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Denoising by Spatial Domain Averaging for Wireless Local Area Network Terminal Localization

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Abstract—Terminal localization for indoor Wireless Local Area Networks (WLANs) is critical for the deployment of location-aware computing inside of buildings. A major challenge is obtaining high localization accuracy in presence of fluctuations of the received signal strength (RSS) measurements caused by multipath fading. This paper focuses on reducing the effect of the distance-varying noise by spatial filtering of the measured RSS. Two different survey point geometries are tested with the noise reduction technique: survey points arranged in sets of clusters and survey points uniformly distributed over the network area. The results show that the location accuracy improves by 16% when the filter is used and by 18% when the filter is applied to a clustered survey set as opposed to a straight-line survey set. The estimated locations are within 2 m of the true location, which indicates that clustering the survey points provides better localization accuracy due to superior noise removal.

Keywords—Position measurement, Wireless LAN, Radio navigation, Filtering

I. Introduction

SEVERAL applications have been proposed for wireless networks that require knowledge of terminal location. The uses of terminal localization include providing user navigation, supplying location context for web browsing, and aiding network resource allocation [1]–[3]. Low cost Global Positioning System (GPS) receivers have been shown to give good localization accuracy in outdoor locations but they cannot be used indoors or in dense urban environments since GPS satellite signals are received only intermittently in these locations [4], [5]. For these reasons, indoor radio location based on measuring the radio received signal strength (RSS) of several wireless access points (WAPs) at the terminal is proposed [6], [7]. Location estimates are calculated by comparing the radio RSS values at the terminal with radio RSS values measured at known locations during radio surveys [8]–[12]. Several location schemes based on this technique have been demonstrated to provide accurate localization [13]–[15].

The accuracy of localization is limited by the measurement noise which can cause two separate locations to appear identical with respect to RSS measurements. This noise is created by thermal noise and random variations of the RSS created by multipath propagation. The presence of noise increases the number of survey points required to achieve the desired localization accuracy, thereby increasing the required cost of survey collection. Survey data collection is labor intensive and expensive, so significant effort has been expended on finding noise removal techniques to reduce the required survey collection cost. Past efforts on noise removal have processed the RSS measurements over time, with several filters being proposed [16]–[19]. If a mobile terminal is immobile during data collection, much of the measurement noise created by multipath propagation is time-invariant over the period of survey data collection [20], [21]. In the indoor environment, there are radio signal scatterers and reflectors such as furniture and doors which create multipath propagation and are immobile during the period of a data collection session, but are unlikely to all remain in the same position from the time of survey data collection to the time of terminal localization. The effects of these scatterers on the survey measurements is considered as time-invariant measurement noise. The time-averaging filtering algorithms proposed in the previous literature will not remove this portion of the noise so radio location accuracy is still below optimal levels.

The multipath propagation noise that is time invariant over the period of survey collection can be removed by collecting several survey sets at points significantly separated in time, i.e. several hours or days, and then averaging the RSS measurements over the multiple survey sets, but this significantly increases the cost of survey data collection. In this paper, a spatial domain filter is proposed to process the collected RSS survey data to remove more multipath propagation noise than the previously proposed filtering techniques. The lower level of measurement noise in the survey data provided by this filter creates a substantial accuracy improvement in the localization. A new geometry of survey data collection for RSS radio location is proposed where survey data points are collected in small clusters of points located close together with the clusters uniformly distributed over the network area. It is shown that this new survey geometry, when used with the spatial domain filter, provides an 18% improvement over the standard survey data collection of points uniformly spaced over the network area. The efficiency of the noise removal and new survey data collection is tested via radio location over two floors of the engineering classroom building at the University of Victoria, British Columbia, Canada. The main contributions of this paper are:

- Introduction of a spatial domain noise reduction technique to reduce time-invariant measurement noise caused by multipath propagation and improves radio location root mean square error (RMSE) by 16%.
- Proposes survey data collection at uniformly distributed

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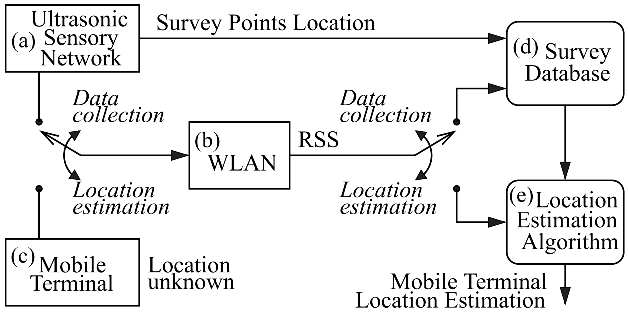

Fig. 1. Radiolocation System Architecture

tight clusters of locations, as opposed to at locations uniformly distributed over the network area, to facilitate efficient noise removal. This improves mean radio location RMSE by 18%.

