Radio Tomographic Imaging Based On Quartile Outliers Filter and PCA

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ABSTRACT

Device-free wireless localization (DFL) that does not need the target equipped with any device is a new technique which could estimate the location by analyzing its shadowing effect on surrounding wireless links. This technique neither requires the target to be equipped with any device nor involves privacy concerns, which makes it an attractive and promising technique for many emerging smart applications. Therefore, how to characterize the influence of human behaviors is the key question. However, the distance estimation based on received signal strength indicator (RSSI) is easily affected by the temporal and spatial variance due to the multipath effect, which contributes to most of the estimation errors in current radio tomographic imaging (RTI) system. This paper proposes a device-free passive localization algorithm based on Quartile Outliers Filter (QOF) and Principal Component Analysis (PCA). In this work, we explore and exploit lower quartile and upper quartile of the original RSSI to identify and remove the outliers caused by the multipath effect or hardware facilities, and apply PCA to extract the most useful features. Extensive experiments performed in a clutter indoor laboratory and a building courtyard with 20 wireless nodes demonstrate that the outstanding performance of the proposed scheme.

Keywords: Radio tomographic imaging (RTI); Device-free localization (DFL); Quartile outliers filter (QOF); Principal component analysis (PCA)

1. INTRODUCTION

Localization is one of the essential modules of many mobile wireless applications. Navigating in indoor environments. Many papers have proposed

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various indoor positioning methods based on Wi-Fi, UWB, etc. UWB with the function of robust signaling, through-wall propagation and high-resolution ranging [1], which needs high cost and professional infrastructure to provide high localization accuracy. Instead, Wi-Fi-based approaches are most widely used and regarded as the most convenient and economic localization method in indoor environments.

According to propagation loss model [2], the foundation of the model-based localization is that received signal power monotonically decreases with increasing distance from the source. The fingerprint systems [3], which is a huge database that store the received signal strength index (RSSI) data. It can match the RSS with the databases earned in advance to realize positioning, while the radio fingerprint data are seriously contaminated. Radio Tomographic Imaging (RTI) establishes a linear model of the RSS measurements and the moving objects [4]. RTI may be useful with using the real-time RSS measurement to realize localization, which is superior to the fingerprinting method. However, its model fail to provide positioning accuracy and robustness.

To enhance the sensitivity of RSS variations to shadow fading to address the impact of environmental noise. Literature [5] proposes a hierarchical RSS model that contributes to refining the granularity to describe RSS variations. Literature [6] takes advantage of the temporal and spatial properties of the shadowed links to cancel the interference link, thus achieving very good positioning accuracy. In short, our work here focuses on distinguish effective signal strength values and noise due to multipath interferences, as well as in improving the RTI performance with the proposed method. Moreover, the experimental results are reported to demonstrate the effectiveness of the proposed approach.

The remainder of the paper is organized as follows. First we introduce the system model for this article and provides the background information on RTI in section 2. Section 3 and section 4 propose the Quartile Outliers Filter (QOF) and Principal Component Analysis (PCA). The experimental results are provided in section 5. Finally, the conclusion is drawn in section 6.
Figure 1. An illustration of radio tomography network: (a) a monitored area constituted by wireless nodes, (b) the attenuation image constructed by RTI, and (c) original imaging result obtained by RTI.

2. PROBLEM FORMULATION

Figure 1 (a) shows a 2-D radio tomography network consisting of n RF sensors with known coordinates $(\alpha_i, \beta_i)$, $i = 1, 2, \ldots, n$, respectively. The sensors are placed in an indoor environment in the same plane, constituting a monitored area with size $[x_{\text{min}}, x_{\text{max}}] \times [y_{\text{min}}, y_{\text{max}}]$. A target moves in the monitored area with coordinate $(x_t, y_t)$ at time instant $t$. The presence of the target can alter the radio environment, leading to variation of RSS. RTI uses the RSS variation of the links to construct an image reflecting the attenuation happened in the monitored area. The brightest spot in the image reveals the position of the target, as illustrated in Figure 1 (b). Figure 1 (c) shows the RTI imaging result, the RSSI intensity value we obtained directly from the registers of sensors. In the image, there are at least 4 bright spots except the true target spot. One of the spots is even brighter than the true target spot.

3. QUARTILE OOTLIER FILTER

Observations imply that most of the RSSI are stable enough but there are still some occasional outliers caused by environment mutation such as people movement in our experiment. We utilize the refined Hampel identifier [7]-[8] to remove the outliers, we define the outliers for RSS of link k by:

$$
R_{\text{emp},m}^k, R_{\text{loc},m}^k = \begin{cases} 
R_{\text{emp},t}^k, & R_{\text{loc},m}^k < Q_1^k < R_{\text{emp},t}^k \ni R_{\text{loc},m}^k < Q_3^k \\
\text{Delete} & \text{otherwise} 
\end{cases}
$$

(1)
Where $R_{emp,t}^k$ and $R_{loc,t}^k$ is the RSS without target or with human in network of link k at time t, $Q_1^k$ and $Q_3^k$ denotes the 1st and 3rd quartile for all collected RSS without human, respectively. If $R_{emp,t}^k$ or $R_{loc,t}^k$ is falling out of the closed interval, where will be set prior and considered as an outlier. $R_{emp,m}^k$ and $R_{loc,m}^k$ is the RSS which is deleted the outliers.

