Microwave-Induced Thermal Acoustic Tomography for Breast Tumor Based on Compressive Sensing

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Abstract—Microwave-induced thermal acoustic tomography (MITAT) is an innovative technique to image biomedical tissues based on their electric properties. It has the advantages of both high contrast and high spatial resolution. Image reconstruction method in MITAT is always a critical issue. In this paper, a CS-MITAT (CS: compressive sensing) imaging method is proposed. Compressive sensing (CS) is a recently developed sparse signal representation and analysis framework which handles medical imaging measurements using low sampling rate or increasing imaging quality. The CS-MITAT imaging method applies CS theory to the MITAT for breast tumor imaging. In this method, an over-complete dictionary is established to make sparse measurements in the spatial domain. This treatment greatly saves measurement time. Simulations and experiments with real breast tumor tissues demonstrate the feasibility and effectiveness of the method. Compared with conventional time reversal mirror method which has been used in MITAT research, CS-MITAT provides the same peak signal-to-noise ratio imaging quality by using significantly fewer acoustic sensor positions or scanning times.

Index Terms—Breast tumor, compressive sensing, medical imaging, microwave-induced thermal acoustic tomography (MITAT).

I. INTRODUCTION

BECAUSE the stage of breast cancer has a greater effect on the prognosis than the other considerations, detection of early stage breast cancer is most important. The lower the stage at diagnosis, the better the prognosis will be [1]. To achieve an earlier diagnosis, breast cancer screening tests otherwise-healthy women for breast cancer. A number of screening tests have been employed, including clinical and self-breast exams, mammography, genetic screening, ultrasound, and magnetic resonance imaging. The first two methods are currently widely used at diagnosis, the better the prognosis will be [1]. To achieve an earlier diagnosis, breast cancer screening tests otherwise-healthy women for breast cancer. A number of screening tests have been employed, including clinical and self-breast exams, mammography, genetic screening, ultrasound, and magnetic resonance imaging. The first two methods are currently widely used due to their advantages of the price and the feasibility. However, clinic and self-breast exams are very subjective and usually cause misdiagnosis [1]. Mammographic screening uses x-rays to examine the breast for any uncharacteristic masses or lumps. The Cochrane Collaboration in 2011 concluded that mammograms reduce mortality from breast cancer by 15% but also result in unnecessary surgery and anxiety; along with the risks of more frequent x-rays exposure include a small but significant increase in breast cancer induced by ionizing radiation [2]–[4].

Microwave-induced thermal acoustic tomography (MITAT) is an innovative technique for tumor detection. It employs modulated microwave pulses (no ionizing radiation) to irradiate biological tissues [5]. Due to the contrast in the absorption coefficient between tumor and background medium, the consequent thermal expansion caused by heating effect induces an acoustic wave at the position of the tumor. In the breast environment, the background tissue (normal breast tissue) is fat and lobules, which has much lower blood ratio than tumors. Malignant tumors can have distinct permittivity and electrical conductivity ten times higher than the surrounding normal tissues at some specific microwave frequencies such as L or S band [5]–[7]. This is the physical foundation of MITAT. For MITAT, a microwave pulse is used as an irradiating signal to provide a high contrast in thermal expansion between normal and malignant tissues. The induced acoustic pulse is acquired as a received signal at an ultrasound transducer to guarantee high spatial resolution. The high quality image of the tissue absorption properties can be reconstructed from the recorded thermal acoustic signals. Fig. 1 is a sketch map of a typical MITAT system for detecting breast tumor. An MITAT system requires many critical techniques, one of them being the imaging method. MITAT has been widely researched. In 1984, Guo et al. introduced thermo dynamical process [8]. Lin et al. built a prototype of 2-D imaging system for biological tissue [9]–[11]. In 2002, Fernandez et al. used ultrasound array and adaptive imaging method to improve the image quality [12]. Xu and Wang proposed a filtered backprojection imaging method [13]. In 2004, Xu and Wang applied

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Fig. 1. Sketch map of MITAT system for breast tumor.
time reversal imaging method on MITAT [14]. Liu proposed the pseudospectral time domain (PSTD) algorithm for acoustic waves [15], and the spectral element method [16] for MITAT. Time reversal mirror (TRM) imaging method with PSTD was applied in MITAT, which gave out much better contrast than back projection (BP) method [17].