- Presentation of a cross-validation technique to find the parameters for the noise removal and location estimation algorithms from survey data.

The total gain from the application of clustered survey set collection and spatial-averaging improves radio location RMSE by 23% (reducing the RMSE to 193.3 cm from 250.5 cm for radio location on one floor of a standard office building).

The remainder of this paper is arranged as follows. Section II describes the data collection methods for the survey and how noise removal is performed. Section III describes the localization algorithm. Section IV presents the results from use of the new noise removal. Section V presents the conclusions of the paper and describes future research directions.

II. Data Collection and Training

The localization system proposed in this paper consists of a number of elements: (a) the WLAN to provide the radio RSS measurements, (b) the mobile terminal whose location is to be estimated, (c) the survey database, (d) the localization algorithm. The localization system architecture is presented in Figure 1.

The location-sensing system operates in three phases: data collection, training, and localization. During the data collection phase, an ultrasonic sensory network provides accurate true locations for a set of survey points [22], while the WLAN provides radio RSS measurements. The ultrasonic sensors can locate the survey terminal to within 5 cm of its true location which is better than what is needed for radio location [23]. The survey point locations and radio RSS measurements are combined and stored in a survey database. The ultrasonic sensors are only used for localization during survey data collection. After the completion of the data collection phase, the acoustic sensors are removed. In the training phase, the parameters of the localization algorithm are found. During the localization phase, mobile terminals at unknown locations make RSS measurements which the estimation algorithm processes using the survey database to provide estimated locations.

Ideally, the RSS measurements stored in the survey database are not contaminated with measurement noise. During data collection, one of the prior art time filtering algorithms is employed to remove the time-variant noise from the survey RSS measurements [16]–[19]. The reduction of time-varying noise is well studied with many algorithms presented in the literature [24]–[28]. These algorithms cannot remove time-invariant noise created by the multipath propagation by averaging measurements collected at a single location over a window of time [20], [21]. Thus, there will be some noise remaining in the survey set. This paper proposes the use of spatial-averaging of the survey RSS data during the training phase to remove the remaining time-invariant multipath propagation noise.

The goal of the localization system is to estimate the wireless terminal location vector $\boldsymbol{\theta} = [x\ y]^T$ from the measured radio RSS vector $\boldsymbol{v}$ where superscript T denotes matrix transpose. The estimated location given the radio RSS vector, $\boldsymbol{v}$, is denoted as $\hat{\boldsymbol{\theta}}(\boldsymbol{v};\boldsymbol{P})$ where $\boldsymbol{P}$ is a vector containing the parameters of the estimation algorithm. The parameters $\boldsymbol{P}$ are a function of the network environment and are obtained survey data sets [13]–[15], [23], [29], [30]. More information on the exact form of the estimator used to generate the reported accuracy results is provided in Section III. The survey database entries contain the ground truth coordinates for each survey point, the information on all WAPs currently detected by the mobile terminal, and the RSS measurements for each WAP detected at each survey point. For a given selection of measuring WAPs, the i^{th} survey point is specified as $(\boldsymbol{\theta}_i, \boldsymbol{v}_i)$ where $\boldsymbol{v}_i$ is the vector of radio RSS measurements made at location $\boldsymbol{\theta}_i$. The total number of survey points is denoted as N.

A. Noise Removal

Key to the design of our noise removal algorithm and estimator is the assumption that the terminal locations, $\boldsymbol{\theta}$, are samples of a random vector $\boldsymbol{\Theta}$ and the measured radio RSS vectors, $\boldsymbol{v}$, are samples of the random vector $\boldsymbol{V}$ which have the joint probability density function (PDF) of terminal locations and measurements denoted as $\mathrm{f}_{\boldsymbol{\Theta},\boldsymbol{V}}(\boldsymbol{\theta},\boldsymbol{v})$.

