Distributed Incremental Strategy for Radio Tomographic Imaging

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***Abstract*—Radio Tomographic Imaging (RTI) finds extensive application in modern day problem. The RTI achieved this using received signal strength (RSS) power and transmitted power by sensor nodes. RTI being an ill-posed inverse problem, requires regularization for proper estimation of spatial loss field(SLF) and able to detect the object. Centralized solution of RTI system requires large communication overheads. This motivates to develop distributed algorithm for RTI. Two novel distributed algorithms using incremental approach are developed in this paper. The first approach is the direct extension of the centralized approach to distributed incremental approach. Second algorithm requires less communication overheads compared to the first one by incorporating data censoring technique. The performance metrics show that the performance of distributed Incremental RTI is comparable to the centralized RTI system. Again the impact of censoring is studied by increasing the censoring ratio , which results in a trade-off between detection performance and computational complexity.**

***Index Terms*—Radio tomography; tomographic imaging; Spatial loss field; regularization methods; Distributed Incremental RTI; Data Censoring..**

I. Introduction

RTI is a technique of imaging a portion or section of interest from a large area or environment with the help of radio waves. The RTI in wireless networks has a great application in detecting and imaging obstructions present in the pathway between transceivers. RTI has applications in medical imaging [1], surveillance, survivor localization after earthquakes and through-the-wall imaging [2]. The advantages of RTI include device-free passive localization. RTI relies on incoherent techniques, hence it does not have the burden in estimating the phase of the received signal. The most significant notion behind RTI system is SLFs, that provide the amount of attenuation observed by electromagnetic waves in radio frequency bands at every spatial location [3]. This attenuation is experienced when there is an obstruction in the line of sight(LOS) path between transceiver nodes. The absorption obtained by the SLFs helps in detecting the objects and their imaging.

The static object has negligible impact on the variance of the power of the received signal. Thus, shadowing based RTI (SRTI) is preferred over variance-based RTI (VRTI).The shadowing loss in SRTI is same as the attenuation obtained by the SLFs. In SRTI relies on the fact is that closely located radio links possess similar shadowing. This is due to the presence of obstructions which are common to closely placed links [4]. Already many regularization methods are addressed in different literature. Tikhonov regularization with low and high smoothing [5] and with a normalized weight model is developed in [6]. The work in [6] uses the application of truncated singular value decomposition(TSVD) regularization is used for inverse problem. From all the above literature, we opt Tikhonov regularization for simplicity and hence used in this paper. The sensor network lifetime is one important factor, that should be given highest priority during the development of the algorithm for wireless sensor network. Network life time can be enhanced by facilitating the in-network processing capability of the network. In-network processing based strategies are broadly classified into;(i) incremental;(ii) diffusion and (iii) consensus. Incremental approach is simple but it requires an incremental path connecting each sensor nodes. Since in this paper the sensor nodes are placed in a uniform manner, so finding the incremental path is not troublesome. Hence distributed incremental strategy is used for imaging vector estimation in RTI. Moreover in order to find the global incremental path a local decision based algorithm is proposed.

The first part of the paper contributes to two distributed approaches, where in the first case imaging vector of each node is shared with its neighborhood node.This method requires large computations at each node due to matrix inversion operation. This is handled in second approach by using a data censoring technique. A proper selection of censoring ratio leads to a trade-off between detection performance and energy efficiency.

The paper is organized in the following way. Section II describes the problem statement. The distributed strategy is proposed in Section III. Section IV shows the experimental results, followed by performance metrics analysis. Section V concludes the paper.

II. Problem Formulation

Consider a rectangular region comprising a square grid of size 7×7. On the periphery, J=24 number of wireless sensors are placed uniformly as shown in Fig.1. The entire region is divided into M=900 voxels. The objective is to find the position and size of an object present in the region. This is achieved using the RSS values of transceivers. When

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communication between the nodes in a wireless network area takes place then due to the presence of objects inside the network few transmitted power is getting absorbed, scattered, or reflected by the object. RTI system find an imaging vector of dimension $\mathbf{f} \in \Re^M$ that indicates the extent by which transmitted radio power is getting attenuated due to presence of objects within M voxels of the square grid. The total number of unique two-way links is $N= \frac{J^2-J}{2}$., for $n = 1, 2...N$. Consider the following notations for a particular link.

1) P_{jn}: Gain of transmitter antenna of the j^{th} senor node for link n in dB.
2) $S_n(t)$: shadowing loss due to objects for the n^{th} link in dB.
3) $FL_n(t)$:Fading loss for the n^{th} link in dB.
4) L_n: Loss due to Antenna patterns of the n^{th} node in dB.
5) $e_n(t)$: Measurement noise at n^{th} link.

