Wavelet-Based Compressive Sensing for Head Imaging

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***Abstract*—A wavelet based compressive sensing technique for head imaging is presented. The non-sparsity of the dielectric profile of the human head brings about difficulties when applying traditional compressive sensing technique to image the profile of the head. In this paper, the wavelet transform is implemented to convert the non-sparse profile into a sparse domain then a compressive sensing framework named block sparse Bayesian learning (BSBL) is applied on the Born iterative method (BIM) model to reconstruct the original profile of the non-sparse domain. The proposed method is evaluated on a realistic human head phantom. The results show that a very low normalized error rate at a short computation time using small number of antennas can be achieved. The obtained results indicate that the presented technique can enable detecting an early stroke in the realistic non-sparse environment of the human head using only six antennas.**

***Keywords*—Compressive sensing, wavelet transform, head imaging, microwave imaging.**

I. INTRODUCTION

Microwave imaging system for brain stroke detection is being widely researched in recent years because of the portable, non-ionizing and low-cost characteristics of microwave techniques. To that end, several algorithms for microwave head imaging system are proposed [1]-[8]. Two general methods are usually applied in microwave head imaging algorithms; tomography [1]-[3] and radar-based techniques [4]-[7]. The algorithms presented in [1]-[2] and [4]-[7] require numerous number of antennas for improving the quality of the obtained images. However, this requirement is undesirable under the head imaging environment due to the limited available space. Moreover, small antennas and thus small data sets are preferred as the computational time for analysis and imaging is critical for head injury patients. Therefore, it is necessary to develop new algorithms which use small number of antennas and retain the quality of the obtained image. A radar-based compressive sensing algorithm is proposed in [8] to reduce the number of stepped frequencies required in the head imaging task. Nevertheless, the proposed algorithm cannot reduce the number of utilized antennas.

In this paper, a wavelet-based compressive sensing method is proposed to largely reduce the number of antennas used in

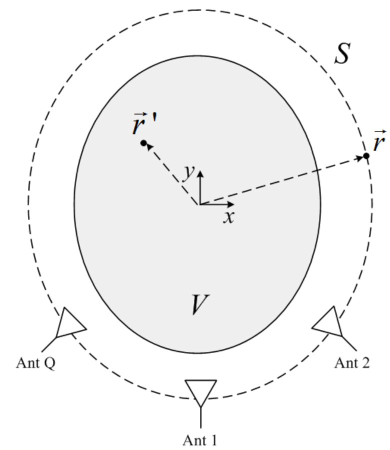

Fig. 1. Configuration of the imaging domain.

the head imaging system. Due to the "smooth" representation of the contrast-field profile (CFP) of the head, the non-sparse CFP can be transformed into a sparse domain using wavelet transform. The block sparse Bayesian learning (BSBL) method [9]-[10] is then used to solve the inverse problem in the sparse domain after implementing the wavelet transform and the Born iterative method (BIM) [11] to guarantee the convergence of the entire imaging process. The proposed method is assessed using a realistic MRI-derived head phantom. The results indicate that the method can detect an early stroke inside the head accurately using only six antennas with a short computation time.

II. THE PROPOSED TECHNIQUE

The imaging configuration is shown in Fig. 1. There are Q uniformly spaced antennas positioned at the measurement contour S. The scattering domain V is illuminated at a certain frequency by a TM wave. The domain V is discretised into N square cells with certain dielectric properties. The normalized dielectric profile (NDP) of the imaging problem is defined as

$$\mathcal{X}(x,y) = \left[\varepsilon_r(x,y) + \frac{\sigma(x,y)}{j\omega}\right] / \widetilde{\varepsilon_s} \qquad (1)$$

where $\widetilde{\varepsilon_s}$ is complex dielectric constant and conductivity of the surrounding material which is defined as $\widetilde{\varepsilon_s} = \varepsilon_s + j\sigma_s/\omega$. The NDP possess non-sparse characteristic in realistic head phantom, however, due to the "smooth" feature of the NDP (the

