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Image Reconstruction for Electrical Impedance Tomography Using Enhanced Adaptive Group Sparsity With Total Variation

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Abstract—A novel image reconstruction algorithm for electrical impedance tomography using enhanced adaptive group sparsity with total variation constraint is proposed in this paper. The new algorithm simultaneously utilizes the prior knowledge of regional structure feature and global characteristic of the conductivity distribution. The regional structure feature is encoded by using an enhanced adaptive group sparsity constraint. Meanwhile, the global characteristic of inclusion boundary is considered by imposing total variation constraint on the whole image. An enhanced adaptive pixel grouping algorithm is proposed based on Otsu’s thresholding method, which demonstrates good noise immunity. An accelerated alternating direction method of multipliers is utilized to solve the proposed problem for a faster convergence rate. The performance of the proposed algorithm is thoroughly evaluated by numerical simulation and experiments. Comparing with the state-of-the-art algorithms, such as the L1 regularization, total variation regularization, and our former work on adaptive group sparsity, the proposed method has demonstrated superior spatial resolution and better noise reduction performance. Combined with the total variation constraint, distinct boundary of inclusions has also been obtained.

Index Terms—Electrical impedance tomography, enhanced adaptive group sparsity, image reconstruction, total variation.

I. INTRODUCTION

ELECTRICAL Impedance Tomography (EIT) images the spatial conductivity distribution in an electrode-bounded sensing domain by generating an electric field and measuring the induced boundary voltage non-intrusively [1]–[3]. Since the emerging of EIT [4], to date it has been extensively studied in many imaging applications, such as multiphase flow imaging [5], chemical processes measurement [6], artificial robot skin [7], cell culture imaging [8] and hip surgery assistant imaging [9]. Although the temporal resolution of EIT is sufficiently high (up to 1164 frames per second according to [10]) for fast changing processes, its spatial resolution is relatively poor due to the intrinsic ill-posed and ill-conditioned nature of the EIT image reconstruction problem. As the maturity of hardware evolves, the poor image quality has become one of the major bottlenecks for further application development of EIT.

Thus far, a great deal of work related to the EIT image reconstruction problem has been reported. The prevailing methods can be roughly categorized into two classes, i.e., the regularization based methods and direct reconstruction methods. Regularization is an effective technique for dealing with ill-posed inverse problems by means of encoding a certain prior information of the conductivity distribution, either in the spatial domain or in other particular domains [11]. The state-of-the-art regularization based methods for EIT image reconstruction include Total Variation (TV) regularization [12]–[14], L1 or sparsity regularization [15]–[17] and sparsity representation based regularization [18], and joint regularization of several different methods [19], etc. Beyond that, another type of EIT image reconstruction algorithms, namely direct methods, solves the nonlinear reconstruction problem directly by reducing it to two linear integrals [20]. This interesting methodology has been well investigated in both impedance and capacitance tomography modalities [21], [22]. A summary of common image reconstruction algorithms for electrical tomography can be referred to [23].

Most of the conventional algorithms utilizing regularization technique usually focus on the global characteristics of the conductivity distribution and constraint is posed on the image as a whole. Recently, the effect of regional structure information on image quality improvement has aroused a lot of interest. In [24], the encoding of regional structure information based on an adaptive group sparsity method named AGSP is investigated by the authors, and we have demonstrated the effectiveness of utilizing structure information as prior. In this paper, as a further study of our former work [24], we propose a novel image reconstruction algorithm with constraints not only on regional structure features but also global characteristics. The regional structure feature is encoded by using an enhanced adaptive group sparsity constraint compared with [24]. Meanwhile the global characteristic of inclusion boundary is taken into account by imposing total variation constraint on the whole image. The enhanced adaptive group sparsity with TV method is named as EAGS-TV. An enhanced pixel grouping algorithm is proposed by using Otsu’s thresholding method for adaptive structure features extraction with good noise immunity. An accelerated alternating direction method of multipliers is introduced to solve the resulting optimization problem for a faster convergence rate. The performance of the
The proposed algorithm is evaluated by both numerical simulation and phantom experiments. The results based on conventional L1 regularization, TV regularization, and AGSP in [24] are presented for comparison purpose.