All these methods perform coherent summation of sensor data. They require both intensive spatial sampling and temporal sampling to improve resolution, resulting in a long data acquisition time. During the detection period, the patients must hold steady, because their movements will cause smearing and blurring in the processed image. Long time staying will make the patients very uncomfortable. Moreover, longer sampling time means more microwave radiation. Therefore, decreasing the acquisition time is very important in MITAT.

Aiming to significantly decrease the sampling number and measurement time, a CS-MITAT imaging method is proposed. This method casts MITAT problem into an emerging framework of compressive sensing (CS) [18]–[20]. It is based on the sparse circular array which significantly reduces the data acquisition time and creates fewer artifacts compared with conventional time domain BP and TRM imaging methods. The proposed method depends on a basic assumption of a sparse distribution of early stage tumors, which means the tumors cover a very small area in the imaging area (one tomography of breast). This prior information is also called as spatial sparsity. This feature has never been utilized by current literature.

The basic theory of CS has been proven to be very challenging with remarkable performance by Donoho, Romberg, Tao and et al. [18]–[20]. Many areas have benefited from the sparsity property of signals including image optimization [21], wireless communications [22], medical imaging [23], radar [24], and so on.

The basic framework of CS is reviewed as follows. Suppose that a signal $x \in \mathbb{R}^N$ of length $N$ is $Q$-sparse and can be represented by an orthogonal and complete dictionary $\Psi \in \mathbb{R}^{N \times N}$, i.e.,

$$x = \Psi s$$

(1)

with only $Q$ nonzero elements of $s$.

Suppose that $K$ measurements of $x$ given as $y$ are acquired by a linear projection, which is described as

$$y = \Phi x$$

(2)

where $\Phi$ is a $K \times N$ matrix called as measurement matrix.

As long as the measurement matrix $\Phi$ is incoherent with the dictionary $\Psi$, scan be reconstructed using only $K = O(Q \log N)$ nonadaptive measurements (e.g., random projection onto a random basis $\Phi$) with high probability, by solving a convex optimization problem,

$$\min \|s\|_1 \text{ s.t. } y = \Phi \Psi s.$$  

(3)

The proposed CS-MITAT well exploits the spatial sparsity of the tumors along with the mutual time domain incoherence of the MITA single pulse signals. We formulate the imaging problem as a dictionary selection problem. To create an appropriate over-complete dictionary, the target space is discretized into small cells (cell of image, not the biological tissue cell). Due to the linearity of the MITA mechanism, the MITA signal of a large tumor can be represented as a summation of signals from a cluster of small tumors. Each spatial cell can be considered as a tumor element or a normal tissue element (fat or lobule). The sparsity of the image domain indicates that the number of tumor cells is much less than the total number of discrete cells, which depends on the spatial resolution used.

It is important to point out that the goal of CS-MITAT is not to reconstruct the MITA signal of tumor but rather to directly recover the information of the tumor element spatial distribution in an interested area of breast. The MITA pulse signal is an acoustic signal, usually ranging from 50 KHz to 2 MHz. The difficulties in temporal sampling and data storage are not as crucial as in microwave systems. Nevertheless decreasing the spatial sampling numbers without degrading the image quality is the goal of the CS-MITAT method. Furthermore, the reduction of sampling numbers will significantly reduce the microwave radiation to a patient.

The remainder of this paper is organized as follows. In Section II, the idea of CS-MITAT is described, including a brief review of the physical mechanism of MITA, the creation of the over-complete dictionary, the choice of compressive measurement matrix, and the recovery procedure of MITAT. In Section III, the parameters of the method are discussed. Simulations and real breast tumor tissue experiments are given to demonstrate the effectiveness of the CS-MITAT method. Conclusions are drawn in the final section.