Mathematically, the RSS power at node j due to link n is expressed as

$$r_{jn}(t) = P_{jn} - L_n - S_n(t) - FL_n(t) - e_n(t) \quad (1)$$

In the above expression P_{jn},L_j and $FL_n(t)$ are known. $S_n(j)$ is the shadowing loss that has experienced by the link n. The difference between the transmitted and received power can be expressed in terms of the weighted sum of spatial loss field values of all voxels in the region. Fading loss of a link can be made zero by taking average of the different RSS power at different time. The shadowing loss $S_n(t)$ can also be expressed as the line integral of absorption at every spatial location multiplied with the weight that quantifies the amount of absorption at that location. For M number of voxels present in the network area, using discretization method the shadowing loss for the n^{th} link can be expressed as

$$S_n(t) = c \times \sum_{m=1}^{M} w_{nm} f_m(t) \quad (2)$$

where c is a constant assumed as unity by absorbing any scaling factor of $\mathbf{f}$, $f_m(t)$ is the attenuation value in voxel m at time t, and w_{nm} is the associated weight for a voxel m for link n. For finding the w_{nm} normalized elliptical weight model is used.

A. Normalized Elliptical Weight Model

This is used for obtaining the weighting factor for each link [4], [5] by the voxel. For a voxel, if it lies inside the ellipse it is weighted, whereas pixels outside the 1st Fresnel zone are weighted with value of zero. Also, the weight for each pixel is normalized by length of link [5]. The weight model is

$$w_{nm} = \frac{1}{\sqrt{l}} \begin{cases} 1 & \text{if } l_{nm}(tx) + l_{nm}(rx) < l + \delta \\ 0 & \text{else} \end{cases} \quad (3)$$

where the distance between transmitter and receiver foci is denoted as l ,the distances from the center of voxel m to the transmitter and receiver locations for link n are $l_{nm}(t_x)$ and $l_{nm}(r_x)$, respectively. δ is an adjustable parameter representing the ellipse width. With the knowledge of transmitter,

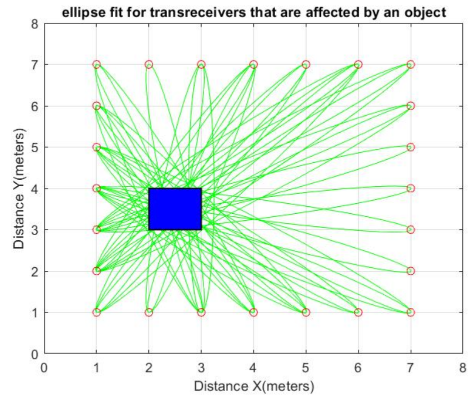


Fig. 1: The ellipse fit shows that only the affected LOS signals are considered for the weighting model.

receiver antenna power gain and total noise which is a combination of shadow fading and measurement noise, we have the ground truth information of shadowing measurements. This noisy information along with one appropriate regularization term is used for the development of the cost function of the RTI. The following assumptions are considered to simplify the problem:

1) The sensors are spread on the perimeter of grid uniformly in a flat surface so that The $z-$ coordinates are same.
2) The sensors know their positions and also the positions of their neighboring sensor nodes. The sensors can know their position using the sensor localization algorithm already present in different literature.

The voxels which are not interacted by a link are treated as zero weighted voxels. This is illustrated by Fig. 1 [7]. All transceivers form ellipse with each another and the non weighted ellipses are not useful. The change in RSS Δr_n from time t_1 to t_2 is considered to remove all the static losses over time.

$$\Delta r_{n,j} \equiv r_{n,j}(t_2) - r_{n,j}(t_1) \quad (4)$$

which can be written as

$$\begin{aligned} \Delta r_{n,j} = S_j(t_2) - S_j(t_1) + FL_j(t_2) - FL_j(t_1) \\ +e_n(t_2) - e_n(t_1) \end{aligned} \quad (5)$$

where noise is the combination of measurement and fading noise.

$$v_n = FL_n(t_2) - FL_n(t_1) + e_n(t_2) - e_n(t_1) \quad (6)$$

Define the RSS vector at node j as $\Delta \mathbf{r}_j = \begin{bmatrix} \Delta r_{j,1} & \Delta r_{j,2} & \cdots & \Delta r_{j,J} \end{bmatrix}^T$ where, each entry is for one link (each link is associated with two sensor nodes). Considering the vector $\Delta \mathbf{r}_j$, the RSS for j^{th} node can be structured in the following form

$$\Delta \mathbf{r}_j = \mathbf{W}_j \Delta \mathbf{f} + \mathbf{v}_j, \quad (7)$$

