaging methods such as X-ray, magnetic resonance imaging (MRI), and ultrasound to monitoring HIFU lesions.[3-6] MRI allows tissue contrast for localization of target volume, characterization of diffusion, temperature detection, and enabling detection of tissue damage. However, low image acquisition speeds (low temporal resolution) and high costs have restricted the use of MRI for HIFU treatment monitoring. One of the techniques based on ultrasound, developed so far in the field of HIFU monitoring, is measuring the acoustic characteristics of the tissue using ultrasound RF echo signals, which is based on processing backscattered RF signals from the region of interest (ROI) in tissue for estimating the tissue characteristics in that region. Quantitative tissue properties such as coefficient of attenuation, nonlinear parameter (B/A), speed of sound, and tissue vibration are calculated in these methods.[3,7,8] Coussios *et al*. indicated that focal cavitation activity could lead to an increment in the tissue acoustic absorption and further enhance treatment efficacy.[9] However, this process can be effectively used to monitor the HIFU. A variety of different ultrasound-based techniques have been developed to noninvasively monitor therapy progress by estimating changes in temperature.[10] However, these temperature tracking methods were developed under treatment conditions employing subablative intensities and the range of temperature rise was limited to a maximum of 10°C–20°C above body temperature.

In another work, Chen[11] indicated that the harmonic motion imaging, a method based on tracking tissue vibrations caused by acoustic radiation force, can be used for determining tissue elasticity toward controlling and monitoring HIFU treatment. In recent years, researchers have shown that an optoacoustic imaging technique can be used as a real-time and noninvasive. In a different work, Chen[11] indicated that the harmonic motion imaging, a technique based on tracking tissue vibrations caused by acoustic radiation force, can be used for determining tissue elasticity toward controlling and monitoring HIFU treatment. In recent years, researchers have shown that an optoacoustic imaging method can be used as a real-time and noninvasive method for determining the optical characteristics of the tissue during HIFU therapy. In a paper, Adams *et al*.[12] indicated that this methods is especially suitable for monitoring nonbubble thermal HIFU lesions with a minimal acoustic contrast. In another work, Alhamami *et al*.[13] showed quantitative measurements of optical properties of a coagulated HIFU thermal lesion versus a native untreated tissue and demonstrated an approximately fourfold increase in the amplitude of the optoacoustic signal generated in a HIFU-induced thermal lesion versus a native untreated tissue. method for determining the optical characteristics of the tissue during HIFU therapy. In a study, Adams *et al*.[12] indicated that this method is especially appropriate for monitoring nonbubble thermal HIFU lesions with a minimal acoustic contrast. In another paper, Alhamami *et al*.[13] showed quantitative measurements of optical properties of a coagulated HIFU thermal lesion versus a native untreated tissue and demonstrated an approximately fourfold increase in the amplitude of the optoacoustic signal generated in a HIFU-induced thermal lesion versus a native untreated tissue.

In the present study, compressive sensing based on empirical mode decomposition (CS-EMD) method is proposed to improve the monitoring of HIFU lesioning. In recent years, we have witnessed the ever-increasing use of CS and sparse representation concepts in various signal processing applications. To the best of our knowledge, so far, no research has been conducted to use CS and sparse representation in the monitoring of HIFU and only a few research works have been done on reconstruction of ultrasound signals or images using compressive sampling. Recently, a signal processing method suitable for nonlinear and nonstationarity data series, the EMD, has been proposed by Huang *et al*.[14] This method has already received much more attention and has been applied to many areas, such as the biological and physiological signals,[15] voiced speech signals,[16] and the fault diagnosis.[17] It performs a time-adaptive decomposition of a complex signal into elementary, almost orthogonal components that do not overlap in the frequency. EMD can be as a nonlinear filter in time domain. EMD filter can remove unwanted noise of short periods and leave fundamentals unchanged. In this study, a new application of CS in the field of monitoring of HIFU is presented. In the past, we worked on the CS based on the threshold algorithm. The results of the study showed that the modified CS method could effectively detect HIFU thermal lesions *in vitro*.[18] In the current work for enhancement of lesion detection, a new application of CS-EMD is presented. One method of multidecomposition that does not require preselection functions unlike wavelet transform is the EMD method. This algorithm was first introduced by Huang *et al.* for the decomposition of nonstationary signals that in this method, the fundament of decomposition is based on the extremum points of a signal and the extraction of its intrinsic mode functions (IMFs). In fact, there are two main reasons for combining CS-EMD method. First, the EMD method decomposes each RF echo signal into separate frequency components, and then, by applying the thresholding algorithm to sparse space of the IMFs, it can be expected that when we reconstruct the signal from these coefficients, the noise is significantly reduced. Second, using the EMD method, a sparse presentation of the signal is obtained, so the efficiency of the CS approach increases in signal reconstruction. In this paper, we present an adaptive CS scheme of RF echo signals based on EMD.