II. THEORY FOR COMPRESSIVE MITAT

A. Signal Model of MITA

To analyze the characteristic of microwave-induced thermal acoustic (MITA) signal, the mathematical representation of the physical energy transition process is briefly given. Firstly, an electromagnetic pulse is absorbed by a biological tissue in breast, causing a sudden heat change and volume expansion [25], which generates a thermal acoustic wave described by wave function as

$$\nabla^2 p(\vec{r}, t) - \frac{\partial^2 p(\vec{r}, t)}{c^2 \cdot \partial t^2} = -\rho \beta \frac{\partial^2 T(\vec{r}, t)}{\partial t^2}$$

$$= -\frac{\beta}{C_p} \frac{\partial H(\vec{r}, t)}{\partial t}$$

$$\approx -\frac{\beta H(\vec{r})}{C_p} \frac{\partial \delta(t)}{\partial t}$$

(4)

where $p(\vec{r}, t)$ is the induced acoustic pressure; $T(\vec{r}, t)$ is the temperature rise at position $\vec{r}$; $c$ is the ultrasound speed, varying around 1510 m/s with small variation of $\pm5\%$ in human female breast; $C_p$ is the specific heat capacity with 1% variation between breast tissue and tumor [25]; and $\beta$ is the thermal expansion coefficient. Under the assumption of thermal confinement [25], [27], such that the acoustic pulse is launched before significant heat conduction occurs, heating function $H(\vec{r}, t)$ can be separated into spatial part $H(\vec{r})$ and temporal part $\delta(t)$ [24].
large tumor can be regarded as several small tumors clustered together for MITAT system. This linearity property is the basic theory foundation of CS-MITAT method in this paper, especially the creation of the over-complete dictionary in the following subsection.

B. Dictionary of MITAT for Breast Tumor

The dictionary of MITAT for breast tumor can be created by discretizing the 2-D image plane spatially and synthesizing the MITA signal propagation model at each discrete spatial position.

For convenience of mathematical description, assume that target space (the breast area) \( \Pi_T \) lies in a product space \( [r_1, r_f] \times [\theta_i, \theta_f] \). Here, \( r_1, \theta_i \), and \( r_f, \theta_f \) denote the initial and final position, respectively, of the target space to be imaged in a polar coordinates. Discretization of \( \Pi_T \) generates a set of target points (small tumor cells) \( \Pi = \{ \pi_1, \pi_2, \ldots, \pi_N \} \), where \( N \) determines the resolution and each \( \pi_n \) is a vector \([r_n, \theta_n]\). Vector \( b \) is defined to be a weighted indicator. If there is a tumor at \( \pi_n \), the \( n \)th element of \( b \) is nonzero. Its value represents the strength of the MITA signal generated at \([r_n, \theta_n]\), which corresponds to its electric parameters, as described in (4) and (5).

From (4), the MITA signal generated by the discretized tumor at \( \pi_n \) is \( p(\pi_n, t) \). After propagating in the breast tissue, the MITA signal sampled by sensor \( m \) at time \( t \) and position \( \vec{r}_m \) is given as

\[
\psi_{n,m}(t) \approx \frac{\exp(-\alpha||\pi_n - \vec{r}_m||)}{||\pi_n - \vec{r}_m||} p(\pi_n, t - \tau_m(\pi_n)) \tag{6}
\]

where \( \alpha \) is the attenuation coefficient in Nepers/m, and \( \tau_m(\pi_n) \) is the propagation time delay from \( \pi_n \) to sensor \( m \). The approximation in (6) is under the assumption of narrow band MITA signal compared with ultrasound tomography, which means the attenuation coefficient \( \alpha \) and the propagation delay \( \tau_m(\pi_n) \) are not related to frequency at this situation [28]. In other words, the propagation of the narrow band MITA signal in breast tissue can be assumed as nondispersive. That is different with the ultrasound tomography (UT); for UT system it may use very large bandwidth of acoustic signal from 2 up to 12 MHz, and in that situation, those breast tissues cannot be approximate to be nondispersive as the proposed narrow band MITA signal. The small (less than 10%) variations in acoustic properties and the nondispersive characteristic of MITA signal in breast tissue support the proposed linear signal model, the simulation, and the experiment setup. Furthermore, because the small variation of sound velocity between different breast tissues, the multisattering effects of narrow band MITA signal are small; thus the environment can be approximately considered as a statistically random heterogeneous medium, which will not ruin the linearity of MITA signal.