The paper is divided into the following sections. Section II is the principle of the proposed method. Section III illustrates the numerical simulation and experimental results. Finally, Section IV makes concluding remarks and discusses the future work.

II. Adaptive Group Sparsity With Total Variation
A. Principle of EIT Image Reconstruction

Considering the time-difference EIT, which focuses on the conductivity change \( \Delta \sigma \in \mathbb{R}^n \) between two time points, the following linear approximated relation exists between the conductivity change and measured voltage on boundary electrodes [25]:

\[
J \Delta \sigma = \Delta V
\]  
(1)

where \( J \in \mathbb{R}^{m \times n} \) denotes the Jacobian matrix which is also known as the sensitivity matrix; \( \Delta V \in \mathbb{R}^m \) denotes the measured voltage changes on selected boundary electrodes.

In general, given \( J \) and \( \Delta V \), the conductivity change distribution can be reconstructed by solving the following constrained optimization problem:

\[
\begin{align*}
\min_{\Delta \sigma} & \quad R(\Delta \sigma) \\
\text{s.t.} & \quad J \Delta \sigma = \Delta V
\end{align*}
\]  
(2)

where \( R \) is a function of \( \Delta \sigma \) encoding the prior knowledge of the conductivity change. The state-of-the-art forms of \( R \) can be found in [11].

B. Enhanced Adaptive Structure Features Extraction

Assume that the conductivity change \( \Delta \sigma \) can be split into a number of subsets or groups based on amplitude similarity and Euclidean distance of individual pixels, as expressed by

\[
\begin{align*}
\Delta \sigma_s &= \begin{bmatrix} \Delta \sigma(s_1(1)), \cdots, \Delta \sigma(s_i(K_i)) \end{bmatrix}, \\
\Delta \sigma_s &\subseteq \Delta \sigma, \\
\bigcup_{i=1}^N \Delta \sigma_s_i &= \Delta \sigma
\end{align*}
\]  
(3)

where \( s_i \) denotes the index vector of the \( i \)-th group, \( i = 1, 2, \ldots, N \); \( K_i \) is the length of \( s_i \) and \( N \) denotes the total number of subsets or groups after partition. Then the structure features of conductivity change can be encoded by a reasonable group partition of all pixels.

To extract the structure features based on this idea, we firstly propose an enhanced adaptive pixel grouping method using the conductivity change estimated by the filtered one-step Gauss-Newton solver with regularization. In this work, the Laplacian regularization [26], which is able to generate fairly good estimation for pixel grouping with a low computation cost, is adopted. Its filtered form for improved noise immunity is formulated as

\[
\Delta \hat{\sigma} = P \left\{ (J^T J + \lambda B^T B)^{-1} J^T \Delta V \right\}
\]  
(4)

where \( \lambda \) and \( B \in \mathbb{R}^{n \times n} \) denote the regularization factor and the Laplacian operator matrix [26], respectively. The operator \( \| \) denotes each element of the vector taking its absolute value. The filtering operator \( P \) is defined as

\[
P[f(x)] = \begin{cases} f(x), & f(x) > t^* \\ 0, & f(x) \leq t^* \end{cases}
\]  
(5)

where \( t^* \) is the optimal threshold derived based on Otsu’s thresholding method [27]. The Otsu’s thresholding method is commonly used in image processing to extract objects from the background. The purpose of using filter operation is to obtain good robustness against noise. Refer to [27], \( t^* \) is calculated by maximizing the between-class variance:

\[
t^* = \arg \max_{1 \leq t < L} \left[ \frac{1}{\sum_{i=1}^t (i p_i)} \left( \frac{1 - \sum_{i=1}^t (i p_i)}{p_i} \right)^2 \right]
\]  
(6)

where \( L \) denotes the total gray levels of the absolute value of reconstruction image, and \( p_i = e_i / n; e_i \) is the number of pixels at the \( i \)-th gray level and \( n \) is the total number of pixels.