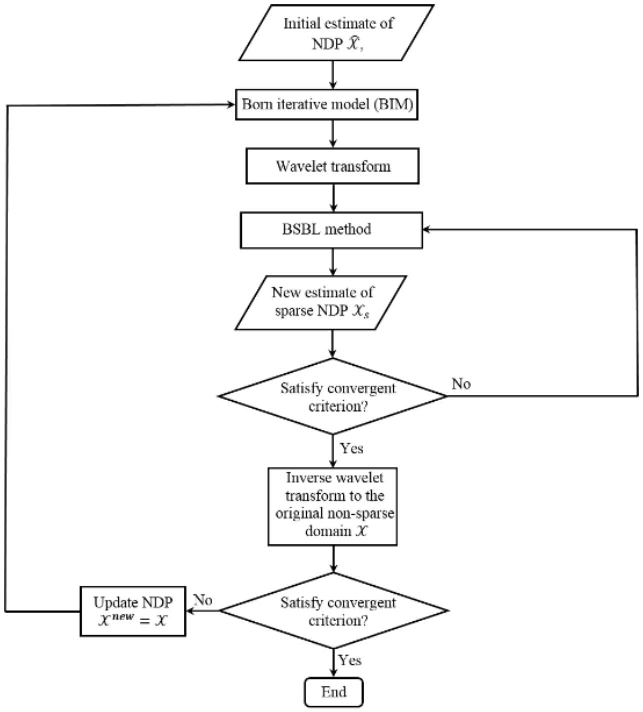

Fig. 2. Flowchart of the proposed imaging algorithm.

variation between two adjacent square cells is small with regard to the NDP), the non-sparse $\mathcal{X}$ can be transferred into a sparse domain using Haar wavelet. The flowchart of the proposed imaging algorithm is shown in Fig. 2. It can be seen from Fig. 2 that the unknown NDP of the head $\mathcal{X}$ is firstly assumed to have unit distribution, then the pre-assumed $\mathcal{X}$ is used to construct the BIM model [11]. In the constructed BIM model, the Haar wavelet transform is used to transfer the non-sparse $\mathcal{X}$ into a sparse domain $\mathcal{X}_s$. After the wavelet transformation, $\mathcal{X}_s$ is used in a compressive sensing framework named BSBL [9]-[10] to solve the inverse problem constructed by using the BIM model. After a convergent solution of $\mathcal{X}_s$ is achieved from BSBL method, the inverse wavelet transform is applied to transfer the sparse $\mathcal{X}_s$ back to the original non-sparse domain $\mathcal{X}$ and $\mathcal{X}$ is used as the new estimate NDP of the head to construct a new BIM model. This process is repeated until a convergent criterion is satisfied.

III. Simulation Results

To assess the proposed method, a realistic head model acquired from MRI scans [12] and consists of $256 \times 256 \times 128$ cubical elements is used in the performance assessment. Each of the elements has the dimensions (mm) of $1.1 \times 1.1 \times 1.4$. Seven head tissues are contained in the model which are flat, blood, skeletal muscle, skin, skull, dura, cerebral spinal fluid, white and gray matter. A transverse slice of the model at around 30 mm from the top of the head is taken as the imaging domain. These tissues were assumed to have the realistic dielectric properties as a function of frequency. Fig. 3 shows the normalized dielectric profile (NDP) of the used head model

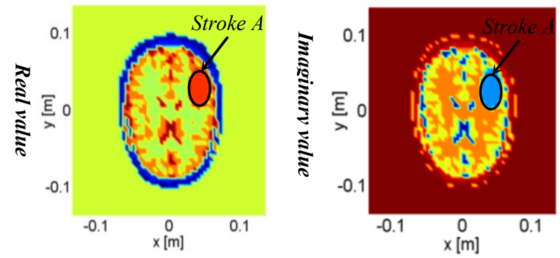

Fig. 3. Real part and imaginary part of the realistic head NDP with a hemorrhagic stroke placed inside the head.

