Noise Reduction for Variance-Based Radio Tomographic Localization

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***Abstract*—We propose to demonstrate a new radio tomographic localization algorithm – subspace variance-based radio tomography (SubVRT), which is more robust to RSS variations caused by objects that are intrinsic parts of the environment. We first introduce the subspace decomposition method, then we derive the formulations of SubVRT, and finally we describe the demonstration setup, requirements and procedures.**

I. Introduction

Device-free localization (DFL) using radio frequency (RF) sensor networks has potential application in detecting intruders in industrial facilities, and helping police and firefighters track human motion inside a building during an emergency [1]. Human motion in the vicinity of a wireless link causes variations in the link received signal strength (RSS). DFL systems, such as variance-based radio tomographic imaging (VRTI) use these RSS variations in a wireless network to detect, locate and track people in the area of the network. However, for variance-based DFL methods, variance can be caused by two types of motion: *extrinsic motion* and *intrinsic motion*. Extrinsic motion is defined as the motion of people and other objects that enter and leave the environment. Intrinsic motion is defined as the motion of objects that are intrinsic parts of the environment, objects which cannot be removed without fundamentally altering the environment. If a significant amount of variance is caused by intrinsic motion, then it may be difficult to detect extrinsic motion. For example, rotating fans, leaves and branches swaying in wind, and moving or rotating machines in a factory all may impact the RSS measured on static links. We call variance caused by intrinsic motion and extrinsic motion, the *intrinsic signal* and *extrinsic signal*, respectively. We consider the intrinsic signal to be "noise" because it does not relate to extrinsic motion which we wish to detect and track.

The subspace decomposition method has been used in spectral estimation, sensor array processing, and network anomaly detection [2], [3]. This method decomposes the measurement space into two subspaces, an intrinsic subspace and an extrinsic subspace. We find by projecting measurements onto the extrinsic subspace, the impact of intrinsic motion on a DFL system can be greatly reduced. We apply the subspace decomposition method to VRTI, which leads to a new algorithm we refer to as SubVRT. In this demo, we propose to demonstrate real-time DFL of people using SubVRT.

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II. Methods

A. Problem statement

For an RF sensor network with N sensors (radio transceivers) deployed at static locations, we use $\mathbf{z}_{s,j}$ to denote the coordinate of sensor j. Since each sensor makes an RSS measurement with all other sensors, we use $s_{l,t}$ to denote the RSS measured at node i_l sent by node j_l at time t, where i_l and j_l are the receiver and transmitter number for link l, respectively. We assume constant transmitter power so that changes in $s_{l,t}$ are due to the channel, not to the transmitter. Then we denote the windowed RSS variance as:

$$y_{l,t} = \frac{1}{m-1}\sum_{i=0}^{m-1}(\bar{s}_{l,t} - s_{l,t-i})^2 \tag{1}$$

where m is the length of the window, and $\bar{s}_{l,t} = \frac{1}{m}\sum_{i=0}^{m-1} s_{l,t-i}$ is the sample average in this window period.

Consider that the network has L directional links on which we measure signal strength. We let $\mathbf{y} = [y_1, y_2, \cdots, y_L]^T$ be the vector of windowed RSS variance from all L links, and $\mathbf{y}^{(t)} = [y_{1,t}, y_{2,t}, \cdots, y_{L,t}]^T$ be the measurement vector $\mathbf{y}$ at time t. Then we use $\mathbf{y}_c$ to denote the calibration measurements collected during the calibration period, when no people are present in the environment; and we use $\mathbf{y}_r$ to denote the measurements from the real-time experiment period. The goal of DFL is to locate people during real-time operation.

B. Subspace decomposition method

From the L-dimensional calibration measurement vector $\mathbf{y}_c$, we may estimate its covariance matrix $C_{\mathbf{y}_c}$ as:

$$C_{\mathbf{y}_c} = \frac{1}{M-1}\sum_{t=0}^{M-1}(\mathbf{y}_c^{(t)} - \boldsymbol{\mu}_c)(\mathbf{y}_c^{(t)} - \boldsymbol{\mu}_c)^T \tag{2}$$

where M is the number of sample measurements, $\mathbf{y}_c^{(t)}$ is the calibration measurement vector $\mathbf{y}_c$ at time t, and $\boldsymbol{\mu}_c = \frac{1}{M}\sum_{t=0}^{M-1}\mathbf{y}_c^{(t)}$ is the sample average. Performing singular value decomposition (SVD) on $C_{\mathbf{y}_c}$, we obtain:

$$C_{\mathbf{y}_c} = U\Lambda U^T \tag{3}$$

where Λ is a diagonal matrix $\Lambda = \text{diag}\{\lambda_1, ..., \lambda_L\}$, and U is a unitary matrix $U = [\mathbf{u}_1, \cdots, \mathbf{u}_L]$, in which $\mathbf{u}_i$ is the ith column vector.

Right multiplying U on both sides of (3), we can see that $\mathbf{u}_i$ are eigenvectors of $C_{\mathbf{y}_c}$, and λ_i are corresponding eigenvalues:

$$C_{\mathbf{y}_c}\mathbf{u}_i = \lambda_i \mathbf{u}_i \tag{4}$$

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If the eigenvalues λ_i are in descending order, then the first principal component eigenvector $\mathbf{u}_1$ points in the direction of the maximum variance of the measurement, the second principal component $\mathbf{u}_2$ points in the direction of the maximum variance remaining in the measurement, and so on.