where the weighting matrix and the change in image vector are given by $\mathbf{W}_j$ and $\Delta \mathbf{f} = [\Delta f_1, \Delta f_2, ..., \Delta f_M]^T$. Each row of $\mathbf{W}_j$ is the weighting vector of each voxel to one link. Thus the dimension of $\mathbf{W}_j$ is $(J-1) \times M$. The expression (8) is the regression equation for j^{th} node. Collecting Δr_j of all node into a vector $\Delta \mathbf{r}$, we get the global regression formulation which is given as

$$\Delta \mathbf{r} = \mathbf{W} \Delta \mathbf{f} + \mathbf{v} \tag{8}$$

where $\Delta \mathbf{r} = [\Delta \mathbf{r}_1, \Delta \mathbf{r}_2, ..., \Delta \mathbf{r}_J]^T$, , $\mathbf{v} = \left[\mathbf{v}_1^T, \mathbf{v}_2^T, ..., \mathbf{v}_J^T\right]^T$, $\mathbf{W} = \left[\begin{array}{cccc} \mathbf{W}_1^T & \mathbf{W}_2^T & \cdots & \mathbf{W}_J^T \end{array}\right]^T$ In summary,$\Delta \mathbf{r}$ is the observed difference RSS measurements vector for all links and is of length N. $\mathbf{v}$ is the noise vector, and $\Delta \mathbf{f}$ is the estimated imaging vector indicating the attenuation occurred due to object and is of length M. All the measurement variables are in decibels (dB). For simplification $\mathbf{f}$ and $\mathbf{r}$ are used in place of $\Delta \mathbf{F}$ and $\Delta \mathbf{r}$, respectively. Thus the expression (8) can be represented as

$$\mathbf{r} = \mathbf{W} \mathbf{f} + \mathbf{v} \tag{9}$$

RTI being an ill-posed inverse problem the objective function is associated with a regularization term [7]–[9]. This takes the form

$$g_{reg}(\mathbf{f}) = g(\mathbf{f}) + \lambda h(\mathbf{f}) \tag{10}$$

where $\mathbf{f}$ is the imaging vector to be estimated. λ is the regularization parameter $g(\mathbf{f})$ is the data fidelity term and $h(\mathbf{f})$ is the regularization term and $g_{reg}(\mathbf{f})$ is the new objective function. This global problem leads to an increase in communication overheads. The expression (9) is a linear regression problem in which both input regression matrix $\mathbf{W}$ and desired vector $\mathbf{r}$ are known. The objective is to estimate $\mathbf{f}$. The Tikhonov regularization is most commonly used regularization as stated in [4], [5] and [7] for the case of smooth $\mathbf{f}$. Thus, the global cost function for RTI is

$$g(\mathbf{f}) = \frac{1}{2} \|\mathbf{W}\mathbf{f} - \mathbf{r}\|_2^2 + \lambda \|\mathbf{D}\mathbf{f}\|^2 \tag{11}$$

The relative importance of $\|\mathbf{D}\mathbf{f}\|^2$ compared to $\|\mathbf{W}\mathbf{f} - \mathbf{r}\|_2^2$ is controlled by the regularization λ. $\mathbf{D}$ is the Tikhonov matrix. The optimal solution of (11) can be calculated taking the gradient of (11) and finding the value of $\mathbf{f}$ for which gradient is zero, which is given as

$$\mathbf{f}_{TIK} = (\mathbf{W}^T \mathbf{W} + \lambda \mathbf{D}^T \mathbf{D})^{-1} \mathbf{W}^T \mathbf{r} \tag{12}$$

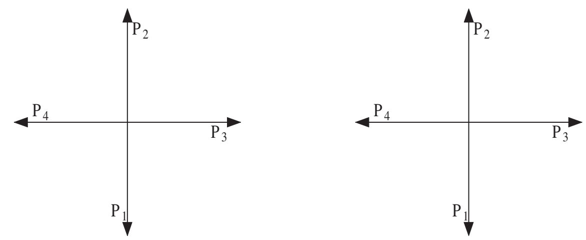
The above solution is linear projection of the measurement data $\mathbf{r}$ to the range space of $\mathbf{w}$. Projection matrix is given as

$$\mathbf{Pr}_{Tikhonov} = (\mathbf{W}^T \mathbf{W} + \lambda \mathbf{D}^T \mathbf{D})^{-1} \mathbf{W}^T \tag{13}$$

The Tikhonov matrix $\mathbf{D}$ can be (i) identity matrix, (ii) 1st and 2nd order derivative matrices or (iii) an error covariance matrix. In this paper Tikhonov error covariance matrix is used. As shadowing loss is a function of loss field $\mathbf{f}$, it can model SLF as a Gaussian distribution with certain covariance between points which are $l_{tx,rx}$ distance apart from each another.

$$\mathbf{R}_{\mathbf{f}}(l_{tx,rx}) = \frac{\sigma_p^2}{k} \exp(\frac{-l_{tx,rx}}{k}) \tag{14}$$

where k is the parameter signifies that how fast correlation between pixels falls off with distance. Parameter σ_p^2 is the



(a) (b)

Fig. 2: Formation of the distributed incremental path. (a) clockwise path (b) anticlockwise path.

covariance due to shadowing. The square root of the inverse of covariance matrix $\mathbf{R}_{\mathbf{f}}{}^{-1/2}$ can be used for imaging vector estimation.