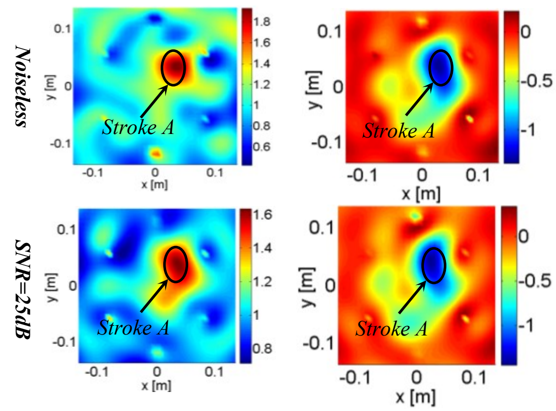

Fig. 4. The reconstructed dielectric profiles of a realistic head phantom with a hemorrhagic stroke. The performance is evaluated under different SNR levels at the incident frequency 0.85 GHz.

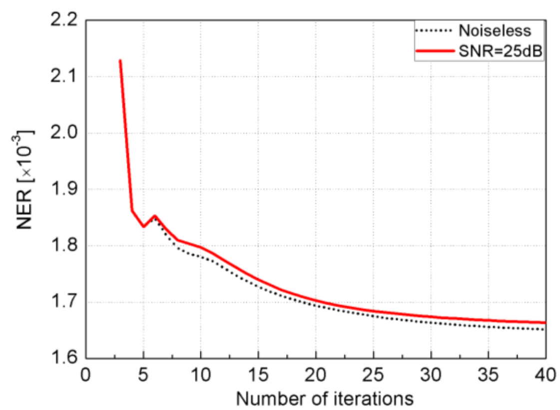

Fig. 5. NER as the function of iteration time under different noise levels.

with an elliptical hemorrhagic stroke was placed inside the head (x=2cm, y=1.5cm) with a major axis of 5.5 cm and minor axis of 1.6cm. The selected size of the stroke is chosen based on the available data from MRI and CT scan.

Six uniformly distributed antennas were used to illuminate the head model at a suitable frequency and capture the scattered signals. Based on the results concluded in [2], the most suitable frequency for microwave tomography imaging is 0.85 GHz. The proposed imaging technique was then used to detect the position of the hemorrhagic stroke in the head model under different signal to noise ratio (SNR). Fig. 4 shows the reconstructed dielectric profiles using the proposed imaging

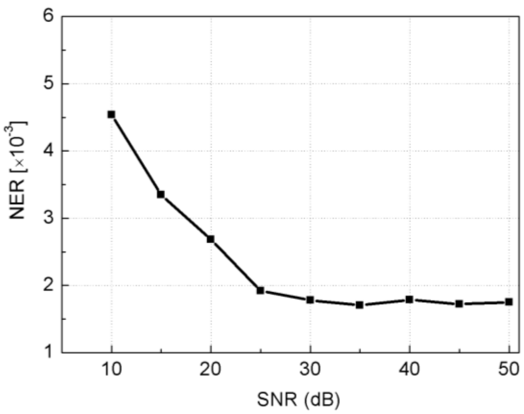

Fig. 6. NER of the proposed algorithm when used in head imaging with different SNR level and incident frequency is 0.85 GHz.

algorithm. The obtained results indicate that the technique can successfully detect the position of the assumed stroke when the SNR is around 25 dB, which is a realistic value for the imaging environment.

The convergent rate is another vital issue in microwave head imaging algorithm since it influences the computation time, which is a critical factor in head imaging due to the need for a fast detection and medication of any brain injury. To evaluate the convergence rate and the performance of the imaging algorithm, the reconstruction normalized error rate (NER) is used as:

$$NER = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left|\frac{\mathcal{X}_G(x_n, y_n) - \vec{\mathcal{X}}(x_n, y_n)}{\mathcal{X}_G(x_n, y_n)}\right|^2} \qquad (2)$$

where $\mathcal{X}_G(x_n, y_n)$ is the NDP of the ground truth, i.e. the real profile, and N is the number of discrete squall cells. Fig. 5 shows NER as a function of the iteration time under different noise levels. It can be seen that the proposed algorithm quickly converges after 40 iterations with a total time of around 400s.