Based on this new method, called the compressive sensing, for signals and images with the possibility of sparse representation, one can attain reconstruction of these signals with good quality via incoherent measurements. The number of these measurements can be much less than the number of samples commonly taken in the traditional sampling method (known as the Nyquist rate), which has been developed in the area of information theory and signal processing. In recent years, we have witnessed increasing development of utilizing the concept of CS and sparse representation in various signal and image processing applications, including pattern recognition and machine vision.[18-21]

Generally, signal reconstruction from compressive measurements is done by optimization algorithms. In many engineering applications, the signal is contaminated with a variety of noises. Noise does not only corrupt the signal but also has an effect on the reconstructed signal. To this end, CS theory can be introduced as a method for reducing noise if the sparse space of the signal is known.[22,23] In this study, all experiments and results were performed in *ex vivo* porcine muscle tissue. Simulation results show the effectiveness of the proposed method in the detection of HIFU thermal lesion. This article has been organized as follows. In Materials and Methods, the content of the data acquisition and the CS-EMD method are presented, and in Suggested Method, the proposed algorithm is presented. The results of simulations and conclusions are presented in Results and Discussion and Conclusion, respectively.

Materials and Methods

Ultrasound radiofrequency echo data acquisition and high-intensity focused ultrasound systems

Data used for analysis in this work are achieved in the Advanced Biomedical Ultrasound Imaging and Therapy Laboratory, in the Department of Physics at Ryerson University, Toronto, Canada.[8] To gather the necessary information, HIFU exposures were performed on porcine muscle tissue *in vitro*. An ultrasound imaging system (Sonix RP scanner, Ultrasonix Inc., Richmond, BC, Canada), with an endocavity array probe of 128 elements, operating at a center frequency of 7 MHz and bandwidth of 3 MHz, was used to record B-mode images and RF backscattered data.[18]

Detailed description of the image-guided HIFU system used in this work has been given elsewhere.[8] A typical HIFU exposure used in this paper was 40 s of 45W acoustic power delivered with a 77% duty cycle. The HIFU exposures induced thermal lesions in the pork muscle tissue *in vitro*. The RF data frames were captured before, during, and 10 min after each HIFU exposure. All RF data processing and image formation were performed in the Cartesian system of coordinates. Each image frame included 70 RF lines, and each line contained 4680 samples equal to 90.1 mm tissue depth. The data acquisition sampling frequency was 40 MHz.[18] The total HIFU treatment time was 40 s for total acoustic power (TAP) levels of 34, 37, 39, 44, and 49 W. Figure 1 illustrates the thermal lesions induced at TAPs ranging from 34 to 49. As illustrated in

Figure 1: Tissue slices revealing high-intensity focused ultrasound lesions in their middle parts at acoustic powers of 34, 37, 39, 44 and 49 W

Table 1: Total acoustic powers and ISA calculated at corresponding input electric power levels

Input electric power (W)	Total acoustic power (W)	ISA (W/cm^2)
70	34	737
75	37	801
80	39	845
90	44	961
100	49	1068

Figure 1, the depth of lesions from the tissue surface was measured. For the HIFU transducer, the free-field (in water) spatially averaged intensity, I_{SA}, was computed by[24]

$$I_{SA} = 0.867\frac{P}{D^2} \tag{1}$$

Where P was the TAPs measured using the calibrated acoustic power meter at the surface of the transducer and D is the focal beam width at full width at half maximum (FWHM) measured using the calibrated hydrophone. Table 1 shows a summary of the input electric powers with the corresponding TAP values and free-field spatially averaged intensities. I_{SA} was estimated using Eq. 1 for a duty cycle of 77% and maximum beam width at FWHM of 2 mm.