III. Distributed Incremental Strategy

This section deals with the development of distributed incremental strategy for the RTI. Distributed strategy requires the following condition on the global cost function (11)

$$g(\mathbf{f}) = \sum_{i=1}^{J} g_i(\mathbf{f}) \tag{15}$$

where $g_i(\mathbf{f})$ is the local cost function, which uses only the information available at the sensor node i. Sensor node i has the received signal information from the sensor node $\{j\}_1^J$ through the link (i, j). Thus the local cost function at each sensor node can be given as

$$g_i(\mathbf{f}) = \frac{1}{2} \|\mathbf{W}_i \mathbf{f}_i - \mathbf{r}_i\|_2^2 + \frac{\lambda}{J} \|\mathbf{D}\mathbf{f}_i\|_2^2 \tag{16}$$

The global cost can be written as

$$g(\mathbf{f}) = \frac{1}{2} \sum_{i=1}^{J} \left[\|\mathbf{W}_i \mathbf{f}_i - \mathbf{r}_i\|_2^2 + \frac{\lambda}{J} \|\mathbf{D}\mathbf{f}_{\mathbf{i}}\|_2^2 \right] \tag{17}$$

Incremental strategy requires a cyclic path connecting each sensor nodes in the network [10]–[12]. For this a distributed algorithm is developed in which local decision based on the neighbor sensor nodes position is used to find the global incremental path. First each sensor node needs to know the next node in the incremental path. In order to find the incremental path, a sensor uses the following approach. Assuming the first sensor is initially at the origin, it searches a sensor in the direction with order $p1$,$p4$,$p2$,$p3$ as shown in Fig 2 for finding a neighboring sensor. A sensor does not consider another sensor from which it has just received the data for incremental path. The direction order in Fig. (2a) forms a clockwise incremental path and Fig. (2a) forms anti- clockwise incremental path. Initially the algorithm started from the first sensor node and the imaging vector is calculated using the data $\mathbf{W}_1$ and $\mathbf{r}_1$ using the estimation as given in (12). Thus the imaging vector is $\mathbf{f}_1 = (\mathbf{W}_1^T \mathbf{W}_1 + \frac{\lambda}{J} \mathbf{D}^T \mathbf{D})^{-1} \mathbf{W}_1^T \mathbf{r}_1$. Then the updated $\mathbf{f}_1$ is transmitted to the next node. Second node uses several parameters such as $\mathbf{f}_1$, $\mathbf{W}_2$ and $\mathbf{r}_2$ to get the

$\mathbf{f}_2$. Indirectly $\mathbf{f}_2$ uses the information $\mathbf{W}_1$, $\mathbf{W}_2$, $\mathbf{r}_1$ and $\mathbf{r}_2$. In the similar vein it can be stated that $\mathbf{f}_i$ for any node i requires information $\mathbf{W}_{1:i} = \begin{bmatrix} \mathbf{W}_1^T & \mathbf{W}_2^T & \cdots & \mathbf{W}_i^T \end{bmatrix}^T$ and $\mathbf{r}_{1:i} = \begin{bmatrix} \mathbf{r}_1^T & \mathbf{r}_2^T & \cdots & \mathbf{r}_i^T \end{bmatrix}^T$. The imaging vector at $(i-1)^{th}$ node can be written as

$$\mathbf{f}_{i-1} = (\mathbf{W}_{1:i-1}^T \mathbf{W}_{1:i-1} + \lambda \mathbf{D}^T \mathbf{D})^{-1} \mathbf{W}_{1:i-1}^T \mathbf{r}_{1:i-1} \quad (18)$$

The weight matrix $\mathbf{W}_{1:i} = \begin{bmatrix} \mathbf{W}_{1:i-1}^T & \mathbf{W}_i^T \end{bmatrix}^T$ and the received RSS $\mathbf{r}_{1:i} = \begin{bmatrix} \mathbf{r}_{1:i-1}^T & \mathbf{r}_i^T \end{bmatrix}^T$ can be used to obtain the f_i as given below

$$\begin{aligned} \mathbf{f}_i = \Big(& \begin{bmatrix} \mathbf{W}_{1:i-1}^T & \mathbf{W}_i^T \end{bmatrix} \begin{bmatrix} \mathbf{W}_{1:i-1}^T & \mathbf{W}_i^T \end{bmatrix}^T + \lambda \mathbf{D}^T \mathbf{D} \Big)^{-1} \\ & \times \begin{bmatrix} \mathbf{W}_{1:i-1}^T & \mathbf{W}_i^T \end{bmatrix} \begin{bmatrix} \mathbf{r}_{1:i-1}^T & \mathbf{r}_i^T \end{bmatrix}^T \end{aligned} \quad (19)$$