Based on the estimation by Eq. (4), we further identify the number and centers of inclusions by calculating all of the local maximum points of \( \Delta \hat{\sigma} \). The pixel index vector of all local maximum points is denoted by \( D \in \mathbb{R}^q \) and the coordinate matrix of all pixels is denoted by \( C \in \mathbb{R}^{n \times 2} \). The pixel grouping result is then represented by a group index vector \( G \in \mathbb{R}^s \), where the pixels belong to the same group are given the same index value. According to these definitions, we further define the index set of the pixels having amplitude similarity with the \( i \)-th local maximum point \( D_i \) to be:

\[
A_s = \left\{ j \left| \Delta \hat{\sigma}_j > \frac{1}{4} \Delta \hat{\sigma}_{D_i}, j = 1, \ldots, n \right. \right\}
\]  
(7)

and the index set of the pixels having proximity Euclidean distance with the \( i \)-th local maximum point \( D_i \) to be:

\[
E_s = \left\{ j \left| \| C_j - C_{D_i} \| < \frac{d_{max}}{2} \right. \right\}, j = 1, \ldots, n
\]  
(8)

Accordingly, the \( i \)-th local maximum point centered pixel group \( Q \) is defined to satisfy both the amplitude similarity and proximity Euclidean distance criteria, which is expressed as

\[
Q = A_s \cap E_s
\]  
(9)

Eq. (9) regards a pixel belong to a group centered by a local maximum point if the amplitude of this pixel is larger than a quarter of that of the local maximum point and meanwhile the Euclidean distance between this pixel and the local maximum point is smaller than \( d_{max}/2 \). By these criteria, the amplitude similarity and geographic proximity are guaranteed. The value of \( d_{max} \) is not critical and it can be determined empirically according to specific applications. Basically, there are two methods to find an appropriate value for \( d_{max} \). The first way is that if the prior information of the rough geometry dimension
Eq. (4) can be applied first and an appropriate value of \(d\) is not known, the filtered one step algorithm in case of the prior information of the geometry dimension of effect of \(d\) can be determined based on the filtered images. Note that the \(d\) is available, the value of \(YANG\) achieved by using the detail information. The group-level sparsity constraint can be in imaging processing. We refer the readers to [28] for pixel groups rather than individual ones, is a novel concept sparsity, which implements sparsity constraint on the level of feature by using the concept of group sparsity. Group

C. The EAGS-TV Algorithm

In [24], we studied the encoding of the regional structure features by using the concept of group sparsity. Group sparsity, which implements sparsity constraint on the level of pixel groups rather than individual ones, is a novel concept in imaging processing. We refer the readers to [28] for detail information. The group-level sparsity constraint can be achieved by using the \(l_{2,1}\) norm as defined below:

\[
\| \Delta \sigma \|_{2,1} =: \sum_{i=1}^{N} \| \Delta \sigma_s_i \|_2
\]

(10)

In this work, as a further study of [24], we not only consider to utilize the regional structure features as prior information but also simultaneously merge certain global properties such as the explicit boundary of conductivity change. Consequently, an EIT image reconstruction algorithm using the enhanced adaptive group sparsity with total variation (named as EAGS-TV) is presented, which is formulated as

\[
\min_{\Delta \sigma, z} \sum_{i=1}^{N} \omega_i \| \Delta \sigma_s_i \|_2 + \| \Delta \sigma \|_{TV}
\]

s.t. \(J \Delta \sigma = \Delta V\)

(11)

where \(\sum_{i=1}^{N} \omega_i \| \Delta \sigma_s_i \|_2\) is known as the weighted \(l_{2,1}\) norm, i.e., \(\| \Delta \sigma \|_{l_{2,1}}\); \(\omega_i\) is the weight for the \(i^{th}\) group. \(\| \Delta \sigma \|_{TV}\) is the isotropic TV norm which is defined as [29]

\[
\| \Delta \sigma \|_{TV} = \sum_{x,y} \sqrt{(D_{x,y}^b(\Delta \sigma))^2 + (D_{x,y}^h(\Delta \sigma))^2}
\]

(12)

where \((x, y)\) is the coordinate of a certain pixel. The first order finite difference operator in horizontal direction is expressed as

\[
D_{x,y}^h(\Delta \sigma) = \begin{cases} \Delta \sigma_{x,y} - \Delta \sigma_{x+1,y}, & 1 \leq x < h_n \\ 0, & x = h_n \end{cases} \quad x = h_n
\]

(13)

where \(h_n\) denotes the pixel number along the horizontal direction; and the first order finite difference operator in vertical direction is expressed as

\[
D_{x,y}^v(\Delta \sigma) = \begin{cases} \Delta \sigma_{x,y} - \Delta \sigma_{x,y+1}, & 1 \leq y < v_n \\ 0, & y = v_n \end{cases} \quad y = v_n
\]

(14)

where \(v_n\) denotes the pixel number along the vertical direction;

The coupled constraint problem depicted in Eq. (11) is solved using the alternating direction method of multipliers (ADMM). ADMM is a splitting method which takes a sequence of steps to decouple the target constraint problem [30]. In this work, we introduce the accelerated alternating direction method of multipliers (A-ADMM) [31]. A-ADMM is an accelerated variants of ADMM which exhibits faster convergence than the conventional ADMM method by an over-relaxation step [31]. To implement this method, we firstly introduce an auxiliary vector \(z\), then Eq. (11) can be equivalently rewritten as

\[
\min_{\Delta \sigma, z} \sum_{i=1}^{N} \omega_i \| z_{s_i} \|_2 + \| \Delta \sigma \|_{TV}
\]

s.t. \(z = \Delta \sigma, J \Delta \sigma = \Delta V\)

(15)
The augmented Lagrangian scheme of Eq. (15) is formulated as

\[
\min_{\Delta \sigma, z} \sum_{i=1}^{N} w_i \|z_i\|_2 + \|\Delta \sigma\|_{TV} \\
- \ldots \mu_1^T(z - \Delta \sigma) + \frac{\eta_1}{2} \|z - \Delta \sigma\|_2^2 \\
- \ldots \mu_2^T(J\Delta \sigma - \Delta V) + \frac{\eta_2}{2} \|J\Delta \sigma - \Delta V\|_2^2
\]  

(16)

where \(\mu_1\) and \(\mu_2\) are multipliers and \(\eta_1\) and \(\eta_2\) are penalty parameters. Then Eq. (16) can be split into two subproblems, i.e., the \(z\)-subproblem and the \(\Delta \sigma\)-subproblem, and can be solved separately.

The \(\Delta \sigma\)-subproblem is expressed as

\[
\Delta \sigma^{(k+1)} = \arg \min_{\Delta \sigma} \left\{ \|\Delta \sigma^{(k)}\|_{TV} + \mu_1^T \Delta \sigma^{(k)} + \frac{\eta_1}{2} \|z - \Delta \sigma^{(k)}\|_2^2 \\
- \ldots \mu_2^T J^{\Delta \sigma^{(k)}} + \frac{\eta_2}{2} \|J^{\Delta \sigma^{(k)}} - \Delta V\|_2^2 \right\}
\]

(17)

A gradient-based recovery algorithm is proposed to solve Eq. (17), and its iteration form is given by

\[
\Delta \sigma^{(k+1)} = \Delta \sigma^{(k)} - \alpha \left( H + \nabla(\|\Delta \sigma^{(k)}\|_{TV}) \right)
\]

(18)

where \(\alpha\) is the step length, and

\[
H = \mu_1 + \eta_1 (\Delta \sigma^{(k)} - z) + J^T (\eta_2 (J^{\Delta \sigma^{(k)}} - \Delta V) - \mu_2)
\]

(19)

The gradient of TV norm is calculated based on a smooth approximation strategy to avoid a zero denominator, which is expressed as

\[
\nabla_{x,y}(\|\Delta \sigma\|_{TV}) = \frac{D_{x,y}^h(\Delta \sigma) + D_{x,y}^v(\Delta \sigma)}{\sqrt{(D_{x,y}^h(\Delta \sigma))^2 + (D_{x,y}^v(\Delta \sigma))^2 + \epsilon}} \\
- \frac{D_{x-1,y}^h(\Delta \sigma)}{\sqrt{(D_{x-1,y}^h(\Delta \sigma))^2 + (D_{x-1,y}^v(\Delta \sigma))^2 + \epsilon}} \\
- \frac{D_{x,y-1}^v(\Delta \sigma)}{\sqrt{(D_{x,y-1}^h(\Delta \sigma))^2 + (D_{x,y-1}^v(\Delta \sigma))^2 + \epsilon}}
\]

(20)

where \(\epsilon\) is a relaxation factor which is \(1e^{-7}\) in this paper. Note that the relaxation factor is selected based on a series of practice. If the relaxation factor is too large, the approximation will incur significant errors. The value chosen in this work is small enough to ensure the approximation accuracy and meanwhile guarantees the denominator is not zero under any circumstances.

The \(z\)-subproblem is given by

\[
z^{(k+1)} = \arg \min_{z} \sum_{i=1}^{N} w_i \|z_i^{(k+1)}\|_2 + \mu_1^T z^{(k)} + \frac{\eta_1}{2} \|z^{(k)} - \Delta \sigma\|_2^2
\]

(21)

which is equivalent to solving the following problem:

\[
z^{(k+1)} = \arg \min_{z} \sum_{i=1}^{N} \left\{ w_i \|z_i\|_2 + \frac{\eta_1}{2} \|z_i - \Delta \sigma_{x_i} - \frac{1}{\eta_1} \mu_{1x_i} \|_2^2 \right\}
\]

(22)

and the problem is solved by group-wise soft thresholding:

\[
z_{x_i} = \max \left\{ \|\Delta \sigma_{x_i} + \frac{1}{\eta_1} (\mu_{1x_i})\|_2 - \frac{w_i}{\eta_1}, 0 \right\} \frac{\Delta \sigma_{x_i} + \frac{1}{\eta_1} (\mu_{1x_i})}{\|\Delta \sigma_{x_i} + \frac{1}{\eta_1} (\mu_{1x_i})\|_2}
\]

(23)

To further improve the noise reduction performance, an additional constraint is posed on the solution of the \(z\)-subproblem in each iteration by

\[
g(z) \geq 0, \quad t = 1, \ldots, n
\]

(24)
where the operator $g$ is defined as

$$g(z_t) = \text{sign}(\text{sum}(z_{s_i})) \cdot z_t$$  \hspace{1cm} (25)$$

where $\text{sign}$ denotes the sign function; $\text{sum}$ denotes the summation of a vector; $t \in s_i$. Eq. (24) and Eq. (25) calculates the sign of each pixel group and impose a non-negative constraint (if the sign of that group is 1) or non-positive constraint (if the sign of that group is $-1$) on the result of that group. By this means, it is expected that the artefact around the inclusions can be effectively eliminated.

In summary, the detail implementation of the EAGS-TV algorithm is demonstrated in TABLE II.