Compressive sensing

The traditional method of reconstructing signals and images from measured data is based on the Shannon–Nyquist sampling theory, according to which the minimum number of samples necessary for sampling to reproduce without error from the signal is twice the maximum frequency in the sample. This theory is the mainstay of most of the existing technology equipment, including analog-to-digital converters, medical imaging devices, or electronics, and video and audio equipment. The new CS theory, also known as compressive sampling, essentially provides a new method for data collection and replaces the Shannon method. This technique was introduced in 2006 to reconstruct signals that have samples less than the Nyquist rate.[23] It claims that an unknown sparse signal could be reconstructed with a number of measurements below the Nyquist rate. In fact, the CS theory uses a Ψ transformation matrix and a randomized matrix Φ for every sparse signal (x) to obtain a vector of samples for y.[23,25] In mathematical terms,

$$y_{n\times1} = \Phi_{n\times m} x_{m\times1} = \Phi_{n\times m}\Psi_{m\times m}\theta_{m\times1} = A_{n\times m}\theta_{m\times1} \tag{2}$$

Where $\theta = \Psi^{-1}x$ is the sparse representation of *x*, with the assumption that the signal *x* is k sparse and *x* is a vector with at most k nonzero elements. In solving Eq. 1, one might consider having infinite number of solutions for the reconstruction of vector *x* from *y*, since the number of equations, *n*, is less than the number of variables, *m*. However, an initial knowledge of the sparse signal, which is applicable in many cases, limits the set of solutions, and L1-norm minimization (basis pursuit) and reverse conversion, making the reconstruction feasible. There are many algorithms for finding solutions to a sparse set of over-complete equations, including matching pursuit algorithms, which are fast, but inaccurate, and the family of basic pursuit algorithms, which are developed based on L1-norm minimization to obtain the solution to the sparse equations as shown by

$$\operatorname{argmin} \|\theta\|_{L_1} \text{ s.t } y = \Phi\Psi\theta \tag{3}$$

Where the L_1 norm is $\theta_{L_1} = \sum_{i=1}^{n} |\theta_i|$.

This family of algorithms is more accurate than matching pursuit algorithm but has more computational complexity.[23]

Empirical mode decomposition

The EMD method is proposed for the first time in fluid mechanics and is used in various fields of signal processing. The main idea of this method is based on the decomposition of the main signal on a series of bases obtained from the original signal. If the signal is decomposed in terms of the Fourier series, the basic foundations are linear in terms of sinusoidal and cosine functions, which are true only for linear signals. In the EMD method, the bases are nonlinear and they come straight from the main information. In other words, we can use an IMF, provided that it is an IMF signal that[14] (i) in the whole data set, the number of extrema and the number of zero crossings must be same or differ at most by one, and (ii) at any point, the mean value of the envelope defined by the local maxima is zero.

The steps to get the IMF from the signal X(t) are as follows: Step 1: First, two soft splines are drawn up to connect each and every one of the maximum and minimum points. Thus, the upper and lower extremities are obtained by $X_{UP}(t)$ and $X_{low}(t)$, respectively. Step 2: To reduce the average of the two of the main signals until the X(t) signal is obtained.