The above expression can be simplified to

$$\begin{aligned} \mathbf{f}_i = & \left(\mathbf{W}_{1:i-1}^T \mathbf{W}_{1,i-1} + \lambda \mathbf{D}^T \mathbf{D} + \mathbf{W}_i^T \mathbf{W}_i \right)^{-1} \\ & \times \left(\mathbf{W}_{1:i-1}^T \mathbf{r}_{1,i-1} + \mathbf{W}_i^T \mathbf{r}_i \right) \end{aligned} \quad (20)$$

Take $\mathbf{P}_{1:i-1}^{-1} = \mathbf{W}_{1:i-1}^T \mathbf{W}_{1,i-1} + \lambda \mathbf{D}^T \mathbf{D}$,the above expression can be written as

$$\begin{aligned} \mathbf{f_i} &= (\mathbf{P}_{i-1}{}^{-1} + \mathbf{W}_i^T \mathbf{W}_i)^{-1} (\mathbf{W}_{1:i-1}{}^T \mathbf{r}_{i-1} + \mathbf{W}_i^T \mathbf{r}_i) \\ &\overset{(a)}{=} (\mathbf{P}_{1,i-1} - \mathbf{P}_{1,i-1} \mathbf{W}_i^T (\mathbf{I} + \mathbf{W}_i \mathbf{P}_{1,i-1} \mathbf{W}_i^T)^{-1} \\ &\quad \mathbf{W}_i \mathbf{P}_{1,i-1}) \times (\mathbf{W}_{1:i-1}^T \mathbf{r}_{1,i-1} + \mathbf{W}_i^T \mathbf{r}_i) \\ &\overset{(b)}{=} \mathbf{f}_{i-1} + \mathbf{P}_{1,i-1} \mathbf{W}_i^T (\mathbf{I} + \mathbf{W}_i \mathbf{P}_{1,i-1} \mathbf{W}_i^T)^{-1} \\ &\quad \times [(\mathbf{I} + \mathbf{W}_i \mathbf{P}_{1,i-1} \mathbf{W}_i^T) \mathbf{r}_i - \mathbf{W}_i \mathbf{P}_{1,i-1} \\ &\quad (\mathbf{W}_{1:i-1}^T \mathbf{r}_{1,i-1} + \mathbf{W}_i^T \mathbf{r}_i)] \\ &\overset{(c)}{=} \mathbf{f}_{i-1} + \mathbf{P}_{1,i-1} \mathbf{W}_i^T (\mathbf{I} + \mathbf{W}_i \mathbf{P}_{1,i-1} \mathbf{W}_i^T)^{-1} \\ &\quad (\mathbf{r}_i - \mathbf{W}_i \mathbf{f}_{i-1}) \end{aligned} \quad (21)$$

In step (a), matrix inverse lemma $(\mathbf{A} + \mathbf{BCD})^{-1} = \mathbf{A}^{-1} - \mathbf{A}^{-1} \mathbf{B} \left(\mathbf{C}^{-1} + \mathbf{D} \mathbf{A}^{-1} \mathbf{B} \right) \mathbf{D} \mathbf{A}^{-1}$ is used taking $\mathbf{A} = \mathbf{P}_{1,i-1}$, $\mathbf{B} = \mathbf{W}_i^T$, $\mathbf{C} = \mathbf{I}$ and $\mathbf{D} = \mathbf{W}_i$. In the step (b) the $\mathbf{f}_{i-1}$ is used for $\mathbf{P}_{1:i-1} \mathbf{W}_{1:i-1} \mathbf{r}_{1:i-1}$ and $\mathbf{P}_{1,i-1} \mathbf{W}_i^T \left(\mathbf{I} + \mathbf{W}_i \mathbf{P}_{1,i-1} \mathbf{W}_i^T \right)^{-1}$ is taken common. In the step (c) the expression is further simplified. Further consider the term $\mathbf{K}_i$ as

$$\mathbf{K}_i = \mathbf{P}_{i-1} \mathbf{W}_i^T \left(\mathbf{I} + \mathbf{W}_i \mathbf{P}_{i-1} \mathbf{W}_i^T \right)^{-1} \quad (22)$$