The performance of the proposed method is also numerically assessed with regard to NER and the result is shown in Fig. 6 for different SNRs. It can be seen that the presented method can achieve NER values when the SNR level is greater than 25 dB. This value is sufficient to detect the hemorrhagic stroke inside the head.

IV. Conclusion

An innovative imaging method based on wavelet transform and a compressive sensing framework has been proposed. Since the contrast-field profile of the realistic head is not sparse, the wavelet transform was applied to convert the non-sparse profile into a sparse domain, then block sparse Bayesian learning method along with the Born iterative method are used to recover the contrast-field profile of the head. The proposed method was able to reconstruct the non-sparse head normalized dielectric profile using small number of antennas within a fast convergent time. To assess the proposed method, it was used to reconstruct the dielectric profile of a realistic head model. The results indicate that the proposed method has the capability to reconstruct the dielectric profile of the head successfully and accurately detect a hemorrhagic stroke placed inside the head.

References

[1] M. Jalilvand, C. Wu, J. Schmid, and T. Zwick, “Quantitative imaging of numerically realistic human head model using microwave tomography,” *Electron. Lett.,* vol. 50, no. 4, pp. 255-256, Feb. 2014.

[2] D. Ireland, K. Bialkowski, and A. Abbosh, “Microwave imaging for brain stroke detection using Born iterative method,” *IET Microw. Antennas Propag.,* vol. 7, no. 11, pp. 909-915, May. 2013.

[3] L. Guo and A. Abbosh, “Microwave imaging of non-sparse domains using Born iterative method with wavelet transform and block sparse Bayesian learning,” *IEEE Trans. Antennas Propag.,* no. 99, 2015.

[4] L. Guo and A. Abbosh, “Optimization-based confocal microwave imaging in medical applications,” *IEEE Trans. Antennas Propag.,* no. 8, vol. 63, pp. 3531-3539, Aug. 2015.

[5] S. Mustafa, B. Mohammed, and A. Abbosh, “Novel preprocessing techniques for accurate microwave imaging of human brain,” *IEEE Antennas Wireless Prop Lett.,* vol. 12, pp. 460-463, 2013.

[6] A. Mobashsher, A. Abbosh, and Y. Wang, “Microwave system to detect traumatic brain injuries using compact unidirectional antenna and wideband transceiver with verification on realistic head phantom,” *IEEE Trans. Microw. Theory Tech.,* vol. 62, no. 9, pp. 1826-1836, Sep. 2014.

[7] B. Mohammed, A. Abbosh, S. Mustafa, and D. Ireland, “Microwave system for head imaging,” *IEEE Trans. Instrum. Meas.,* vol. 63, no. 1, pp. 117-123, Dec. 2013.

[8] L. Guo and A. Abbosh, “Microwave stepped frequency head imaging using compressive sensing with limited number of frequency steps,” *IEEE Antennas Wireless Prop Lett.,* vol. 14, May. 2015.

[9] Z. Zhang and B. D. Rao, “Sparse signal recovery with temporally correlated source vectors using sparse Bayesian learning,” *IEEE J. Sel. Topics Signal Process.,* vol. 5, no. 5, pp. 912-926, 2011.

[10] Z. Zhang and B. D. Rao, “Extension of SBL algorithms for the recovery of block sparse signals with intra-block correlation,” *IEEE Trans. Signal Process.,* vol. 61, no. 8, pp. 2009-2015, Apr. 2013.

[11] W. Chew, *Waves and Fields in Inhomogeneous Media.* Piscataway, NJ: IEEE Press, 1995.

[12] I. G. Zubal, C. R. Harrell, E. O. Smith, Z. Rattner, G. Gindi, and P. B. Hoffer, “Computerized three-dimensional segmented human anatomy,” *Med. Phys.,* vol. 21, no. 2, pp. 299-302.