$$X_L(t) = X(t) - (X_{UP} + X_{low})/2 \tag{4}$$

Step 3: Repeat Steps 1 and 2 for the signal $X_L(t)$ until the signal obtained meets the IMF criteria. Performing these three nonlinear and nonstationary signal operations is known as sifting. Therefore, after repeating Steps 1 and 2 on the signal X(t) repeatedly, the signal $C_L(t)$ is obtained that satisfies the two conditions of the IMF. The signal $C_L(t)$ is called the first IMF signal X(t), which has a mean value of zero. The remaining $R_L(t)$ (t) = X(t) − $C_L(t)$ is also obtained as new information for the IMF.[14] The steps are repeated until the domain is less than a predetermined level or that the remainder of the oscillating state is exited. To reconstruct the X(t) signal, we can use the following equation:

$$X(t) = \sum_{I=1}^{N} C_j(t) + R_N(t) \tag{5}$$

Where N is the number of bases of the IMF and $R_N(t)$ of the final remaining, which can be either trend or fixed. The functions $C_j(t)$ are, in addition to the orthogonality, of the mean zero. In this method, the signal is decomposed into a main N, each of which has a different timescale. In other words, the first one is the smallest time scale that relates to the fastest changes in the original signal. When the parsing signal operation goes ahead, the time scale increases. Therefore, the average frequency is also reduced, because this kind of analysis is based on local information on a time scale and the bases are obtained comparatively, this method can be used for nonstationary signals.

Suggested Method

In our suggested method, using the EMD algorithm, the RF echo signal is decomposed into a number of IMFs, then, by applying the thresholding algorithm to the IMFs sparse coefficients in the CS algorithm, the RF signal is reconstructed. In the proposed method, each of IMF is considered as a signal, and using the CS, the reconstruction of the IMFs is done separately. Sparsity has important role for the quality of CS and we must design a set of dictionaries to make the RF signal be sparse. For example, wavelet transform is a very suitable tool for representing ultrasound signals. When ultrasound signal is wavelet transformed, we will observe the sparsity: Most of the wavelet coefficients are very small and they can be discarded without too much effects on the reconstruction of ultrasound signal. To improve the wavelet property, we can decompose the ultrasound signal into IMFs with EMD. Since EMD is a dyadic filter bank, the different IMFs have their own characteristics and so can be transformed separately.

An example of RF echo signal decomposition is shown in Figure 2. Figure 2 indicates RF signal and its eight IMFs. The sparsity of IMFs coefficients is obvious. In the proposed method, with regard to the structural difference of the lesion area with other areas and the increase in the amplitude of the ultrasound backscattered signals in the lesion area and the reduction of noise of the proposed method, the accuracy of the diagnosis of the lesion region improves. In the proposed algorithm, a random sampling matrix, various wavelet transforms, and the basis pursuit (L1-minimization) reconstruction algorithm, are used.[23]

In this technique, universal thresholding been used to determine the threshold level. This type of thresholding uses a constant threshold method[26] which can be calculated by

$$\mathrm{THR}_{\mathrm{UNI}} = \sigma\sqrt{2\log(\mathrm{N})} \tag{6}$$

Where N denotes the number of sampling point in one scale and σ is the noise variance, which can be used to estimate noise when the information is not primarily available about noise. One of the most important and most widely used estimators is the median absolute deviation estimator, which is given in[26]