This term is called Kalman gain it helps in extracting the information from the new data that is the error $(\mathbf{r}_i - \mathbf{W}_i \mathbf{f}_{i-1})$. As we consider a total of 24 transceivers for each node therefore there are 23 links from all the 23 different nodes excluding the concerned node. The update expression for the imaging vector is

$$\mathbf{f}_i = \mathbf{f}_{i-1} + \mathbf{K}_i \left(\mathbf{r}_i - \mathbf{W}_i \mathbf{f}_{i-1} \right) \quad (23)$$

Matrix inverse lemma can be used to recursively update the $\mathbf{P}_i$ from its previous estimate $\mathbf{P}_{i-1}$as given below

$$\begin{aligned} \mathbf{P}_{1,i} &= \mathbf{P}_{1,i-1} - \mathbf{P}_{1,i-1} \mathbf{W}_i^T (\mathbf{I} + \mathbf{W}_i \mathbf{P}_{1,i-1} \mathbf{W}_i^T)^{-1} \\ &\quad \mathbf{W}_i \mathbf{P}_{1,i-1} \\ &= (\mathbf{I} - \mathbf{K}_i \mathbf{W}_i) \mathbf{P}_{1,i-1} \end{aligned} \quad (24)$$

The distributed incremental strategy for RTI is outlined in Algorithm 1 and the detected object using the algorithm with it's intermediate steps are shown in Fig. 3.

Algorithm 1 Distributed incremental strategy for RTI

1: Initialization: $\mathbf{P}_0 = \left(\lambda \mathbf{D} \mathbf{D}^T \right)^{-1}$, $\mathbf{f}_0 = \mathbf{0}_M$. i=1,2...J
2: Receive $\mathbf{P}_{i-1}$, $\mathbf{f}_{i-1}$ from the $(i-1)^{th}$ node.
3: Calculate the error using $(\mathbf{r}_i - \mathbf{W}_i \mathbf{f}_{i-1})$
4: Calculate the Kalman gain $\mathbf{K}_i$ using (22)
5: Calculate the $\mathbf{f}_i$ using (23)
6: Calculate $\mathbf{P}_i$ using (24)
7: Transmit $\mathbf{P}_i$ and $\mathbf{f}_i$ to $(i+1)^{th}$ node.

A. *Energy Efficient Distributed Incremental Strategy*

The distributed incremental strategy explained in Algorithm 1 require matrix inverse operation of order $O(M)$ which requires more computational cost. To avoid this a modified incremental strategy is proposed. Here we reduce the number of less informative links by applying data censoring technique, by means of which we censor the less informative links by comparing the absolute error at a particular link with a threshold. The threshold is designed in such a way that it is dependent on the censoring ratio. Therefore defining the censoring ratio (C) as:

$$\mathrm{C} = \frac{\text{Number of uncensored RSS values}}{\text{Total number of RSS obtained using all links}}$$

A data-adaptive Censoring uses all censored data $\{\mathbf{w}_i, r_i\}_{i=1}^n$ up to time n. It uses the most recent estimated SLF to find the absolute error. Defining data-adaptive censoring for RTI [13]

$$(y_n, c_n) = \begin{cases} (r_n, 0), & \text{if } \left| \frac{r_n - \mathbf{w_n} \mathbf{f_{n-1}}}{\sigma} \right| >= \tau \\ (0, 1) & \text{otherwise} \end{cases} \quad (25)$$

So $\mathbf{f}_{n-1}$ is feed back to the censoring module. The most important part is, by having a moderate censoring ratio we have almost similar detection performance like conventional distributed incremental RTI along with the advantage of low communication and computational complexity. Unlike the previous case the matrix inversion computational complexity reduces because we have to consider only those points that are non-censored or used for updating the imaging vector. So the data points become C×N rather than N number of points without censoring. C value lies between 0 to 1. The distributed incremental strategy using data censoring technique for RTI is outlined in Algorithm 2 and the detected object using the algorithm with it's intermediate steps are shown in Fig. 4.

Algorithm 2 Updating Imaging vector using adaptive data censoring

1: Initialize $\mathbf{f}_0$=0; n=1,2...N $|r_n$-$\mathbf{w}_n \mathbf{f}_{n-1}|$>=$\tau\sigma$
2: Obtain r_n,$\mathbf{w}_n$, when c_n=0.
3: Calculate the $\mathbf{f}_n$ using (23)
4: No information received by estimator for c_n=1.
5: Store the estimate $\mathbf{f}_n$=$\mathbf{f}_{n-1}$
6: Repeat algorithm 1 for all nodes.

For more practical scenario data censoring technique is used that used to censor data if the error is bellow certain threshold. This is more suitable for large scale networks.

