Demo Abstract: Histogram Distance-Based Radio Tomographic Localization

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ABSTRACT

We present an interactive demonstration of histogram distance-based radio tomographic imaging (HD-RTI), a device-free localization (DFL) system that uses measurements of received signal strength (RSS) on static links in a wireless network to estimate the locations of people who do not participate in the system by wearing any radio device in the deployment area. Compared to prior methods of RSS-based DFL, using a histogram difference metric is a very accurate method to quantify the change in RSS on the link compared to historical metrics. The new method is remarkably accurate, and works with lower node densities than prior methods.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

Keywords

Localization, Sensor networks

1. INTRODUCTION

Localization of people in wireless sensor networks has significant benefits for elder care, security, and smart facilities. An emerging technique is to use radio signal changes caused by the human body to locate people who do not carry any radio devices. Since this new technique does not require people to wear any devices, we call it device-free localization (DFL). Recent research work has focused on DFL using received signal strength (RSS) measurements from a wireless mesh network [3], due to the fact that RSS measurements are inexpensive and available in almost all wireless devices. However, the reported methods are ad hoc and incomplete. For example, methods that use the change in mean of RSS measurements require calibration measurements to be made when the area is empty in order to provide the baseline mean RSS, and are not robust to non-line-of-sight (non-LOS) environments. Variance-based DFL methods such as [4] do not require an empty calibration period. However, they cannot locate stationary people, since they use certain forms of RSS variance to locate human motion, and stationary people do not cause much RSS variance. Thus, we need a new DFL method that is capable of locating both moving and stationary people without an empty-area calibration.

Our proposed approach is built upon two innovations designed to improve current DFL systems: (1) histogram difference to quantify change in RSS, rather than using change in mean or using variance as a metric, which allows DFL systems to locate both moving and stationary people; (2) online calibration, which allows DFL systems to operate without an empty-room calibration. The use of histogram differences is motivated by experimental observations in a variety of environments. A person in motion on or near the line between two wireless devices tends to increase the variance of RSS measurements, but may or may not significantly change the mean. A person standing still at a location tends to change the mean of the RSS, but may show very little variance while the person is stationary. Using either the variance or the change in mean of the RSS value will measure their presence in the "in motion" or stationary case, respectively, but not both. Using a measure of histogram difference captures both changes. In terms of online calibration, we show that online RSS measurements allow one to keep a long-term histogram in memory without significant computational complexity. This long-term histogram is close enough to the histogram which would have been measured in an empty-room calibration to perform as well as, or better than, with empty-room calibration.

We demonstrate some initial results for the use of histogram difference in RTI, and call this new method histogram distance-based radio tomographic imaging (HD-RTI). Compared to VRTI, which cannot detect or locate people without any motion, our HD-RTI can capture the difference caused by stationary human body on RSS histograms, and thus is able to locate stationary people. Compared to mean-based RTI, which needs offline calibration, in which measurements are made without any people present in the network, our HD-RTI does not need such offline calibration measurements, and works well using online calibration measurements. Finally, HD-RTI provides a significantly more accurate radio tomographic images than previous RTI methods, and works successfully with lower node densities.

2. METHODS

2.1 Distance between histograms

From many indoor experiments, we have observed that when a person (either stationary or moving) is present near

*This material is based upon work supported by the National Science Foundation under Grant Nos. #0748206 and #1035565.

IPSN'12, April 16–20, 2012, Beijing, China.
ACM 978-1-4503-1227-1/12/04.

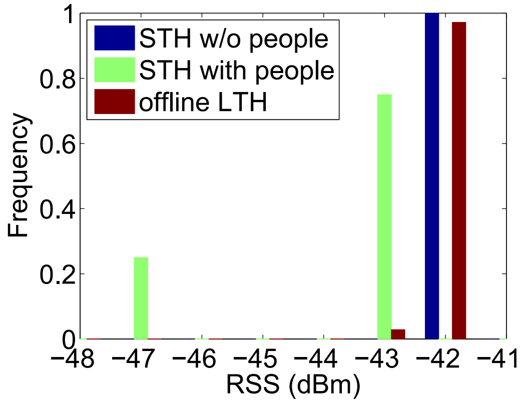

Figure 1: Long-term histogram (LTH) and short-term histograms (STH) with and without moving people near the LOS of a link.