In this section, a discrete Wiener filter is developed to reduce the time-invariant noise and to complement the time-variant noise reduction algorithm already in place in the data collection phase. For a location, $\boldsymbol{\theta}$, the random vector of noisy RSS measurements $\boldsymbol{V}(\boldsymbol{\theta})$, is composed of a deterministic portion, $\bar{\boldsymbol{v}}(\boldsymbol{\theta})$, and an additive random portion, $\boldsymbol{N}(\boldsymbol{\theta})$, so that

$$\boldsymbol{V}(\boldsymbol{\theta}) = \bar{\boldsymbol{v}}(\boldsymbol{\theta}) + \boldsymbol{N}(\boldsymbol{\theta}). \tag{1}$$

The objective of the noise reduction technique developed in this paper is to decrease the random noise process over location, $\boldsymbol{N}(\boldsymbol{\theta})$, in the RSS. The measured survey RSS for location $\boldsymbol{\theta}_i$ is one sample value of the random vector $\boldsymbol{V}(\boldsymbol{\theta}_i)$ The goal of noise removal is to obtain an estimate of $\bar{\boldsymbol{v}}(\boldsymbol{\theta}_i)$ for $i = 1, ..., N$ from the noisy measurements $\boldsymbol{v}_i$.

Noise removal is done for the RSS measurements for each WAP independently. For the m^{th} WAP, a random vector $\boldsymbol{V}_m$ is defined. The measured survey data for the m^{th} WAP, $\boldsymbol{v}_m$, is one sample vector of the random vector $\boldsymbol{V}_m$. This vector is modelled as the sum of two processes: $\bar{\boldsymbol{v}}_m$, which is the deterministic RSS signal for radio location created by immobile features in the network area, and $\boldsymbol{N}_m$ which is the measurement noise not useful for radio location. $\boldsymbol{N}_m$ reflects the influence of furniture, shadowing effects, and the opening and closing for doors on the RSS in the network environment. $\boldsymbol{N}_m$ is time-invariant over the measurement period when the survey data is measured at $\boldsymbol{\theta}_i$, but it is unlikely to have the identical value when a mobile terminal moves to this position during radio location. The measurement model for the m^{th} WAP is given by

$$\boldsymbol{V}_m = \bar{\boldsymbol{v}}_m + \boldsymbol{N}_m. \tag{2}$$

A discrete filter matrix, $\boldsymbol{W}$, is derived so that noise reduced measurements for the m^{th} WAP are calculated with

$$\hat{\boldsymbol{V}}_m = \boldsymbol{W}^T \boldsymbol{V}_m \approx \bar{\boldsymbol{v}}_m. \tag{3}$$

The method we propose in this paper is to use a Wiener-Hopf formulation of $\boldsymbol{W}$. It is assumed that the measurement noise vector is independent of $\bar{\boldsymbol{v}}_m$ so the Wiener-Hopf solution for $\boldsymbol{W}$ is given by

$$\boldsymbol{W} = [\mathrm{Cov}\,(\boldsymbol{V}_m)]^{-1}\,\mathrm{Cov}\,(\bar{\boldsymbol{v}}_m) \tag{4}$$

where $\mathrm{Cov}\,(\cdot)$ is the covariance operator [31], [32]. In (4), $\bar{\boldsymbol{v}}_m$ is treated as a random vector.

The covariance matrix of $\bar{\boldsymbol{v}}_m$ is assumed to be exponential with respect to separation distance of two points so that if $\boldsymbol{C}_{MM}^m\,[j,k]$ refers to the k^{th} entry of the j^{th} row of $\mathrm{Cov}\,(\bar{\boldsymbol{v}}_m)$ then

$$\boldsymbol{C}_{MM}^m\,[j,k] = \exp\left(-\frac{|\boldsymbol{\theta}_j - \boldsymbol{\theta}_k|}{d}\right) \tag{5}$$

where d is a correlation distance constant. Exponential correlation of RSS signals is often used for shadow fading in outdoor locations [33]. The optimal correlation for indoor locations is not known but it will be shown in Section IV that the correlation in (5) provides good noise removal performance. The measurement noise is assumed to be identically distributed and independent for each survey point measurement so that

$$\mathrm{Cov}\,(\boldsymbol{V}_m) = \boldsymbol{C}_{MM}^m + \sigma^2 \boldsymbol{I} \tag{6}$$

where σ^2 is the mean noise power for each survey RSS measurement normalized to the mean squared value of the deterministic portion of the RSS and $\boldsymbol{I}$ is an appropriately sized identity matrix. To remove noise from the measurements, the covariances calculated from (5) and (6) are substituted into (4) to obtain $\boldsymbol{W}$ which is then applied as demonstrated in (3) to the vector of RSS measurements for each WAP. The noise removal is performed on a given survey set once and the noise reduced survey set is then used for radio location. The cost of online radio location is not increased.

In Section IV, the results of this noise removal are presented and compared with the use of uniform survey point collection. It is known that noise removal works better if the correlation of the components of the RSS signals $\bar{\boldsymbol{v}}_m$ is higher; i.e. the noise removal is more efficient for a given survey point if many other survey points are located in close proximity. If survey points are spread uniformly over a network area, the noise removal for the RSS signal of each point will work less effectively than if survey points are clustered together. It will be demonstrated in the next section, that clustering points for better noise removal provides substantial gains in location accuracy.

B. Training

The accuracy of the radio location is a function of the noise removal algorithm parameters d and σ^2 and the estimation algorithm parameters $\boldsymbol{P}$.

The technique to calculate the optimal parameters for radio location accuracy uses two independent survey sets A and B of RSS measurements taken at known locations [34]. Dataset A is the survey set and dataset B is a so-called validation set. The location of each data collection point in dataset B is estimated using the estimation algorithm using survey set A after noise removal for a several sets of parameter values. The parameter that produces the minimum error are then used for location estimation in the localization phase. If the sample locations for validation dataset B are drawn from the same density $\mathrm{f}_{\boldsymbol{\Theta}}\,(\boldsymbol{\theta})$ as the probability density function of terminal locations during the localization phase then the parameter values found during the training phase will approach the optimal value as the size of the validation dataset B goes to infinity. In practice, only finite size data sets may be used so sub-optimal calculations of parameter values are performed.

Because collecting multiple datasets is costly and time consuming, it is useful to determine the parameter values using only the survey dataset with a so-called cross-validation approach [34]. The cross-validation involves removing a single point from the survey set, performing noise removal on the remaining survey set and then localizing that survey point using the rest of the survey points and their measurement vectors. The localization error for the survey point is then calculated. This process is iterated for all points in the survey set and the cross-validation error value is calculated. For a suitably large survey set, the noise removal and estimation algorithm parameter values that produces the minimum cross-validation error will be approximately equal to the optimal values.

III. WLAN Terminal Localization

This section describes how this survey data is used by the location estimation algorithm shown in Figure 1. In indoor locations, the relationship between RSS characteristics and location is non-linear due to multipath and non-line-of-sight radio signal propagation [20]. For terminal localization, a Minimum Mean Square Error (MMSE) estimator using an approximate joint density function of the RSS measurements and terminal location created using the Parzen window estimator is described below. For processing purposes, a subset of the survey database is created by selecting all survey points with the same measuring WAPs as the terminal to be located. This selection method must be consistent from the survey data collection procedure and the mobile terminal localization procedure or otherwise an unwanted bias is created. A typical selection method is to choose those m WAPs belonging to a publicly maintained network that have the highest RSS viewed by the mobile computing device; all survey points that have visibility to these m WAPs make up the subset of survey points used for localization.

A. Parzen Window Estimator

The Parzen Window Estimator is an approximation to the MMSE estimator. The Mean Square Error (MSE) of mobile terminal localization, defined as

$$\mathrm{MSE} = \mathrm{E}\left\{ \left| \hat{\boldsymbol{\theta}}(\boldsymbol{v}) - \boldsymbol{\Theta} \right|^2 \right\}, \tag{7}$$

where $|\cdot|$ is the Euclidean length operator, is used as the criterion to determine the quality of our localizations. The MMSE which minimizes the expected MSE estimator is known to be $\hat{\boldsymbol{\theta}}_{MMSE}(\boldsymbol{v}) = \mathrm{E}[\boldsymbol{\Theta}|\boldsymbol{V} = \boldsymbol{v}]$ where $\mathrm{E}[\cdot|\boldsymbol{V} = \boldsymbol{v}]$ denotes the expectation operator conditioned on the measured RSS vector taking the value $\boldsymbol{V} = \boldsymbol{v}$ [29]. The MMSE estimation is expanded as

$$\begin{aligned} \hat{\boldsymbol{\theta}}_{MMSE}(\boldsymbol{v}) &= \int_{\boldsymbol{S}} \boldsymbol{\theta}\, \mathrm{f}_{\boldsymbol{\Theta}}(\boldsymbol{\theta}|\boldsymbol{V} = \boldsymbol{v})\, \mathrm{d}\boldsymbol{\theta} \\ &= \frac{\int_{\boldsymbol{S}} \boldsymbol{\theta}\, \mathrm{f}_{\boldsymbol{\Theta},\boldsymbol{V}}(\boldsymbol{\theta}, \boldsymbol{v})\, \mathrm{d}\boldsymbol{\theta}}{\int_{\boldsymbol{S}} \mathrm{f}_{\boldsymbol{\Theta},\boldsymbol{V}}(\boldsymbol{\theta}, \boldsymbol{v})\, \mathrm{d}\boldsymbol{\theta}} \end{aligned} \tag{8}$$

where $\boldsymbol{S}$ is the region where the mobile terminal is known to reside determined by the measuring WAP selection procedure [29], [35]. The difficulty with mobile terminal localization via direct application of (8) is the joint PDF, $\mathrm{f}_{\boldsymbol{\Theta},\boldsymbol{v}}(\boldsymbol{\theta}, \boldsymbol{v})$, of locations, $\boldsymbol{\Theta}$, and RSS measurements, $\boldsymbol{V}$, must be known. This problem is circumvented by using a Parzen window technique to approximate the joint PDF as a sum of kernel functions with each kernel function centered on the joint location vector and RSS measurement vector for each survey point [36]–[38]. The approximate joint PDF of terminal locations and measurements based on the survey data using the Parzen window technique is given by

$$\mathrm{f}_{\boldsymbol{\Theta},\boldsymbol{V}}(\boldsymbol{\theta}, \boldsymbol{v}) = \frac{(h_v)^{-L}(h_\theta)^{-3}}{N} \sum_{i=1}^{N} \mathrm{K}_v\left(\frac{\boldsymbol{v} - \boldsymbol{v}_i}{h_v}\right) \mathrm{K}_\theta\left(\frac{\boldsymbol{\theta} - \boldsymbol{\theta}_i}{h_\theta}\right) \tag{9}$$

where $\mathrm{K}_v(\cdot)$ is the kernel function for measurements, $\mathrm{K}_\theta(\cdot)$ is the kernel function of terminal locations, N is the number of survey points, and L is the number of RSS measurements in each measurement vector. The constants h_v and h_θ are smoothing parameters known in the PDF approximation literature as kernel widths. For the kernel functions, we use the standard multivariate Gaussian density functions:

$$\mathrm{K}_v(\boldsymbol{v}) = (2\pi)^{-L/2} \exp\left(-\boldsymbol{v}^T \boldsymbol{v}/2\right), \text{ and} \tag{10}$$

$$\mathrm{K}_\theta(\boldsymbol{\theta}) = (2\pi)^{-3/2} \exp\left(-\boldsymbol{\theta}^T \boldsymbol{\theta}/2\right). \tag{11}$$

We use the properties of the first and second moments of a Gaussian random vector to substitute (10) and (11) into (9) and perform the integrations in (8). The terminal localization calculation is then

$$\hat{\boldsymbol{\theta}}(\boldsymbol{v}) = \sum_{i=1}^{N} \mathrm{w}_i(\boldsymbol{v})\, \boldsymbol{\theta}_i, \tag{12}$$

with the weight $\mathrm{w}_i(\boldsymbol{v})$ for each survey point being given by

$$\mathrm{w}_i(\boldsymbol{v}) = \frac{\mathrm{K}_v\left(\frac{\boldsymbol{v} - \boldsymbol{v}_i}{h_v}\right)}{\sum_{j=1}^{N} \mathrm{K}_v\left(\frac{\boldsymbol{v} - \boldsymbol{v}_j}{h_v}\right)}. \tag{13}$$

The value of the smoothing parameter h_v determines the accuracy of the localization procedure. The optimal value of h_v is determined by the spatial correlation of the RSS vectors. Small values of h_v indicate that the RSS vector is subject to large deterministic changes if the mobile devices moves a small distance, while larger values of h_v indicate that the RSS vector undergoes only small deterministic changes with small movements of the terminal.

To perform radio location and noise removal effectively, it is necessary to use proper values of of the estimation algorithm parameter $\boldsymbol{P} = \{h_v\}$; and the noise removal paremeters d and σ^2. To obtain these values, the cross-validation of Section II-B is used. Good search spaces for each value have been found experimentally to be $0.25 \leq d \leq 1.50$ metres, $0 \leq \sigma^2 < 1$, and $0.1 \leq h_v \leq 6.0$. The search foor good values via cross-validation may be time consuming but it is performed offline and only needs to be performed once for a given survey set. The computational cost of online localization is not increased.

IV. Results

Our experimental testbed is located on the fifth and sixth floors of the six storey Engineering and Computer Science Building (ECS) at the University of Victoria. The ECS building has an architectural design with an open atrium structure in the middle of the building extending from the first floor to the top of the sixth floor. Radio RSS measurements from WLAN wireless access points (WAPs) are collected at known locations within the network area. