Sparsity based Radio Tomographic Imaging using Fused Lasso Regularization

Abhijit Mishra
Department of ECE
NIT, Rourkela
Odisha, India
517ec1012@nitrkl.ac.in

Upendra Kumar Sahoo
Department of ECE
NIT, Rourkela
Odisha, India
sahooupen@nitrkl.ac.in

Subrata Maiti
Department of ECE
NIT, Rourkela
Odisha, India
smaiti@nitrkl.ac.in

***Abstract*—The increase in demand of detecting obstructions in a wireless medium without attaching any device with the target is well facilitated by the Radio Tomographic Imaging (RTI) system. Even though it is a promising technique it is a cumbersome task to get the exact position and shape of an object due to ill-posed nature of RTI system. Thus vital task is to effectively choose a regularization technique that not only enhances sparsity by reducing noise after detection but also preserves edges of the object with its appropriate shape by using a heuristic weight model. RTI facilitates us with an imaging vector indicating the loss fields created by obstacles in the medium having knowledge of received signal strength(RSS) values and a weight model that assigns weight to the attenuated pixels in a wireless network. This paper addresses the above-mentioned problem by using a fused lasso regularization via ADMM. The second part of the paper extends performance of fused lasso regularization by implementing it incrementally using distributed learning. The performance metrics shows that fused lasso regularization not only reduces the noise level by increasing the sparsity but also retains the sharp features of the object.**

***Index Terms*—Radio tomographic imaging; SLF's ; regularization methods; Fused lasso regularization , ADMM.**

I. Introduction

Starting from medical imaging [1], Tomographic Imaging has increased it's application to morden day sciences. The priciple behind tomographic technique is to establish spatial loss fields(SLFs) that represents the amount of fading accomplished by radio waves at each spatial location [2]. It has applications in through-the-wall imaging and localization of survivors after earthquakes [3]. The major advantage is device-free passive localization i.e, we can detect it without attaching any sensor with the target. The failure of camera sensors to capture images in dark leads to the necessity of the RTI system. The ability of radiofrequency waves to penetrate through structures like buildings and trees shows the advantages of the RTI system over conventional imaging techniques. The most significant part of the RTI system is spatial loss fields(SLFs) which provide the amount of attenuation observed by electromagnetic waves in radio frequency bands at each spatial location [2]. The obstructing object not only attenuates the LOS path but also the spatial position shadowed by the object. As the radio waves pass through the object it experiences a certain amount of attenuation due to the object. SLFs help us to obtain the absorption inorder to detect the objects and their imaging, which provides us radio tomographic imaging. RTI system helps in the detection of static object and people with their movements. Further RTI helps avoid injuries caused to military and police from terrorists [5]. Static objects in general shows negligible variance therefore variance based RTI is not producing accurate results in comarision to shadowing based techniques. Hence we can use shadowing based RTI (SRTI). In case of SRTI the attenuation mapped by the SLFs is same as the shadowing loss. From [6] it is observed that links that are common to the obstruction posses identical shadowing effects.

$$G(\mathbf{t},\mathbf{r}) = G_{TX}(\mathbf{t}) + G_{RX}(\mathbf{r}) - \beta_0 10\log_{10}\|\mathbf{t}-\mathbf{r}\|_2 - s(\mathbf{t},\mathbf{r}), \quad (1)$$

where $G_{TX}(\mathbf{t})$ (resp. $G_{RX}(\mathbf{r})$) stands for the gain of the power amplifier for transmitter and receiver antenna respectively. β_0 is the path loss exponent, and $s(\mathbf{t},\mathbf{r})$ is the shadow fading.

$$s(\mathbf{t},\mathbf{r}) = \int_A w(\mathbf{t}, \mathbf{r}, \bar{\mathbf{x}})\, l(\bar{\mathbf{x}})\, d\bar{\mathbf{x}}, \quad (2)$$

where the SLF is $l : A \to \mathbb{R}_+$ and weight function is w. Where as $l(\bar{\mathbf{x}})$ gives the amount of radio power absorbed at position $\bar{\mathbf{x}} \in A$, the weight $w(\mathbf{t}, \mathbf{r}, \bar{\mathbf{x}})$ signifies the weightage to that perticular voxel which indicates that the transmitted radio power is absorbed at that location.

There are various heuristic weight models as discussed in [4]. For simplicity a normalized elliptical weight model is used with foci at the transceiver points. This indicates the attenuation at center is maximum due to the obstructing object and gradually it decays as the distance from the center of object increases [4]. Many of the recent works [11]- [13] are focused on reducing the localization error as well as the computational complexity of RTI system. While very little focus has been given on overburden of fusion center due to a centralized RTI system. An Incremental distributed approach discussed in [18] suggests an incremental approach based on Tikhonov regularization. It was observed that the outputs of above approach is affected by outliers. This motivates us to improve the sparsity of detected object along with its strutural details by using the incremental decentralized approach.

In a dense wireless network, the objective of the RTI system is faithful detection of the obstructing object in the path of transmitted signal and removal of noise from reconstruction to an optimum level so that ambiguity in detecting an object is

minimized. Considering all RTI works so far using heuristic weight model and conventional regularization techniques it is very difficult to attain both the above-mentioned objectives irrespective of low or high smoothing [4] [7]. In this paper, we mainly focus to improve the noise removal of detected objects along with the preservation of the object's edge using heuristic weight model. This motivates us to implement a generalized fused lasso algorithm for RTI.
As RTI is an inverse problem, regularization methods play an important role. From tomography works in different literature, we came across different types of regularization. The work carried out in [4] with the normalized weight model shows the application of the Tikhonov regularization with low and high smoothing. This concludes that the Tikhonov solution is the simpler regularization as it is the linear transformation of measurement data. It works best when a smoother estimation is required. Though using Tikhonov regularization object detection is good but noise removal after detection is not appropriate.
In all the above literature detection of object's using shadowing based Radio Tomographic Imaging (SRTI) is done. As our object is static in nature which posseses a negligible variance , therefore variance based Radio Tomographic Imaging does not yeild better detection performance compared to SRTI. Hence using a heuristic weight model our objective is to obtain an estimated loss field that simultaneously provides better result from object detection and noise removal perspective.
section I presents an introduction to the RTI system. problem statement is illustrated in Section II . Section III describes the mathematical model of RTI system and different regularization techniques. Section IV represents the proposed method. Experimental results and performance metrics analysis are presented in Section V. Section VI concludes the paper.

II. Problem Formulation

Considering a close convex set comprises of a grid size of 7×7. A total of $K = 24$ wireless sensors were deployed on the border of grid in exact positions as shown in 1. The entire square grid is defined with $M = 900$ spatial points ,i.e $i = 1, 2...900$. With the insight of transmitter antena power gain, receiver antena power gain and the total noise obtained which is the combination of noise due to shadow fading and measurement error, the observed received signal strength(RSS) are obtained due to shadowing measurements. A noise of variance $\sigma^2 = 10^{-2}$ is added with received observations to get the noisy data, which is used for further processing along with regularization as our objective function. Objective of RTI system is to estimate the loss field vector of dimension $\mathbf{x} \in \Re^M$ which signifies the amount of radio power getting attenuated form transmitter to receiver due to the obstructing medium in the wireless network consisting of M voxels. A total of N= $\frac{K^2-K}{2}$ numbers of unique bidirectional links present among all the nodes. At a given time instance t for a specific link j the follwing symbols are considered.

1) P_j: *Transmitter antenna power in dB.*
2) $S_j(t)$: *shadow fading loss in dB.*
3) $F_j(t)$: *Loss due to fading in dB.*

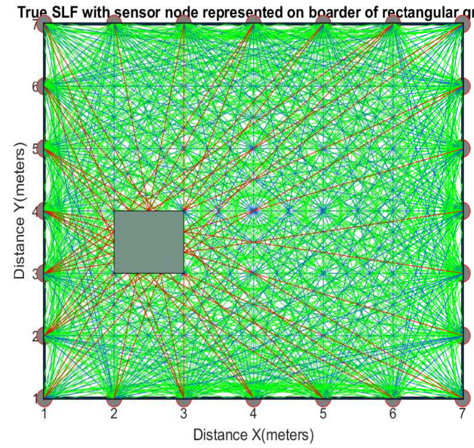


Fig. 1: All 24 nodes are deployed on the boundary of rectangular grid of area 7×7 with distance of 1 meter among each node with position $(1, 1)$ as the starting node.

4) L_j: *Loss due to antenna patterns in dB.*
5) $n_j(t)$: *Measurement noise.*

The RSS is given as,

$$y_j(t) = P_j - L_j - S_j(t) - F_j(t) - n_j(t). \tag{3}$$

Representing the shadowing loss of j^{th} link in it's discrete version with in M voxels of the square grid we have,

$$S_j\,(t) = \sum_{i=1}^{M} w_{ji} x_i(t) \tag{4}$$

$x_i(t)$ indicates the amount of attenuation occured in voxel i at time t, and w_{ji} indicates corresponding weight for the attenuated pixel i for link j. In this paper w_{ji} is found using normalized elliptical weight model.

III. Mathematical model

During communication among sensor nodes in the wireless environment some of the transmitted power attenuated by the objects inside the network. The SLF produced by the object helps us in imaging by providing us with avector of dimension $\Re^M$. This shows how much transmitted power is absorbed by the object in a grid of M pixels. All static losses can be removed by considering the time interval t_a to t_b and the difference of RSS values for j^{th} link are found as Δy_j. Now by taking all the radio links of the network into consideration we can reformulate the RSS system into matrix form as,

$$\mathbf{\Delta Y} = \mathbf{W \Delta X} + \mathbf{v} \tag{5}$$

where $\mathbf{\Delta Y} = [\Delta y_1, \Delta y_2, ..., \Delta y_N]^T$,$\mathbf{\Delta x} = [\Delta x_1, \Delta x_2, ..., \Delta x_M]^T$,$\mathbf{v} = [v_1, v_2, ..., v_N]^T$,$[\mathbf{W}]_{ji} = w_{ji}$
Hence the differnce in RSS values $\mathbf{\Delta Y}$ for all the radio links is considered as a vector of of length N. The noise vector $\mathbf{v}$ of length N and the estimated SLF $\mathbf{\Delta x}$ indicating the attenuation due to obstruction is considered a vector of lenght M. The weight matrix $\mathbf{W}$ is of dimension N× M, where each row of weight matrix associated with weighting for each pixel of a specific link and every column reprsenting a voxel. For

simplicity in presentation the parameters $\Delta\mathbf{X}$ and $\Delta\mathbf{Y}$ are replaced with $\mathbf{x}$ and $\mathbf{y}$ respectively. Due to the illposedness of RTI system the objective function takes the form of data fidelity and regularization term, so it can be represented as:

$$f_{reg}(\mathbf{x}) = f(\mathbf{x}) + \lambda g(\mathbf{x}), \tag{6}$$

$\mathbf{x}$ is the estimated SLF. λ is the parameter that controls regularization. Our goal is to estimate the SLF $\mathbf{x}$ from the noisy observed RSS $\mathbf{y}$ and the weight matrix $\mathbf{W}$. The above expression II is in the form of linear regression where in the transition matrix $\mathbf{W}$ and RSS vector $\mathbf{y}$ are known inorder to determine the SLF $\mathbf{x}$ associated with the obstructing object. There are differnet regularization methods discussed in [4], [5] and [7]. Thus the cost function using regularization can be written as:

$$f_{reg}(\mathbf{x}) = \frac{1}{2}\|\mathbf{W}\mathbf{x} - \mathbf{y}\|_2^2 + \lambda\|\mathbf{D}\mathbf{x}\|_2^2, \tag{7}$$

Where λ stands for the regularization parameter, which controls the relative importance of regularization term compared to data fidelity term. If λ is choosen as small then it tends the solutions to fit the data, but for large λ values provides solution which matches the prior information.

A. Normalized Elliptical Weight Model

The linear effect attenuation field occurred due to path loss for each radio link is used for finding the weight for every link [4], [7]. This models used to give weighting to the pixels that are attenuated by object due it's presence in the LOS path between transmitter and receiver, also it assigns zero weightage to those pixels that are outside the first Freshnel zone. The normalized weight value is used by length of a perticular link. Mathematically it is represented as:

$$w_{nm} = \frac{1}{\sqrt{d}}\begin{cases}1 & \text{if } d_{nm}(\mathbf{t}) + d_{nm}(\mathbf{r}) < d + \Delta \\ 0 & \text{else}\end{cases} \tag{8}$$

where d stands for the distance between two sensor nodes ,i.e the transceiver points, $d_{nm}(\mathbf{t})$ and $d_{nm}(\mathbf{r})$ are the distances from the center of perticular voxel i to the transceiver locations. Δ is the parameter representing the width of ellipse and is an adjustable parameter. As shown in figure 2 it is observed that those voxels which are not shadowed by the object are considered as non-weighted and the ellipse containing non-weighted voxels are not useful for estimating the loss field created by the object.

B. Tikhonov Regularization

Tikhonov regularization, is the most suitable for smoother objects dtection and widely used regularization technique. The amount of regularization is controlled by a regularization parameter λ.

$$g(\mathbf{x}) = \frac{1}{2}\|\mathbf{W}\mathbf{x} - \mathbf{y}\|_2^2 + \lambda\|\mathbf{D}\mathbf{x}\|_2^2 \tag{9}$$

where $\mathbf{D}$ is the Tikhonov matrix. Taking the gradient of equation 9 and equating it to zero we got the Tikhonov solution:

$$\mathbf{x}_{TIK} = (\mathbf{W}^T\mathbf{W} + \lambda\mathbf{D}^T\mathbf{D})^{-1}\mathbf{W}^T\mathbf{y} \tag{10}$$

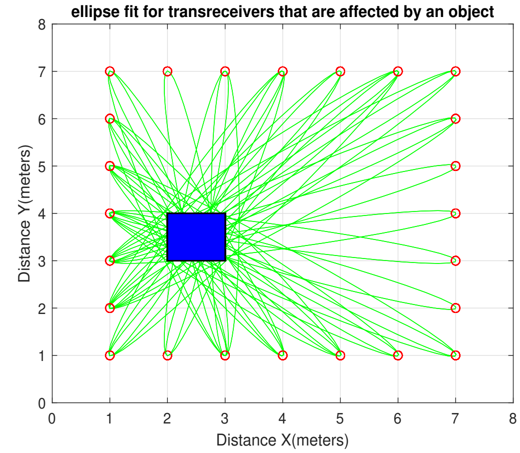


Fig. 2: The pixels shadowd by the object are fitted with an ellipse with width of the ellipse set to the carrier frequency.

$\mathbf{D}$ matrix has different variants like it can be the identity matrix, it may be 1st or 2nd order derivative matrices for improving the smoothness of reconstructed images or $\mathbf{D}$ can be an error covariance matrix. As error covariance matrix produces much smoother reconstruction compared to other form of $\mathbf{D}$, we used this in our work.The advantage of using Tikhonov regularization is the estimation process is simply a linear projection of observed data. Mathematically

$$\mathbf{Pr}_{Tikhonov} = (\mathbf{W}^T\mathbf{W} + \lambda\mathbf{D}^T\mathbf{D})^{-1}\mathbf{W}^T \tag{11}$$

As we know that the loss field $\mathbf{x}$ can be represented as a function of shadowing loss, the SLF is modelled as a Gaussian distribution with covariance between pixels which are separated by distance of $l_{t,r}$.

$$\mathbf{R}_{\mathbf{x}}(l_{t,r}) = \frac{\sigma_p^2}{\delta}\exp(\frac{-l_{t,r}}{\delta}) \tag{12}$$

where δ is the parameter also called as pixel correlation constant and it manifest that how quickly correlation falls off with the distance between pixels. The covariance due to shadow fading is denoted by the parameter σ_p^2 . Hence we can inverse the error covariance matrix $\mathbf{R_x}^{-1/2}$ and use it for estimating the imaging vector. Apart from the advantages of Tikhonov regularization we observe that using heuristic weight model noise removal of reconstructed image to an optimum extent is a cumbersome task.

C. Truncated Singular Value Decomposition (TSVD)

In the transfer or weight matrix all the values are not significant, so there is always a possibility that we can reduce the number of singular values used for reconstruction by removing the small singular values that are not significant from a reconstruction point of view. This is called as TSVD regularization. Here the largest p singular values are used for reconstruction.

$$\mathbf{x}_{tsvd} = \sum_{j=1}^{p<M} \frac{1}{\sigma_j}\mathbf{a}_j^T\mathbf{y}\mathbf{b}_j = \mathbf{B}_p \sum\nolimits_p^{-1} \mathbf{A}_p^T\mathbf{y} \tag{13}$$

where

$$\mathbf{A}_p = [\mathbf{a}_1, \mathbf{a}_2, ..., \mathbf{a}_p] \tag{14}$$

$$\mathbf{B}_p = [\mathbf{b}_1, \mathbf{b}_2, ..., \mathbf{b}_p] \tag{15}$$

$$\sum\nolimits_p^{-1} = diag\left(\sigma_1^{-1}, \sigma_2^{-1}, ..., \sigma_p^{-1}\right) \tag{16}$$

In TSVD the projection is only on the subspace containing the largest singular values, therefore it reduces the dimension of the true solution but it cannot properly reconstruct the object. Again this reconstruction contains a large number of high frequency components during reconstruction. In this paper singular value, bellow threshold ν=3.3 are truncated.

D. Total Variation Regularization

This is one of the non-linear regularization that reduces changes in the solution. TV regularization enhances the detection of sharp features [10] and [16]. For SLF having concrete structures it provides bset results Mathematically, TV takes the form

$$g(\mathbf{x}) = \frac{1}{2}\|\mathbf{W}\mathbf{x} - \mathbf{y}\|_2^2 + \lambda \; TV(\mathbf{x}) \tag{17}$$

where

$$TV(\mathbf{x}) = \sum_i |\nabla \mathbf{x}|_i \tag{18}$$

and the gradient of the ith element of $\mathbf{x}$ is denoted as $\nabla \mathbf{x}_i$. As gradient is difficult to calculate, so we approximate it by a differentiable function.

$$TV(\mathbf{x}) \simeq \sum_i \sqrt{\;\|\nabla \mathbf{x}\|_i^2 + \quad \gamma^2} \tag{19}$$

γ is an adjustable parameter that controls the edge preservation of reconstructed images. Though TV regularization preserves edges it also suffers from the impact of noise after reconstruction.

E. l_1-norm regularization

When the loss field has a scenario where the wireless medium comprises fewer obstructions then we can think of adopting the l_1 norm. This regularization promotes sparsity and helps in reducing noisy reconstruction of images [8] and [9].

$$g(\mathbf{x}) = \frac{1}{2}\|\mathbf{y} - \mathbf{W}\mathbf{x}\|_2^2 + \lambda_1\|\mathbf{x}\|_1 \tag{20}$$

The closed form expression of the above equation in 20 is found as

$$\mathbf{x}[k+1] = \mathcal{S}\left(\tilde{\mathbf{y}}_l[k]\,\mathbf{W}_l[k]\,; \frac{\lambda_1}{2}\right) / \|\mathbf{W}_l[k]\|_2^2 \tag{21}$$

The subscript l denotes that the parameter is found by removing the l^{th} data point. where k is the iteration number to obtain the optimized output and $\mathcal{S}$ is the soft-thresholding operator is designated as

$$\mathcal{S}(\mathbf{y}, \lambda_1) := sign(\mathbf{y}) \max\left\{\;0, \quad |\mathbf{y}| \quad - \lambda_1\right\} \tag{22}$$

The lasso solution sometimes become inconsistent , therefore for every coefficient some weight is attached in the lasso penalty . lasso procedure. Adaptive lasso can be reresented as

$$g(\mathbf{x}) = \frac{1}{2}\|\mathbf{y} - \mathbf{W}\mathbf{x}\|_2^2 + \lambda\|\beta\mathbf{x}\|_1 \tag{23}$$

Where

$$\beta = \frac{1}{\tilde{\mathbf{x}}} \tag{24}$$

Whrer $\tilde{\mathbf{x}}$ is obtained from least square estimation.

IV. Proposed Methodology

The lasso model can be extended to fused Lasso (FL) which not only add l_1 to perticular coefficient but also add l_1 penalty with regularization parameter λ_2 to the neighboring coefficients difference. The resulting loss function [14] and [15].

$$g(\mathbf{x}) = \frac{1}{2}\|\mathbf{y} \text{ - } \mathbf{W}\mathbf{x}\|_2^2 + \lambda_1 \sum_{i=1}^{p} |\mathbf{x}_i| + \lambda_2 \sum_{i=1}^{p} |\mathbf{x}_i - \mathbf{x}_{i+1}|, \tag{25}$$

where the second penalty with parameter λ_2 shrinks neighboring coefficients towards each other. In generalized fused lasso we keep the account for active and inactive sets depending on the estimated value. For a fused set F_i , if $\mathbf{x}_{F_i} = 0$ it is treated as inactive else it is an active set. Here we solve the fused lasso problem via ADMM, hence (25) can be repformulated as

$$g(\mathbf{x}) = \frac{1}{2}\|\mathbf{y} \text{ - } \mathbf{W}\mathbf{x}\|_2^2 + \lambda_1|\mathbf{u}|_1 + \lambda_2|\mathbf{z}|_1, \tag{26}$$

s.t $\mathbf{u} = \mathbf{x}$ and $\mathbf{z} = \mathbf{Q}\mathbf{x}$ where u and z are auxiliary variables of length $M \times 1$. $\mathbf{Q}$ is the first order difference matrix. The augmented Lagrangian is formulated as

$$\begin{aligned} g(\mathbf{x}) = &\frac{1}{2}\|\mathbf{y} \text{ - } \mathbf{W}\mathbf{x}\|_2^2 + \lambda_1|\mathbf{u}|_1 + \lambda_2|\mathbf{z}|_1 \\ &+ \boldsymbol{\eta}_u^T(\mathbf{u} - \mathbf{x}) + \frac{c_u}{2}\frac{1}{2}\|\mathbf{u} - \mathbf{x}\|_2^2 \\ &+ \boldsymbol{\eta}_z^T(\mathbf{z} - \mathbf{Q}\mathbf{x}) + \frac{c_z}{2}\frac{1}{2}\|\mathbf{z} - \mathbf{Q}\mathbf{x}\|_2^2, \end{aligned} \tag{27}$$

where $\boldsymbol{\eta}_u$ and $\boldsymbol{\eta}_z$ are the lagrangian multipliers and c_u and c_z are positive constants. The equation (26) can be solved iteratively by minimizing $\mathbf{x}$,$\mathbf{u}$ and $\mathbf{z}$ sequentially kepping other variables constant. Therefore the closed form solutions can be obtained as

$$\begin{aligned} \mathbf{x}[k+1] = &(\mathbf{W}^\mathbf{T}\mathbf{W} + c_u\mathbf{I} + c_z\mathbf{Q}^\mathbf{T}\mathbf{Q})^{-1} \\ &\times (\mathbf{W}^\mathbf{T}\mathbf{y} + \boldsymbol{\eta}_u[k] + c_u\mathbf{u}[k] + \mathbf{Q}^\mathbf{T}\boldsymbol{\eta}_z[k] + c_z\mathbf{Q}^\mathbf{T}\mathbf{z}[\mathbf{k}]), \end{aligned} \tag{28}$$

Similarly parameter u and z are found as

$$\mathbf{u}[k+1] = \mathcal{S}\left(\left[\mathbf{x}[k] - \frac{\boldsymbol{\eta}_u[k]}{c_z}\right], \frac{\lambda_1}{c_u}\right), \tag{29}$$

$$\mathbf{z}[k+1] = \mathcal{S}\left(\left[\mathbf{x}[k] - \frac{\boldsymbol{\eta}_z[k]}{c_u}\right], \frac{\lambda_2}{c_z}\right), \tag{30}$$

Where $\mathcal{S}$ stands for soft thresholding operation applied at each point of loss field. In a similar way the updated lagrange multipliers are given as

$$\boldsymbol{\eta}_u[k+1] = \boldsymbol{\eta}_u[k] + c_u(\mathbf{u}[\mathbf{k}] - \mathbf{x}[\mathbf{k}]), \tag{31}$$

$$\boldsymbol{\eta}_z[k+1] = \boldsymbol{\eta}_z[k] + c_z(\mathbf{z}[\mathbf{k}] - \mathbf{Q}\mathbf{x}[\mathbf{k}]). \tag{32}$$

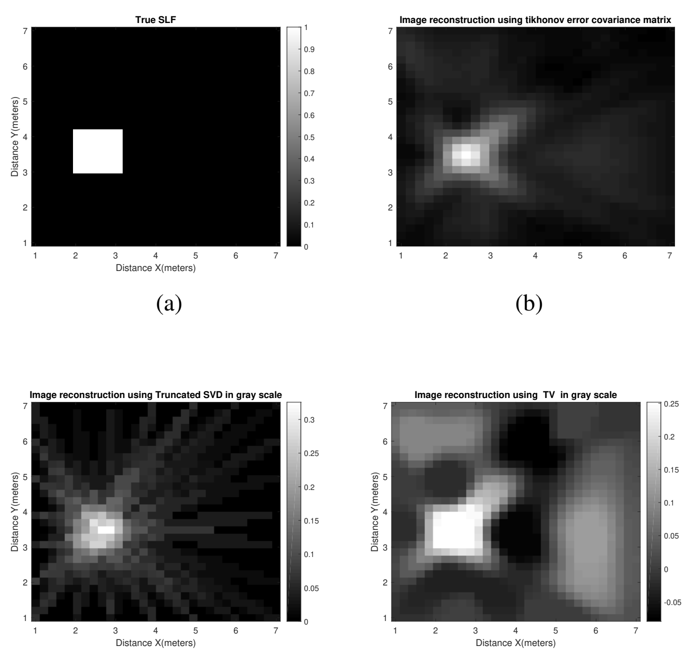
To reduce the overburdening of central processing unit a distributed approch is encouraged in RTI systems. A distributed incremental approach is a simple one discussed in [17] can also be implimented here. As the sensor nodes are uniformly placed on the border of rectangular grid so finding the incremental path is a simple task. The detection performance of Fused lasso regularization on behalf of sparsity as well as preserving sharp features of the object can also be verified in distributed manner. From [18] it is observed that the detectected object for distributed incremental RTI suffers a lot from sparsity point of view , hence the same algorithm is extended for fused lasso regularization based on ADMM to estimate the output SLF which is almost same as underlaying SLF.

V. Results and Analysis

Here a comparision of the estimated SLF's by using the proposed methods of Section III is established. We have synthetically generated the dataset containg the true SLF and observed RSS values. The true SLF is assumed to be a solid square box of one unit at position [2,3,1,1] and the estimated SLF is found using traditional regularization methods and sparsity promoting regularization methods. At last a comparision between estimated SLF and true SLF is done with the help of performance metrics. The regularization parameter λ is selected empirically. **TABLE I** provides model parameters .

TABLE I: Parameters for RTI model

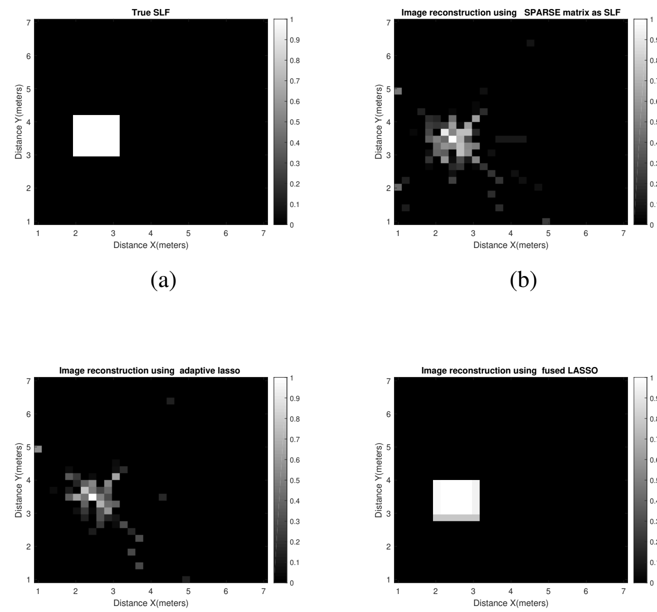
Parameters	Description	Values
K	Number of wireless sensor nodes	24
Δ_p	pixel width(In meters)	0.2
Δ	Carrier wavelength(In meters)	0.01
δ	constant for pixel correlation	2.1
σ_p^2	shadowing variance	0.4
λ	Regularization parameter for Tikhonov and TV	0.5
λ_1	Regularization parameter for lasso	2.75
λ_2	penalty parameter for adjacent pixel difference	0.65



(a) (b) (c) (d)

Fig. 3: True SLF versus estimated SLF (a) True SLF (b) Tikhonov error covariance matrix ,(c) Truncated SVD regularization (d) Total variation regularization regularization.

The results shown in figure 3 reprsents outputs for non sparse based regularization techniques. TIkhonov regularization uses error covariance matrix for estimting the SLF is providing a smoother output and also the detection is affected by noise level. TSVD gives the poor result among all, where as the detection using nonlinear TV regularization is more suffered by noise level even if the detection of sharp features of the object is retained.
The results shown in figure 4 motivates us for sparsity based regularization techniques so that the detected object can be free from noise level to an optimum extent .



(a) (b) (c) (d)

Fig. 4: True SLF versus estimated SLF (a) True SLF (b) Lasso regularization ,(c) Adaptive lasso regularization (d) Fused lasso regularization.

It is observed from figure 4 that application of lasso and adaptive lasso regularization provides encouraging results from noise removal prospective but the object is not properly detected as it is a solid structure it can not be treated as a fully sparse object. Finally the application of fused lasso regularization using ADMM shows that the object is detected with almost similar feature as the true SLF along with proper removal noise sorrounded by the detected object. It s also observed from 5 that the incremental fused lasso provides output almost similar to the centralised case. The results are also verified using performance metrics analysis.

A. Performance metrics of RTI using normalized elliptical weight model

For image quality in [19], we adopt

- The mean square error (MSE) It quantifies the dissimilarity between reconstruted $\mathbf{x}_c$and true SLF $\mathbf{x}_a$. Mathematically $\sigma = 10\log_{10}(\frac{\|\mathbf{x_a}-\mathbf{x_c}\|^2}{M})$.
- SSIM (Structured Similarity Index Method) Here degradation of reconstruted object is due to change in structural information.

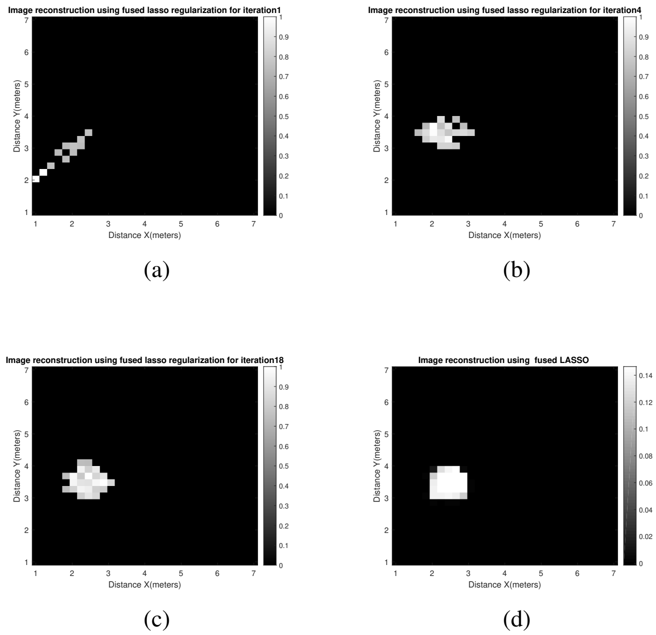


Fig. 5: Estimated SLF (a) At node 2 (b) At node 4 ,(c) At node 18 (d) At the last node.

TABLE II: Image Quality

Parameter	l_2	TV	l_1	Fused lasso(FL)	Incremental FL
RMSE[dB]	-13.630	-11.850	-19.142	-24.426	-21.79
PAR in %	65.04	55.56	76.78	12.11	20.11
SSIM	0.6141	0.7511	0.2280	0.9331	0.9122
FSIM	0.9161	0.9457	.9241	0.9956	0.9843

- FSIM (Features Similarity Index Matrix) It measures the features and find the similarity between reconstruted SLF and true SLF.
- Pixel Attenuation Ratio(PAR)

$$\text{PAR in } \% = \frac{\text{Number of attenuated pixels}}{\text{Total number of pixels in object}}$$

Lower the PAR better is the reconstruction.

VI. Conclusion

Tikhonov regularization gives good detection accuracy but the quality of imaging is not much encouraging due to presence of outliers. The l_1 norm regularization enhances sparsity but fails to provide satisfying results with respect to imaging quality for non sparse medium. TV regularization gives good edge detection ability but the noise removal after detection is poor. Therefore this paper discusses the importance of fused lasso regularization in RTI system with reference to structure preservation along with sparsity in a centralized and decentralized framework. So a generalized fused lasso ADMM based regularization is used for reconstruction of RTI system equip fine structural details along with sparseness. The performance metrics indicate the significant improvement in RTI system by using the fused lasso regularization for both centralized and incremental decentralized networks. This decentralized approach can be extended with some other heuristic weight models as well as for adaptive weight models to improve the estimation accuracy of SLF's.

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