\[
\psi_{n,m}(t) \text{ is discretized in time domain by } L \text{ samples, noted as } \psi_{n,m}(l) \mid_{l=1}^{L}, \text{ } m \text{ ranges from 1 to } M, \text{ } \text{stands for } M \text{ spatial positions of the sensors. Therefore, the temporal-spatial measurements of target at } \pi_n \text{ can be written as}
\]

\[
\psi_n = [\psi_{n,1}, \ldots, \psi_{n,M}]^T |_{M \times L} \tag{7}
\]
The total response of $N$ targets measured by the sensor array can be written as
\[
B = [\psi_1, ..., \psi_N]b = \Psi b
\]  
(8)
where $B$ is $M \times L$.

The goal of the imaging process is to recover information vector $b$ from the received signal $B$. Actually $b$ reflects the electric parameters distributions of the imaging area.

Fig. 3 gives an illustration of the process in (8).

C. Compressive Sensing Data Acquisition

In order to improve the imaging quality, MITAT imaging methods based on energy refocusing, such as TRM and BP, usually require dense spatial sampling and wide aperture. For real aperture, high density of spatial sampling requires huge amount of expensive sensors. And the size of the sensor will also be confined by the wavelength of the acoustic signal in order to satisfy the sampling theorem. For synthesized aperture, usually it requires a long scanning time. The imaging method proposed in this paper is based on CS theory, which significantly reduces the spatial sampling.

The goal of MITAT is to discriminate early state tumors from normal breast tissues according to their differences in electric parameters. Usually normal breast tissues can be treated as a large background. Tumors have very sparse distribution, i.e., the targets are very sparse. This implies that the number of nonzero unknowns in (8) is quite small compared with the large number of equations created by dictionary $\Psi$.

Supported by CS theory, a very small number of “random” measurements carry enough information to completely reconstruct the original signal. In circular array of sensors, a random subset of $K$ positions is chosen to do time domain sampling, which forms a new measurements matrix $Y$ as
\[
Y = \Phi B = \Phi \Psi b = [\Phi \psi_1, ..., \Phi \psi_N]b
\]  
(9)
where $\Phi$ is a $K \times M$ measurement matrix created by randomly selected $K$ rows of an $M \times M$ identity matrix, corresponding to randomly select $K$ sensor positions out of $M$ positions. (Usually $K$ is much less than $M$.)

The time domain samples are not compressed in this paper because for the signals in acoustic band, time domain sampling is quite easy to be realized and the amount of data is small due to low sampling frequency. Compressive sensing is implemented in spatial domain to effectively reduce the spatial sample positions and shorten the scanning time. The saving of scanning time means that the microwave absorptions of human body can be greatly reduced during the diagnosis.

Fig. 4 gives the process from (8) to (9). In (8), $B$ is an $M \times L$ matrix, but after the compressive sensing data acquisition process in (9), the measurement matrix $Y$ is compressed into a $K \times L$ matrix, which contains significantly smaller data and saves a lot of data acquisition time.

D. Compressive Imaging and Performance Indicator

The CS theory proves that with a relatively small number of measurements, which is $K$ in this situation, vector $b$ which maps the tumor distribution can be recovered exactly (with high probability) as long as [29], [19]
\[
K = O \left( Q \left( \mu^2 \left( \Phi, \Psi \right) \log N \right) \right)
\]  
(10)
where $Q$ is the number of tumors, $\mu(\Phi, \Psi)$ is the coherence of the measurement matrix $\Phi$ and the dictionary $\Psi$ [30]. In this CS-MITAT application, $\Phi$ is part of identity matrix, whose rows has the natural orthogonal property. $\Psi$ is built by all possible MITA signal bases in the imaging area. The combination of $\Phi$ and $\Psi$ can be referred to as mutual coherence [31], [32].

The numerical analysis of measurement number $K$ under the specific sparsity $Q$ will be shown in Section III-B.

One state-of-the-art recovery algorithm named as gradient projection for sparse reconstruction (GPSR) is used to recover $b$ by solving the convex unconstrained optimization problem [33]
\[
\min_b \frac{1}{2} \|Y - Ab\|_2^2 + \xi \|b\|_1, A = \Phi \Psi.
\]  
(11)

Parameter $\xi$ is chosen as suggested in [33]
\[
\xi = 0.1 \|A^T Y\|_\infty.
\]  
(12)

Compared with matching pursuit (MP) and orthogonal MP (OMP) [35]–[38], GPSR method is significantly faster and easier to be implemented. It works well across a large range of applications, and does not appear to require application-specific tuning [33].

In order to evaluate the performance of recovery, the recovered $b$ is aligned back to 2-D image by using a transformation from polar coordinate to Cartesian coordinate. The peak signal-to-noise ratio (PSNR) is used as a performance indicator, which
is given as [39]

\[
\text{PSNR} = 20\log_{10} \left( \frac{\max\{I\}}{\sqrt{\frac{1}{PQ} \sum_{p=1}^{P} \sum_{q=1}^{Q} |I(p, q) - \hat{I}(p, q)|^2}} \right) \tag{13}
\]

where \( I \) and \( \hat{I} \) denote the original image and the recovered image, \( \max\{I\} \) is the peak value of \( I \), and \( I(p, q) \) is the value at pixel \((p, q)\) under Cartesian coordinates.

### III. SIMULATIONS AND EXPERIMENTS

#### A. Numerical Simulations

In order to evaluate the performance of the proposed CS-MITAT method, numerical simulations are performed. Fig. 5 shows the sketch map of the simulation environment setup. Tumors are immersed in coupling oil and distributed in a 120 mm diameter round imaging area. Ultrasound sensors are uniformly distributed around a circle with 150 mm diameter, which are used to receive MITA signals at all positions in the forward simulation process. In compressive sensing simulations, positions are randomly chosen to evaluate the performance with different position numbers and SNRs. In order to match with the situations as in the experiments which will be given in the following sub-section, the diameter (i.e., aperture) of ultrasound sensor element is set as 16 mm, the same size as the Olympus V314-SU used in the experimental system. The electric and acoustic parameters of the materials are listed in Tables I and II.

In the numerical simulation, SAR distribution is precalculated by (5). Based on the SAR results, initial pressures of the tumors in Fig. 5 are calculated and loaded in the forward process, which is the MTA signal propagation process from the tumors to the sensors. PSTD algorithm [15] is applied during the procedure.

With the received data of all sensor positions, random position data set is chosen by the measurement matrix \( \Phi \) in (9) to perform the CS-MITAT recovery. An over-complete dictionary, which contains all possible tumor cell signals in the imaging area, is also pregenerated by using PSTD forward propagation method in the environment sketched in Fig. 5. Conventional TRM method [14], [17] is used as a comparison to demonstrate the advantages of CS-MITAT on the sparse spatial sampling.

Fig. 6 shows a comparison of the reconstructed image of the original scenery sketched in Fig. 5. Fig. 6(a) shows the distribution of the original acoustic pressure. The goal is to reconstruct this image. Fig. 6(b) gives the result by using CS-MITAT method. Only 24 spatial sensor positions \((K = 24)\) are used. Fig. 6(c) gives the result by using conventional TRM, where the same acquisition data as in Fig. 6(b) are used. Obviously, the result in Fig. 6(c) is much worse than that in Fig. 6(b). Fig. 6(d) shows the result by using conventional TRM, where 256 uniformly distributed spatial sensor data are utilized. This result is similar to Fig. 6(b). But Fig. 6(b) uses only about 9.4% of the data in Fig. 6(d). This means by using CS-MITAT, one can achieve better imaging result with much less spatial sampling sequences. This is because the TRM method is based on the energy refocusing technique. If the sensor aperture is not large enough [for example, \( K = 24 \) in Fig. 6(c)], the signal energy is not intensively accumulated, thus resulting in fake phantoms in the imaging area. When the spatial sampling is dense enough [for example, \( K = 256 \) in Fig. 6(d)], TRM can also produce a good image. But its scanning time is much longer than that in CS-MITAT. Longer time implies larger microwave energy absorption by a patient.
As in human breast, the imaging area is filled with heterogeneous normal tissue including fat and lobules. From [6], [7], the conductivity of normal tissue is not exactly the same as the coupling oil, especially in conductivity. For a more realistic situation, a new simulation setup is established as shown in Fig. 7. The electric parameters follow the large-scale study results in [6], [7]. They are assumed to be Gaussian distribution in order to simulate the heterogeneous tissue, as shown in Table III. Because of the microwave energy absorption, the normal tissue also generates weak MITA signals, which can be treated as the background. The contrast between the tumor and the background is expected to be lower than the results in Fig. 6.