the line-of-sight (LOS) of a link, the RSS histogram of that link in a short-time window (we call short-term histogram) is significantly different from the RSS histogram from the calibration period without any people present in the network (long-term histogram). For example, in an indoor experiment, a person walks across a link between two nodes at a particular time, and the short-term histogram (STH) from a three-sample window (about 0.2 seconds) is shown in Figure 1. We see that due to human motion, RSS measurements are quite variable. For the same link, the long-term histogram (LTH) from an offline calibration period (about 60 seconds) is also shown in Figure 1, and it is significantly different from STH with people. However, with no people near the link, there is not much difference between STH and LTH. For example, when the person is several meters away from the link, all three RSS measurements in the window are -42 dBm. As shown in Figure 1, STH without people is similar to LTH.

To quantify the difference between STH and LTH. We need a metric to measure the difference between two histograms. A well known way to measure the difference between two distributions is the Kullback-Leibler divergence, which is a bin-to-bin distance assuming the histograms are aligned. Another metric is the earth mover's distance, which does not require aligned histograms. However, it involves solving an optimal transportation problem, and is computationally expensive. Finally, the kernel distance has been used to compare shapes and distributions in the field of computational geometry, it has nice mathematical properties and is easy to compute [2]. We explore using these histogram difference metrics in our demo.

2.2 Histogram distance-based RTI (HD-RTI)

Let $\mathbf{d} = [d_1, d_2, \cdots, d_L]^T$ denote the histogram distance vector from L directional links of a network, we estimate the P dimensional position vector $\mathbf{x}$ representing human presence as:

$$\hat{\mathbf{x}} = (W^T W + \alpha Q^T Q)^{-1} W^T \mathbf{d} \tag{1}$$

where Q is the Tikhonov matrix, α is a regularization parameter, and W is an $L \times P$ matrix representing the weighting of motion in each voxel on each link measurement, which is formulated as [3]. Note that although HD-RTI uses the same formulation as mean-based RTI, it does not need offline calibration, which is necessary for mean-based RTI to obtain the baseline mean RSS.

3. DEMO DESCRIPTION

We plan to use radio nodes made with TI's CC2531 system-on-chip powered by two AA batteries. All nodes are placed on fixed locations (either on stands or on tables) to form a static sensor network. The initial network deployment plan is that we deploy 16 nodes around a 4 m by 4 m square area with a node density of 1 per m^2. The distance between each two adjacent nodes along each side is 1 m so that we have 5 nodes (including one node at each corner) at each side of the square. All 16 nodes are programmed with Spin [1] – a token passing protocol which enables each node to broadcast pairwise RSS measurements between itself and all the other nodes at a particular time. The transmission interval between two nodes is set by the Spin protocol so that more than one link measurement can be recorded each second to match the speed of normal human motion (i.e., 1 m/s). For fast human motion, we can increase the transmission frequency in Spin protocol at the cost of more power consumption. A basestation connected to a laptop is used to collect pairwise RSS measurements from all nodes of the network.

The demo will be performed following procedures below. First, a calibration is performed with people (online calibration) or without people (offline calibration) present in the deployment area. Then, we run different RTI algorithms on two laptops, and ask participators to interact with our RTI systems. Since our RTI algorithms can be implemented in real time, participators can see the RTI images shown on the laptop immediately after they enter the network. We will have a variety of RTI algorithms including mean-based RTI [3], variance-based RTI (VRTI) [4] and HD-RTI in the demo, so that participators can judge their relative performances in different conditions. For example, if we use offline calibration, both mean-based RTI and HD-RTI may work well. However, if online calibration is used, our HD-RTI may still work, but mean-based RTI may not work at all. As another example, a demo participator can keep motionless in the network so that he or she disappears in the motion images from VRTI. However, HD-RTI can locate a person no matter he is moving or not, and the participator can always see his locations from the HD-RTI images. We can also allow multiple people to interact with our RTI systems at the same time and they can test ideas that they have with different RTI algorithms.

4. REFERENCES

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