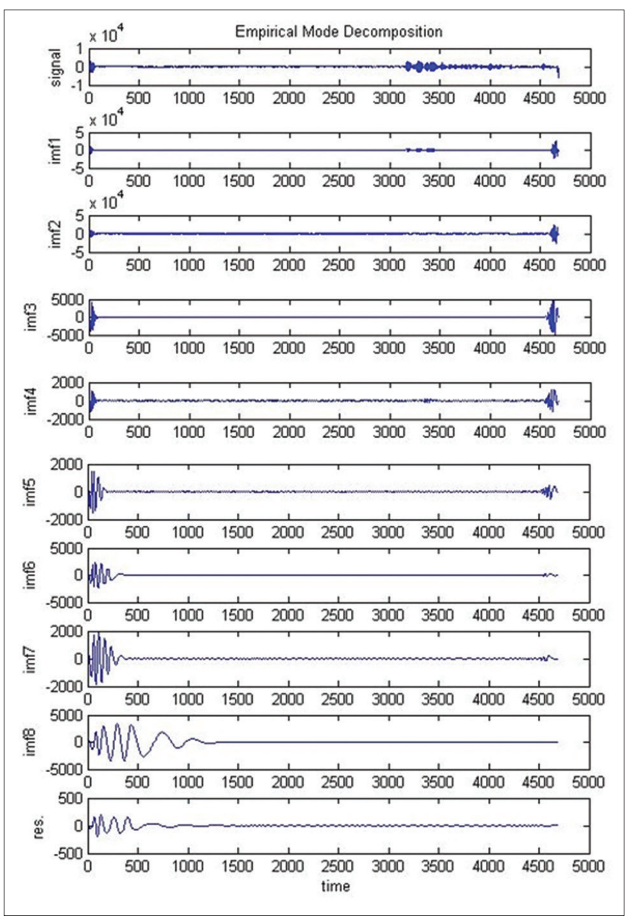

Figure 2: A ultrasound signal and its eight intrinsic mode functions

$$\left|\sigma = \mathrm{median}\left(\left|\mathrm{cD_j}\right|\right)/\,0.6745\right| \tag{7}$$

Where cD_j is the high-frequency coefficient on the scale of the *j* level and the coefficient of normalization is 0.6745. After setting threshold values, then the soft threshold function can be applied to the wavelet transform coefficients.

First, all of the high-frequency coefficients whose values of the magnitudes are lower than the thresholds are taken to be equal to zero, and then, other coefficients are squeezed around zero so that the threshold value of the coefficients is lower than that.[26] This is expressed as follows

$$\mathrm{cD_j} = \begin{cases} \mathrm{sgn}\left(\mathrm{cD_j}\right)\left(\mathrm{cD_j}\text{-}\mathrm{THR_j}\right) & \text{if } \left|\mathrm{cD_j}\right| > \mathrm{THR_j} \\ 0 & \text{Otherwise} \end{cases} \tag{8}$$

Where cD_j is values of coefficients in scale j and THR_j is the threshold level.

In this work, a set of recorded data has been used to demonstrate the effectiveness of the proposed method for monitoring HIFU lesioning. In this study, all experiments

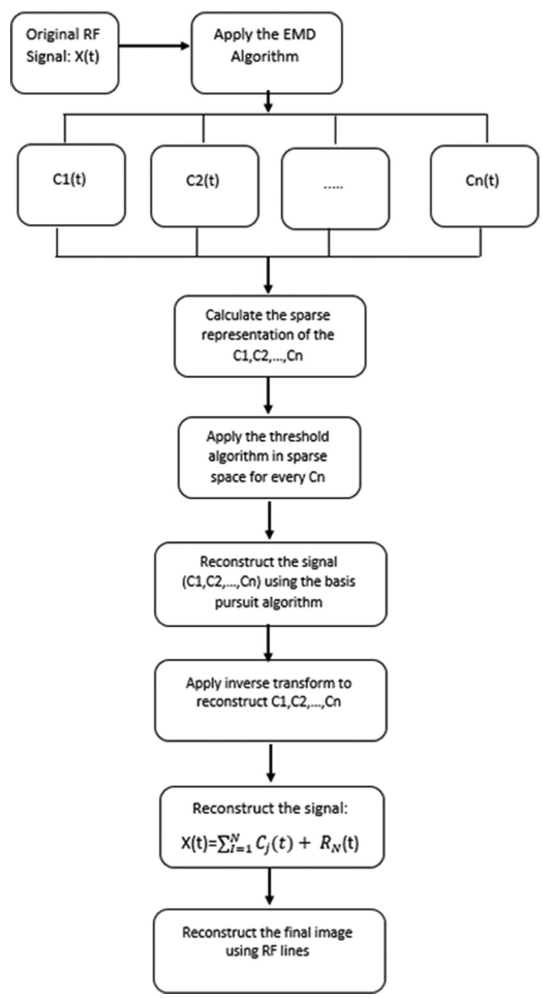

Figure 3: Block diagram of the proposed algorithm

were performed in *ex vivo* porcine muscle tissue. The block diagram of the proposed algorithm is shown in Figure 3.

Results

In this section, the processing results are shown on a set of posttreatment data with acoustic powers of 34, 37, 39, 44, and 49 W. To study the effects of changing the TAP of the HIFU transducer, 18 lesions were created with different TAPs. Table 2 shows the lesion numbers and related acoustic powers. The first frame of each data acquisition (post-HIFU B-mode images) has been used for processing. The ROI in this frame was separated for processing.

Table 3 compares the detected size of lesion (depth × length) with the actual size of the lesion from physical examination

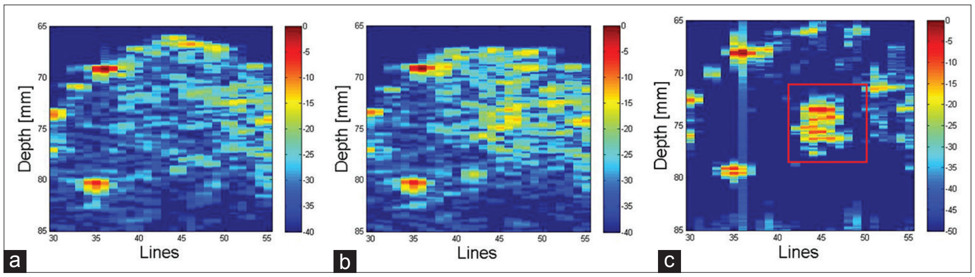

Figure 4: Results related to Tissue#4: Lesion#3: (a) pre-high-intensity focused ultrasound, (b) post-high-intensity focused ultrasound exposure, and (c) proposed algorithm image using 85 % of the data in total acoustic power of 34 W and average focal intensity of 737 W/cm2 at the high-intensity focused ultrasound treatment site

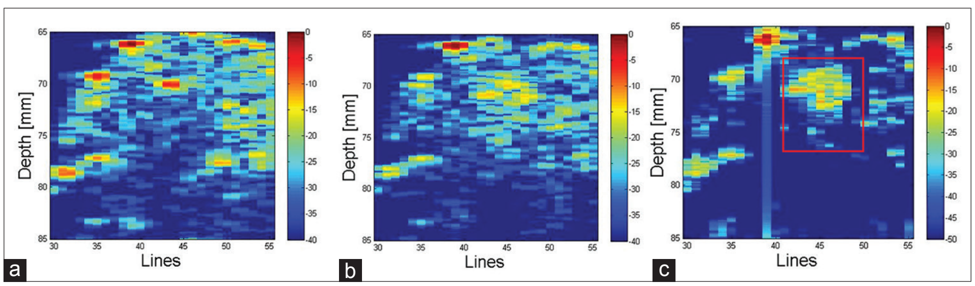

Figure 5: Results related to Tissue#6: Lesion#3: (a) pre-high-intensity focused ultrasound, (b) post-high-intensity focused ultrasound exposure, and (c) proposed algorithm image using 85 % of the data in total acoustic power of 37 W and average focal intensity of 801 W/cm2 at the high-intensity focused ultrasound treatment site

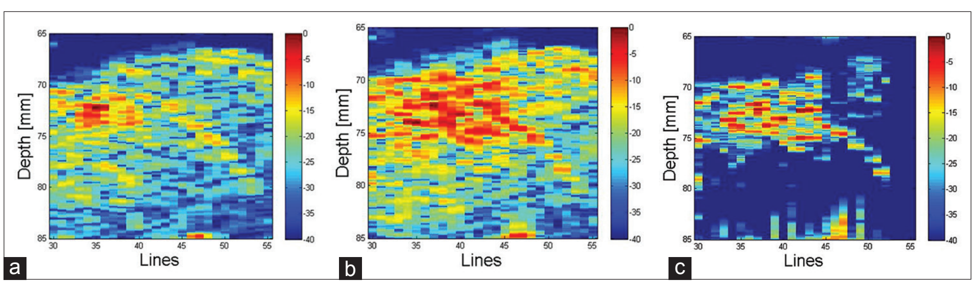

Figure 6: Results related to Tissue#1: Lesion#2: (a) pre-high-intensity focused ultrasound, (b) post-high-intensity focused ultrasound exposure, and (c) proposed algorithm image using 85 % of the data in total acoustic power of 39 W and average focal intensity of 845 W/cm2 at the high-intensity focused ultrasound treatment site