Fig. 8 shows a comparison of reconstructed images of the scenery sketched in Fig. 7. Fig. 8(a) shows the distribution of the original acoustic pressure. Fig. 8(b) shows the result by using CS-MITAT method with 24 spatial scanning positions. Fig. 8(c) and (d) are for the result by using the conventional TRM with 24 and 256 scanning positions, respectively. Compared with the oil background simulation results in Fig. 6, the normal tissue background decreases the sparsity of target space. Although the reconstructed tumor image has the correct position and shape, the contrast between the tumor and the normal tissue is slightly decreased. Note that at this situation, TRM method provides even worse results with $K = 24$; the two small tumors are not even distinguishable from the background.

Fig. 9 shows the evaluation of CS-MITAT reconstruction performance by PSNR as defined in (13). The CS theory proves that the “perfect” recovery probability is affected by the SNR of the measurement, the sparsity of the signal and the number of random measurements. To evaluate the performance versus SNR and sensor position number $K$, the sparsity of the target space is fixed as shown in Fig. 5. The SNR varies from –15 to 40 dB. Note that in real MITAT applications for breast tumor detection, the 14–17 dB SNR of received MITA signal is usually

<table>
<thead>
<tr>
<th>Normal Tissue</th>
<th>Permittivity (F/m)</th>
<th>Conductivity (S/m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oil</td>
<td>2.4</td>
<td>0.4E-12</td>
</tr>
<tr>
<td>Tumor</td>
<td>50</td>
<td>4</td>
</tr>
</tbody>
</table>
considered as “good” situation and is the most common situation in recent MITAT system and experiments [13]. Therefore, the lower bound of $-15$ dB is an extremely bad situation to demonstrate the worst PSNR, while the upper bound of 40 dB is assumed to be the best situation. The $K$ in CS-MITAT varies from 4 to 76. From the figure, it shows that the PSNR of the reconstructed image depends on both the SNR and the $K$ used in the reconstruction. 

Fig. 9(a) shows the curves of PSNR versus SNR for different $K$. Fig. 9(b) and (c) show the reconstructed results at point A and point B in Fig. 9(a). Point A image [i.e., Fig. 9(b)] shows the result of CS-MITAT with $K = 52$ at $-3$ dB SNR. Under this condition, although the two tumors have been roughly reconstructed, the quality of the image is unacceptable. Lots of false alarm points appear. Point B image [i.e., Fig. 9(c)] shows the result of CS-MITAT with $K = 52$ at 15 dB SNR. At this situation, the PSNR of the reconstructed image reaches 37 dB. Also from Fig. 9(a), when $K$ is smaller than 52, for example $K = 76$, though more measurement data are given, the PSNR of the reconstructed image is still similar to that of $K = 52$. More specifically, in this simulation setup, $Q = 61$ nonzero tumor positions out of total $N = 3755$ possible tumor positions in the imaging area, the coherence $\mu$ of measurement matrix $\Phi$ and dictionary $\Psi$ is evaluated as [31]

$$\mu = \max_{j \neq k} \text{cov}(A_j, A_k) = 0.2543, \quad A = \Phi \Psi.$$  

Equation (10) assures that a certain sample number $K$ can be found to reconstruct the original information. Here the $K$ is 52 at the 15 dB SNR situation. The 15 dB SNR situation is specifically concerned in this paper because it is the most common situation for MITAT system and experiments [13]. This phenomenon is consistent with the basic compressive sensing and reconstructing theory as described in [19] and (10).

B. Experimental Results With Real Breast Tumor

Image reconstruction experiment by using the CS-MITAT method is performed on a prototype of MITAT system for real breast tumor. Fig. 10 shows a picture of the system. Microwave pulses of 2.4 GHz with 0.5 μs duration are emitted to the specimens located in a container. Four sensors (Olympus V314-SU) are uniformly mounted on the wall of the container. By gradually rotating across 90° step by step, the four sensors collect all the data at all the receiving positions around the specimens. More details about the system can be found in [40].

The specimens used in the experiment are shown in Fig. 11. Normal breast tissue and tumor tissue are both provided by a patient of West China Hospital, Sichuan University. Fig. 11(b) shows the location of two specimens in the container. Fig. 11(c) is the corresponding 3.5 MHz ultrasound image. They can hardly be distinguished by the ultrasound image. (Note that the sound speed difference between the tumor tissue and the normal tissue is within 10%). On the other hand, this shows the bad contrast between tumor and normal tissue. The two samples are immersed in the coupling oil of MITAT in the scanning container. Note that the background of oil will not generate MITA signal, so the performance of contrast is evaluated by the contrast between the tumor target and the normal tissue target instead of the most common imaging experiments that consider the contrast between target and background. The skin and other structural tissues such as lobules are not included in this experiment to simplify the model. Although the setup is not as complicated as the real breast, it is a reasonable starting point as the goal of this experiment is to demonstrate the main idea of CS-MITAT. Based on the nondispersive characteristics and small multi-scattering effects of narrow band MITA signal propagation, the setup of experiment is realistic enough to demonstrate the whole CS-MITAT concept, including the generation of propagation MITA signal, spatial compressive sensing, and information recovery.

Fig. 12 shows the reconstruction results of different methods. Fig. 12(a) shows the reconstructed image by using CS-MITAT
Fig. 12. Comparison of the reconstructed images by using real normal breast tissue and cancer breast tissue: (a) CS-MITAT method with $K = 82$; (b) TRM method with $K = 82$; and (c) TRM method with $K = 200$.

method with $K = 82$. With respect to the locations and sizes, the normal tissue and the tumor tissue are all well reconstructed in the figure. Compared with the image in Fig. 11(c), the contrast between the tumor image and normal tissue image has been greatly improved. In Fig. 11(c), one cannot discriminate the tumor and the normal tissues according to the contrast between them. While in Fig. 12(a), the contrast between the tumor tissue

and normal tissue is about 4:1. This also proves the advantage of the MITAT system over the traditional ultrasound image in contrast.

The same data as used in Fig. 12(a) were then applied to image by using the TRM method. Fig. 12(b) gives the result. Obviously the TRM reconstructed image is not as good as that in Fig. 12(a). In Fig. 12(c), as the number of sensor positions of TRM method was increased to 200, more energy was refocused. Two targets (the normal and the cancer tissues) have been better reconstructed compared with Fig. 12(b). But the image is still not as clear as the results by using CS-MITAT method in Fig. 12(a).

These experiments with real normal breast tissue and tumor tissue prove that the proposed compressive sensing reconstruct method for MITAT application is significantly more effective than the TRM method. For example, in the scenery of Fig. 12, the scanning time of CS-MITAT is only 45 s to get an image like Fig. 12(a), while the TRM methods take more than 3 min.

IV. CONCLUSION

Aiming to reduce the scanning time and enhance the imaging quality of MITAT for breast tumor, a CS-MITAT method is proposed. The main idea of the method is to apply CS in the data acquisition and the imaging procedure of MITAT. This method fully utilizes the spatial sparsity of early stage breast tumor. The feasibility and effectiveness of the method has been demonstrated through some numerical simulations and experiments using real breast tumor tissues. Numerical simulations show that the CS-MITAT method provides the same imaging quality but with much fewer sensor positions than that needed by the traditional TRM method. In other word, the CS-MITAT can provide significantly better imaging quality than the TRM if they use the same sensor positions. The performance of the CS-MITAT at different SNRs and with different numbers of sensor positions has also been studied. The CS-MITAT has been further investigated through some experiments using real breast tumor tissues. Compared with the result of commercial ultrasound system, the MITAT has dominant advantage on contrast. Also the CS-MITAT imaging method has significant advantage on data acquisition time over the TRM method.

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