III. RESULTS AND DISCUSSION

A. Numerical Simulation

1) Modelling: As illustrated in Fig. 2(a), a 2D 16-electrode EIT sensor which diameter is 95 mm is modelled using COMSOL Multiphysics. The homogeneous saline which conductivity is 0.05 S·m$^{-1}$ is used as background reference for Jacobian matrix calculation and phantom modelling.
Two representative phantoms, i.e., circle with ellipse as shown in Fig. 2(b) and circle with square as shown in Fig. 2(c), are modelled for simulation study. The purpose of the first phantom is to evaluate the algorithm performance for spatially non-sparse distribution and the second phantom is to assess the algorithm performance for spatially sparse distribution with bi-direction conductivity changes. The conductivity value of the red objects is set as 0.0001 S·m⁻¹ and the blue circle is set as 10 S·m⁻¹. The adjacent strategy [32] is adopted in measurement. The current is injected through an adjacent pair of electrodes and voltage measurement is conducted through successive pairs of neighboring electrodes. As a result, a data frame is composed of 104 independent measurements.
2) Comparing Algorithms and Parameters: To thoroughly verify the effectiveness of EAGS-TV, we compare the EAGS-TV with the state-of-the-art image reconstruction algorithms, for example, the L1 regularization algorithm (L1), which detail information can be referred to [15] and [33], the TV regularization algorithm (TV), which detail information can be referred to [34], and our former work AGSP [24].

As for EAGS-TV, the regularization factor \( \lambda \) in Eq. (4) is set as 0.001. The penalty parameters \( \eta_1 \) and \( \eta_2 \) in Eq. (16) are selected as 1/mean(abs(\( \Delta V \))) and 0.6/mean(abs(\( \Delta V \))) based on a series of practices, respectively. Here, mean denotes the average function and abs denote the absolute value function. The step length \( \alpha \) and \( \alpha_a \) are selected as 0.98. The maximum group diameter \( d_{\text{max}} \) is set as 10 pixels, which is large enough for our targeted applications. Regarding the weighting strategy, as discussed in [24], we apply the all-one vector for the non-sparse phantom 1 and [24, eq. (20)] for the sparse phantom 2.

For L1 regularization, the relaxation factor is set as 0.1, and for TV regularization, the regularization factor is set as 0.01. The algorithm parameters of AGSP are the same with [24]. The maximum iteration number is set as 500 for all algorithms, and the stopping criterion is defined as following:

\[
\| \Delta \sigma^{(k+1)} - \Delta \sigma^{(k)} \|_2 < \text{tol}
\]

where \( \text{tol} \) is select to be 1e-5 in this work.

In simulation study, the same parameters are applied for all test phantoms.

3) Image Quality Evaluation: Reconstructed image quality is quantitatively evaluated by relative image error and correlation coefficients with respect to the true phantom. A smaller image error and a larger correlation coefficient indicate a better image quality. The definition of image error \( I_e \) and correlation coefficient \( C_c \) is expressed as

\[
I_e = \frac{\| \Delta \hat{\sigma} - \Delta \sigma \|}{\| \Delta \sigma \|}
\]

and

\[
C_c = \frac{\sum_{i=1}^{E} (\Delta \hat{\sigma}_i - \Delta \sigma_{\text{avr}})(\Delta \sigma_i - \Delta \sigma_{\text{avr}})}{\sqrt{\sum_{i=1}^{E} (\Delta \hat{\sigma}_i - \Delta \sigma_{\text{avr}})^2 \sum_{i=1}^{E} (\Delta \sigma_i - \Delta \sigma_{\text{avr}})^2}}
\]

where \( \Delta \hat{\sigma} \) and \( \Delta \sigma \) denote the estimated conductivity change and ground truth, respectively; \( \Delta \hat{\sigma}_i \) and \( \Delta \sigma_{\text{avr}} \) denote the \( i \)th value and the average of \( \Delta \hat{\sigma} \), respectively. Note that the normalization process is carried out on \( \Delta \hat{\sigma} \) and \( \Delta \sigma \) when calculating \( I_e \) and \( C_c \).