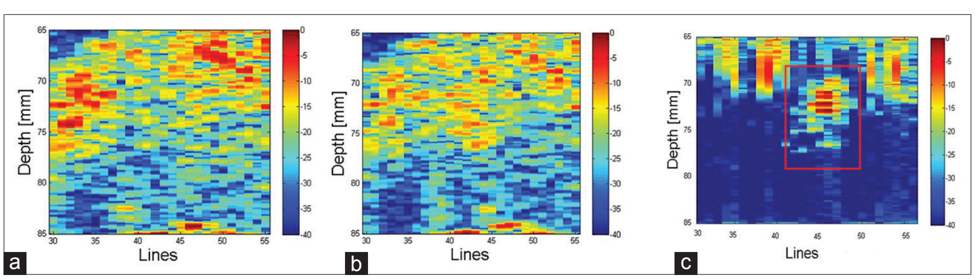

Figure 7: Results related to Tissue#2: Lesion#2: (a) pre-high-intensity focused ultrasound, (b) post-high-intensity focused ultrasound exposure, and (c) proposed algorithm image using 85 % of the data in total acoustic power of 44 W and average focal intensity of 961 W/cm2 at the high-intensity focused ultrasound treatment site

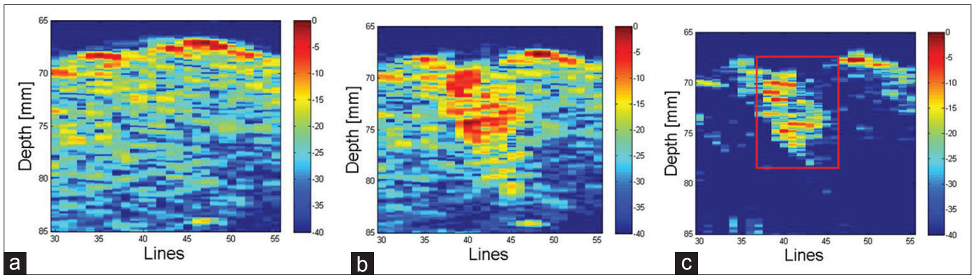

Figure 8: Results related to Tissue#3: Lesion#1: (a) pre-high-intensity focused ultrasound, (b) post-high-intensity focused ultrasound exposure, and (c) proposed algorithm image using 85 % of the data in total acoustic power of 49 W and average focal intensity of 1068 W/cm2 at the high-intensity focused ultrasound treatment site

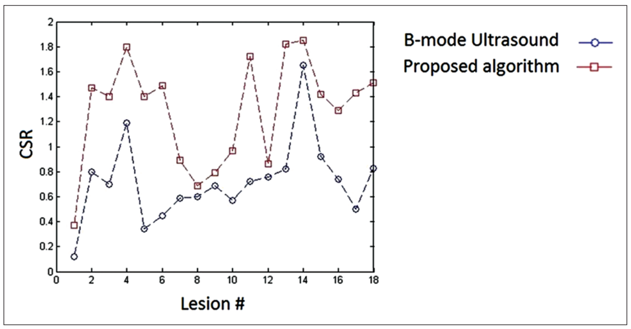

Figure 9: The estimated contrast-to-speckle ratio values of B-mode imaging and the proposed method for detecting 18 thermal lesions induced by high-intensity focused ultrasound

using the proposed method. After processing all acquired data, the tissue was cut and unfolded from middle. Figure 1 shows the depth and the length of the lesions and transducer is set such that it presents an image to a depth of 9 cm and its focus was set at 8 cm, since the lesion occurred at this depth. According to Figure 1, the actual size of the thermal lesion was measured from the experimental results.

It is seen that this method can effectively detect the actual lesion. Figures 4-8 show the results of processing on lesions with acoustic powers of 34–49 W. These figures can be compared with the lesions identified in Figure 1. By increasing the acoustic power, the lesions are clearer in figures. It should be noted that the images in figures are in the Cartesian system of coordinates. As seen in the figures, the proposed algorithm can detect the lesion area with good accuracy at acoustic powers of 34–49 W. As shown in Figure 6, the proposed algorithm cannot detect the lesion area with good accuracy for acoustic power of 39 W. In fact, there are two main reasons for it. First, there are artifacts near the boundary and also at the bottom of the lesion which is due to tissue vibration that generally happens at the time of ultrasound data recording. Second, various studies show that sometimes after the creation of lesions, shadow regions right behind the induced lesions were expected to appear. The reason lied in the fact that the lesions represented high attenuation regions (with respect to the surrounding normal tissue) surrounded by normal tissue. Consequently, all the backscattered ultrasound pulses coming from the regions right behind the lesions would have to travel through the lesions (high attenuation regions) as well and therefore be attenuated resulting in shadow regions.