4. PRINCIPAL COMPONENT ANALYSIS

Next, we apply principal component analysis the proposed in [9] since it can preserve signals extremely well.

Suppose the RSS of link k with target within the network is $R_{loc}^k$, and the reference data obtained without any target within the deployment area of the network is $R_{emp}^k$. The variation of the RSS measurement $\Delta R_{loc}^t$ is determined by

$$\overline{\Delta R}_{loc}^t = \{\Delta R_{loc}^k = R_{loc}^k - R_{emp}^k | k = 1, ..., K\}$$ (2)

Where K represents the total number of links in the network, t is the total polling number. The objective of the system is to estimate target location using the variation of RSS measurement.

In order to make each variable in matrix R has been auto-scaled to zero mean and unit variance, it should be centralized and expressed as:

$$\bar{X} = \{\bar{x}_1, \bar{x}_2, ..., \bar{x}_t\} = \left\{\overline{\Delta R}_{loc}^1, \overline{\Delta R}_{loc}^2, ..., \overline{\Delta R}_{loc}^t\right\}$$ (4)

$$\bar{\mu} = \frac{1}{t} \sum_{i=1}^{t} \overline{\Delta R}_{loc}^i$$ (5)
As covariance matrix $\Sigma$ of matrix $\bar{X}$ is symmetrical, it can be computed via the singular value decomposition (SVD)

$$\Sigma = P^T \Lambda P$$  \hspace{1cm} (6)

With $P^T P = PP^T = I$, where $\Lambda = \text{diag}(\lambda_1, \lambda_2, \ldots, \lambda_k)$ is the eigenvalue matrix with elements in decreasing magnitude order and $P = [p_1, p_2, \ldots, p_k]^T$ is the eigenvector matrix corresponding to $\Lambda$.

The principal components (PCs) can be constructed as a linear transformation of $X$ by combining $P$ in following manner [10]:

$$V = P^T X$$  \hspace{1cm} (7)

Where $V = [V_1, V_2, \ldots, V_k]$ and $V_1, V_2, \ldots, V_k$ are the first, second, $\cdots$, $k$th PC of $X$, respectively.

If the first $m$ PCs retained in the PCA model are chosen [11], matrix $R$ in the measure space can be reconstituted new equivalent matrix

$$R = XVV^T + \bar{\mu}$$  \hspace{1cm} (8)

5. EXPERIMENTAL RESULTS

(a) Experiment setup

Figure 2. (a), (b) are two different experimental scenes.
We design a prototype network to evaluate the performance of the proposed schemes. The network is comprised of 20 nodes that are equipped with TI CC2530 chipsets [12], which work on the IEEE802.15.4 protocol [13] and 2.4GHz frequency. The photographs and layout of the experimental are shown in Figure 2. Figure 2(a) is a 7.5m*5m rectangular area conducted in the lobby of Ge Wu Building at Nanjing Normal University and Figure 2(b) is a 10m*10m square area conducted in the lobby of Xing Jian Building at Nanjing Normal University.

In the RTI, the weight matrix we used is the classic elliptical model [4], and the minor axis length of the ellipse is set to 0.15m. We divide the monitoring area into 2,500 pixels. The size of each pixel is 0.15m * 0.1m.

(b) Analysis of experimental results

Figure 3 is a comparison of RTI imaging of the raw data, the QOF data, and the QOF and PCA data at the (1.5m, 2m) point in the lobby of Ge Wu Building at Nanjing Normal University. Since the QOF can remove the outliers and PCA can

![Figure 3. Images of attenuation in a wireless network. (a), (b) and (c) is a human standing at coordinate (1.5m, 2m) in scene Figure 2(a). (d), (e) and (f) is a human standing at coordinate (6m, 6m) in scene Figure 2(b).](image-url)
TABLE 1. THE COMPARISON OF POSITIONING ERROR IN VARIOUS DATA.

| The type of data | Average (m) | Standard Deviation (m) | Variance (m) |
|-----------------|-------------|------------------------|--------------|
| Raw data        | 3.61        | 2.63                   | 6.93         |
| QOF data        | 0.74        | 1.23                   | 1.52         |
| QOF and PCA data| 0.67        | 1.58                   | 2.50         |

eliminate the noise, it shows a good imaging effect. We can see that the RTI imaging of the raw data exist serious background noise due to environmental interference, which not only exist the pseudo target, but also exist complex background noise, as shown in Figure 3(a). The RTI imaging obtained by the QOF data has no pseudo-target, as shown in Figure 3(b). Perfectly, as shown in Figure 3(c), we can clearly find the target position with no pseudo-target and a clean background. The similar performance is revealed in Figure 3(d), Figure 3(e) and Figure 3(f).

The detailed statistical results of the positioning errors are shown in Table 1, the average positioning error is reduced by 2.94m through the QOF and PCA; and we can see that the positioning error fluctuates due to the existence of noise in each type of data from the variance. Experimental results show that the proposed QOF and PCA method can effectively remove background noise and pseudo-targets, which has a well positioning performance.

6. CONCLUSIONS

In this paper, QOF and PCA is proposed to remove the outliers and the noise of the original RSSI measurements. The experimental results show that this method solves the problem of serious background noise of RTI and the presence of pseudo targets. It can realize localization perfectly, which is beyond performance of existing approaches. In the next step, we will consider a multi-objective scenario and extend the approach to scenes where the ambient noise is more serious.

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