4) Simulation Results: Noise-contaminated voltage data with different SNR levels, i.e., 60 dB, 40 dB, 35 dB and 25 dB, are adopted for image reconstruction to evaluate the noise performance of the proposed EAGS-TV algorithm. The image reconstruction results of the two test phantoms using L1 regularization, TV regularization, AGSP and EAGS-TV are illustrated in Fig. 3 (60 dB SNR), Fig. 4 (40 dB SNR), Fig. 5 (35 dB SNR), and Fig. 6 (25 dB SNR), respectively.

The spatial distribution of conductivity change in phantom 1 is not sparse. Therefore, L1 regularization underestimates the dimension of the inclusions. Moreover, the distortion of the boundary near the center of the sensor indicates that L1 regularization cannot perform well on such kind of phantoms. With the decrease of SNR, more noise and distortion are presented in the reconstructed images. TV regularization can provide slightly better reconstructions than L1 regularization, but is still not able to show the correct shape of the targets. Comparing with L1 and TV regularization, both AGSP and EAGS-TV demonstrate pretty good estimation of the shape of targets and superior background noise reduction. Further comparing the two algorithms shows that the EAGS-TV apparently demonstrates the best reconstruction image quality with more accurate target shape estimation and clearer inclusion boundary. Moreover, the EAGS-TV results show fewer distortion than AGSP results with the decrease of SNR which confirms the improved robustness of the method against noise.

Regarding phantom 2, the spatial distribution of conductivity change is sparse. Under this circumstance, although TV regularization provides clear boundary, it overestimates the dimension of inclusions. Different from the results of phantom 1, L1 regularization performs pretty well on phantom 2 with good background noise reduction and shape estimation. However, the distortion still exists towards the direction of sensor center. As indicated in the figures, both the AGSP and EAGS-TV outperforms the L1 regulation and TV regularization on the sparse phantom. Compared with AGSP regularization, more accurate shape estimation and clearer boundary of inclusions are obtained using EAGS-TV, and its noise performance is much better than the AGSP regularization when SNR is 40 dB and 35 dB.
Fig. 7 shows the image errors and correlation coefficients of the results in Fig. 3, Fig. 4, Fig. 5 and Fig. 6. Overall, the image error decreases and the correlation coefficient increases with the increase of SNR for all given algorithms. The smallest image errors and the highest correlation coefficients are obtained by EAGS-TV. As for phantom 1, EAGS-TV can achieve image errors lower than 52% and correlation coefficients higher than 0.8670 when SNR is larger than 40 dB, and with respect to phantom 2, the image errors are below 67% and correlation coefficients are above 0.7720 when SNR is larger than 40 dB, which apparently outperforms other algorithms. Overall, the image errors of EAGS-TV are improved around 9% with respect to the AGSP when SNR is larger than 40 dB. Based on the quantitative evaluation results, the superior performance of EAGS-TV is further confirmed.

Fig. 8 shows the pixel grouping results of the two phantoms under the given SNR levels. We denote the total number of groups as nG and the number of groups with inclusions as nBG, as highlighted in darker colours. It is shown that reasonable grouping result can be obtained at different SNR levels for phantom 1, whilst the pixel grouping for phantom 2 collapses when SNR is 25 dB as the signal in this case cannot be well distinguished from noise. Overall, in spite of certain noisy spots and distortion, the generated groups can still include the inclusion areas and reflect the correct position of the targets.

Fig. 9 illustrates the elapsed time of the compared algorithms for the two simulated phantoms. The reconstruction procedure is conducted on a laptop with an Intel i7-3537U CPU (2.0 GHz) and 8.0 GB RAM memory. Fig. 9 indicates that all the algorithms can complete the reconstruction within 5 seconds and the elapsed times are comparable. Although EAGS-TV is slightly more time-consuming than other algorithms due to the incorporation of total variation, it apparently outperforms other algorithms in image quality with affordable computation cost.