The best result of simulation on lesions shows that the proposed method based on the soft threshold method with universal threshold parameter and wavelet transform of db4 can detect the actual size of the lesion with a good accuracy. Comparing the estimated size of the thermal lesion using the proposed method with the estimated size obtained[8] (for the same data) shows that this method will be better.

For quantitative comparison of the B-mode image with the reconstructed image using the proposed algorithm, contrast-to-speckle ratio (CSR) parameter, according to the definition given in Eq. 9, was used.[27]

$$\mathrm{CSR} = \frac{S_0 - S_i}{\sqrt{\sigma_0^2 + \sigma_i^2}} \tag{9}$$

Where S_i is the average measured signal inside the cyst and S_o is the average measured signal outside the cyst, and σ_0^2 and σ_i^2 are the signal variances outside and inside the cyst, respectively. The absolute values of CSR computed for 18 lesions are shown in Figure 9. The estimated CSR values using the proposed algorithm are significantly larger than those obtained from B-mode images. These results show that using EMD-based CS, the HIFU thermal lesion detection contrast is significantly higher than the B-mode image.

Discussion and Conclusion

In this study, a new application of CS in the field of monitoring of the HIFU treatment is presented. To the best of our knowledge, so far, no studies on CS have been carried out in the monitoring of the HIFU. Based on the results obtained, it was showed that the number of measurements and IMFs have the function of noise reduction. In addition, results were shown that the successful reconstruction of the compressive sensing signals can be gained using a threshold based algorithm. The results of simulations on different data indicated that the conventional CS technique is not as accurate as the proposed algorithm in detecting the thermal lesion area, because the standard CS method only estimates the main image with a limited ability with regard to noise reduction.

Table 2: Lesion numbers and corresponding total acoustic powers

	Lesion																	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Total acoustic power (W)	34	34	34	37	37	37	37	37	37	39	39	39	39	44	44	44	49	49

Table 3: Detected size of high intensity focused ultrasound induced-lesion using proposal method

Total acoustic power (W)	Lesion	Actual lesion size (mm × mm)	Measured lesion size (mm × mm)	Deviation from actual size (%)
34	Tissue #4:Lesion #3	8.1×8	7.9×7.3	0.2×0.7
37	Tissue #6:Lesion #3	7.9×7.8	5.4×6.6	2.5×1.2
39	Tissue #1:Lesion #2	7×6.9	-	-
44	Tissue #2:Lesion #2	10.1×9	8.3×8.4	1.8×0.6
49	Tissue #3:Lesion #1	9×8	8.2×7.3	0.7×0.7

In the EMD method, due to the lack of strong mathematical principles, it is difficult to predict the behavior of the algorithm on different signals. Furthermore, since this algorithm is based on the use of extremum points, so these points are strongly affected by noise and sampling. As a conclusion the proposed work of the future, we can use the combination of CS and variational mode decomposition to further improve the performance of the EMD method for monitoring the HIFU.[28]

To use the proposed method for monitoring the HIFU treatment *in vivo*, the vibration of tissue due to ultrasound radiation and the effects of blood flow that create significantly different backscattering characteristics than soft tissues should be considered. In addition, the CS method (given the need to reduce the amount of data required and to increase the speed of data acquisition) can be used for higher dimensional data such as three-dimensional (3D) and 4D ultrasound.

Acknowledgments

We thank P. Rangraz from Department of Biomedical Engineering, Islamic Azad University, Tehran, Iran, for her help in data processing.

Financial support and sponsorship

None.

Conflicts of interest

There are no conflicts of interest.

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