In subspace decomposition, we divide all the principal components into two sets: $\hat{U} = [\mathbf{u}_1, \mathbf{u}_2, \cdots, \mathbf{u}_k]$ and $\tilde{U} = [\mathbf{u}_{k+1}, \mathbf{u}_{k+2}, \cdots, \mathbf{u}_L]$. Then we decompose the measurement space into two lower dimensional subspaces spanned by $\hat{U}$ and $\tilde{U}$. Since the variance during the calibration period is caused by intrinsic motion, that is, the variance captured by $\hat{U}$ is intrinsic signal, we call the subspace spanned by $\hat{U}$ the intrinsic subspace, and the other subspace spanned by $\tilde{U}$ the extrinsic subspace. Then we decompose the measurement vector $\mathbf{y}$ into two components – intrinsic signal component $\hat{\mathbf{y}}$ and extrinsic signal component $\tilde{\mathbf{y}}$:

$$\mathbf{y} = \hat{\mathbf{y}} + \tilde{\mathbf{y}} \tag{5}$$

The intrinsic signal component $\hat{\mathbf{y}}$ and the extrinsic signal component $\tilde{\mathbf{y}}$ can be formed by projecting $\mathbf{y}$ onto the intrinsic subspace and the extrinsic subspace, respectively:

$$\hat{\mathbf{y}} = \Pi_I \mathbf{y} = \hat{U}\hat{U}^T \mathbf{y} \tag{6}$$

$$\tilde{\mathbf{y}} = \Pi_E \mathbf{y} = (I - \hat{U}\hat{U}^T)\mathbf{y} \tag{7}$$

where $\Pi_I = \hat{U}\hat{U}^T$ is the projection matrix for the intrinsic subspace, and $\Pi_E = I - \Pi_I$ is the projection matrix for the extrinsic subspace.

C. SubVRT

In VRTI, the presence of human motion within P voxels of a physical space is denoted by $\mathbf{x} = [x_1, x_2, ..., x_P]^T$, where $x_i = 1$ if motion occurs in voxel i, and $x_i = 0$ otherwise. Work in [4] has shown the efficacy of a linear model that relates the motion image $\mathbf{x}$ to the RSS variance $\mathbf{y}_r$:

$$\mathbf{y}_r = W\mathbf{x} + \mathbf{n} \tag{8}$$

where $\mathbf{n}$ is an $L \times 1$ noise vector, and W is an $L \times P$ matrix representing the weighting of motion in each voxel on each link measurement [4].

Once we have the forward model, the localization problem becomes an inverse problem: to estimate P dimensional position vector $\mathbf{x}$ from L dimensional link measurement vector $\mathbf{y}_r$. Here, we use the Tikhonov regularized VRTI solution, which is given as:

$$\hat{\mathbf{x}} = \Pi_1 \mathbf{y}_r \quad \text{where } \Pi_1 = (W^T W + \alpha Q^T Q)^{-1} W^T \tag{9}$$

where Q is the Tikhonov matrix, and α is a regularization parameter.

The key idea of SubVRT is to use the decomposed extrinsic signal component of the measurements in VRTI. We project the real-time measurement vector $\mathbf{y}_r$ onto the extrinsic subspace to obtain the extrinsic signal component $\tilde{\mathbf{y}}_r = (I - \hat{U}\hat{U}^T)\mathbf{y}_r$. Then, we replace $\mathbf{y}_r$ in (9) with $\tilde{\mathbf{y}}_r$ and obtain the solution of SubVRT:

$$\hat{\mathbf{x}} = \Pi_2 \mathbf{y}_r \quad \text{where } \Pi_2 = (W^T W + \alpha Q^T Q)^{-1} W^T \Pi_E \tag{10}$$

From (10), we see that the solution is a linear transformation of the measurement vector. The transformation matrix Π_2 is the product of the transformation matrix Π_1 in (9) with the projection matrix for the extrinsic subspace Π_E: $\Pi_2 = \Pi_1 \Pi_E$. Since the transformation matrix Π_2 does not depend on instantaneous real-time measurements, it can be pre-calculated, and it is easy to implement SubVRT for real-time applications.

III. Demonstration

In the radio tomographic localization demo, we plan to deploy twenty-eight TelosB nodes around a 4.2 m by 4.2 m area. All nodes are programmed with TinyOS program Spin [5], and they are placed on polyvinyl chloride (PVC) stands to form an RF sensor network. A basestation connected to a laptop is used to collect pairwise RSS measurements from the network. A picture from a previous RTI demonstration of RSS mean-based RTI [6] is shown in Fig. 1.

Fig. 1: A real-time demonstration of radio tomography in which a person's location is calculated and projected for attendees to view.

A difference from the previous demonstration of RTI is that in this demo, we use RSS variance caused by human motion to locate moving people instead of using the attenuation effect of the human body on RSS measurements. Another difference between this demo and previous RTI demos is that we add in intrinsic motion, and demonstrate SubVRT's ability to remove its effects from the resulting images. We propose to use electronic rotating fans as sources of intrinsic motion. We set up two rotating fans at two locations inside the deployed area. Before people start to walk in the area, a calibration is performed with fans rotating but without people present inside. After the calibration, a person walks in, and SubVRT is run by a laptop, which calculates and displays the motion images in real-time. We will use another laptop to run VRTI so that we can compare the results from both methods. As an interesting test, we can record calibration measurements for different time periods to see the effect of calibration duration on the localization accuracy of SubVRT.

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