B. Experiment Results

In this subsection, the practical performance of EAGS-TV method is evaluated by phantom experiments on a 16-electrode EIT sensor by using the EIT system developed in the Agile Tomography Group at the University of Edinburgh. The experimental facility is demonstrated in Fig. 10.

In Fig. 10, the inner diameter of the 16-electrode sensor is 95 mm. The background reference is saline which conductivity is 0.05 S·m⁻¹. Under this setup, the highest temporal resolution and SNR achieved by the EIT system are 1014 frames per second and 73 dB, respectively.

For all experiments, the frequency of current excitation is set as 10 kHz and the amplitude of injected current is approximately 1.5 mA peak to peak. The adjacent strategy is
adopted and the amplitude data of the induced voltage signal is acquired for image reconstruction.

Two phantoms, i.e., the non-sparse phantom 1 as shown in the first row of Fig. 11 and the sparse phantom 2 as shown in the second row of Fig. 11, are imaged. The same algorithm parameters and stopping criterion as demonstrated in the numerical simulation part are adopted.

Fig. 11 shows the image reconstruction results of L1 regularization, TV regularization, AGSP and EAGS-TV based on experimental data. In general, the results show good similarity with the numerical simulation results. Comparing the results of phantom 1, EAGS-TV demonstrates the best image quality on noise reduction performance of the background, shape estimation, and boundary estimation. Similar to the simulation result, L1 regularization tends to give a smaller dimension if the target distribution is not sparse. While TV regularization fails to estimate the shape accurately. AGSP shows good noise performance but the boundary of inclusions is not explicit. As for phantom 2, L1 regularization gives relatively good image but there exists distortion towards the center of the sensor. TV regularization cannot accurately estimate the dimension of the inclusions by giving much bigger sizes for the tiny objects. AGSP provides much better image quality than L1 and TV, but a few artefacts exit. Instead, AGS-TV not only shows the correct position of the inclusions but also demonstrates more accurate dimensions with less distortion and few artefacts.

Fig. 12 illustrates the image errors and correlation coefficients of the results in Fig. 11. From the quantitative perspective, EAGS-TV outperforms L1, TV regularization and AGSP in both image errors and correlation coefficients. The image error of phantom 1 using EAGS-TV is more than 20% smaller and that of phantom 2 is more than 40% smaller than L1 regularization. The correlation coefficient of EAGS-TV is 0.15 larger than L1 regularization for phantom 1 and 0.24 larger than L1 regularization for phantom 2. Comparing with AGSP, more than 11% smaller image errors have been obtained by EAGS-TV for the two test phantoms. The results in Fig. 12 further validate the image quality improvement by EAGS-TV.

The adaptive pixel grouping results of the experimental phantoms are shown in Fig.13.

IV. CONCLUSIONS

In this paper, we propose a novel image reconstruction algorithm named EAGS-TV for EIT based on enhanced adaptive group sparsity with total variation constraint. By combining the adaptive group sparsity and total variation, we simultaneously utilize the prior information of regional structure features and global characteristics of the conductivity change distribution. The regional structure feature is integrated by using an enhanced adaptive group sparsity constraint, and the global characteristic of piece-wise conductivity change is considered by imposing total variation constraint on the whole image. An enhanced adaptive pixel grouping algorithm is proposed based on Otsu’s thresholding method and an accelerated alternating direction method of multipliers is introduced to solve the proposed problem for faster convergence rate. The superior image quality has been obtained using EAGS-TV both in numerical simulation and in practical experiments. In comparison with L1 regularization, TV regularization and AGSP, we conclude that EAGS-TV is a more effective algorithm for high definition impedance imaging.

Future work includes the application of the EAGS-TV in potential scenarios such as the biomedical imaging using EIT and multi-phase flow imaging. Moreover, the extension of the algorithm for other tomographic modalities will also be investigated.

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