IV. Simulation Results and Discussion

This section provides a comparison of the images that are obtained using proposed method in Section III. All the reconstructed images are using the same RSS observed data $\mathbf{r}$ from synthetically generated dataset which also includes the true SLF. The normalized weight model having weight matrix $\mathbf{W}$ is used. Finally the estimated SLF is compared with the true SLF of synthetic dataset to obtain calculations for performance metrics.

The model and calibration parameters are listed in Table I. Here λ is chosen empirically. For more complex scenario we can choose regularization parameter as explained in [14].

TABLE I: Model Parameters

Parameter	Description	Value
J	Number of transceivers	24
Δ_p	width of the pixel (in meters)	0.2
δ	weighting ellipse width (in meters)	0.01
k	pixel correlation constant	2.1
σ_p^2	pixel covariance due to shadowing	0.4
λ	Regularization parameter	2.75

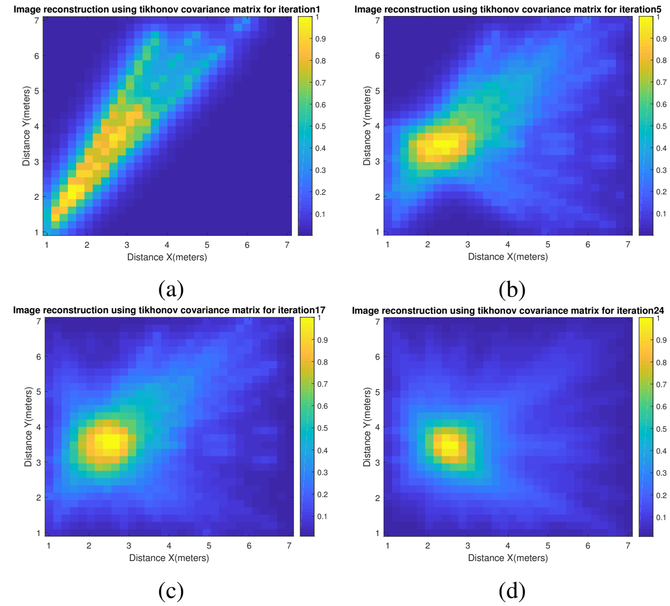
Considering the object is at position as shown in Fig. 1.The above results shows the output at different nodes at different iterations. A clockwise movement from starting node to end node is used as discussed in section II. The final iteration gives the output at node number 24. Looking at the outputs we can say that the imaging vector information from node 1 to node 24 is gradually transferred by distributed Incremental approach. As we observed that both the techniques are providing almost same detection performance while in later case the computational complexity at each node is reduced than the former case. The motivation behind energy efficient data censoring incremental approach is to remove data that are not necessary. By suitably choosing censoring ratio we can achieve performance similar to global RTI. The next result shows a comparison between global and distributed Incremental based RTI. The results are obtained for true object location same as defined in 1 by applying Tikhonov regularization. First the detection is done using Tikhonov identity matrix and in second case reconstruction is done using Tikhonov error covariance matrix. For simplicity we omit the intermediate stages output for a distributed approach. Fig. 6 shows that there is a trade-off between detection performance and communication overheads. So using data censoring we must have a close look towards the censoring ratio by using which we can acheive the detection performance similar to conventional incremental approach.

A. Performance metrics of Distributed RTI

For image quality in [15], the following measures are adopted.

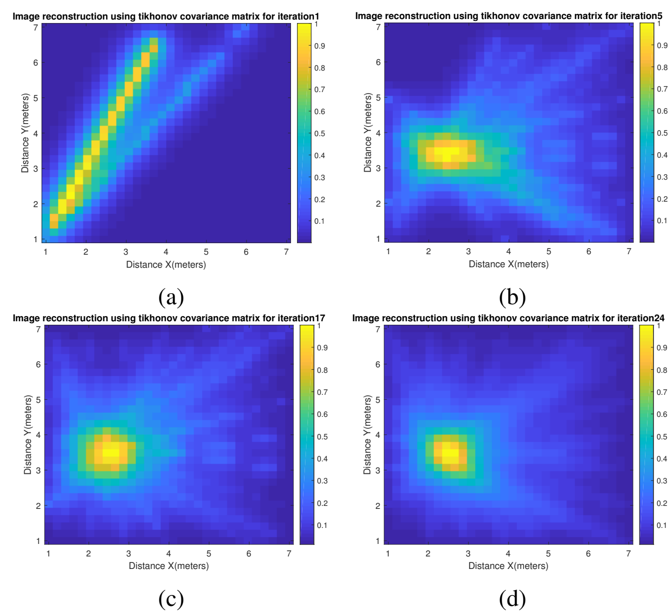
1) The mean square error (MSE) of an image which quantifies the intuitive dissimilarity between the reconstructed image $\mathbf{f}_c$ and the actual image $\mathbf{f}_a$, which is calculated by $\sigma_j = 10\log_{10}(\frac{\|\mathbf{f_a}-\mathbf{f_c}\|^2}{M})$.
2) SSIM (Structured Similarity Index Method) This term is associated with the level of spatially closed pixels.
3) FSIM (Features Similarity Index Matrix) Feature Similarity Index Method maps the features and measures the similarities between the two images.
4) Pixel Attenuation Ratio(PAR)

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



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

Fig. 3: Image formation by distributed incremental approach: (a) initialization (b),(c) intermediate and (d) final output.



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

Fig. 4: Image reconstruction using censoring ratio of 0.2: (a)initialization (b),(c) intermediate and (d) final output.

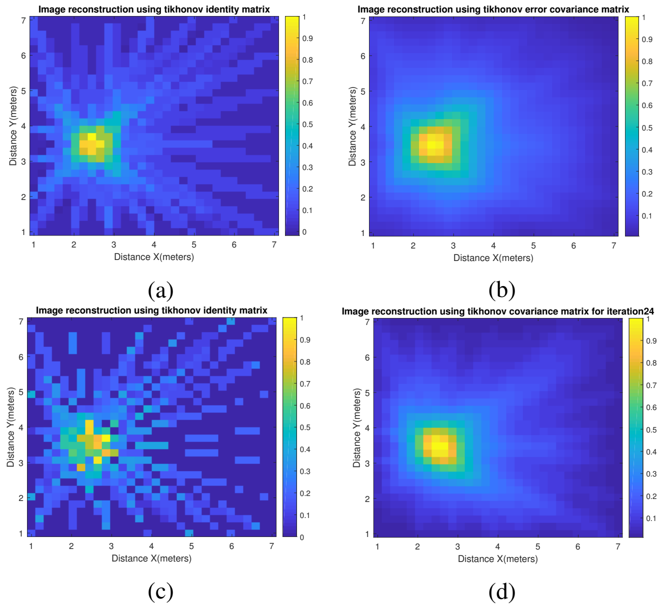


Fig. 5: Image reconstruction for centralized (a-b) and decentralized cases (c-d) for identity and error covariance matrix

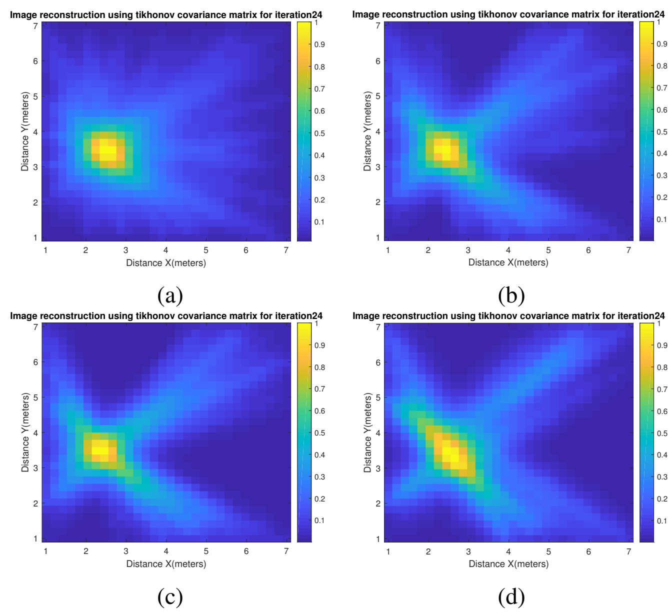


Fig. 6: Reconstructed output using data censoring with censoring ratios (a) $C = 0.2$, (b) $C = 0.4$,(c) $C = 0.5$ (d) $C = 0.7$

TABLE II: Image Quality

Parameter	Global RTI	Distributed Incremental RTI
RMSE[dB]	-1.60	-1.50
PAR in %	25.78	26.11
SSIM	0.8441	0.7831
FSIM	0.9586	.9452

V. Conclusion

Tikhonov provides good localization accuracy but the imaging quality is affected by noise. From the experimental results global RTI has slightly better reconstruction than distributed Incremental RTI which is obvious because all the information is sent to fusion center at a time. All the above results we observed with the advantage of distributed incremental RTI over global RTI in terms of communication overheads. A modified efficient distributed incremental RTI using data censoring is used which further reduces the computation and communication complexity by appropriate selection of censoring ratio. It is concluded that for low to moderate values of censoring ratio our RTI detection is having almost similar performance like global RTI. So this adaptive censoring based Incremental approach can be suitable for large scale RTI systems. This work can be easily extended to sparsity based distributed incremental technique and can be further compared with Sparse Bayesian Learning under multipath fading scenario as discussed in [16].

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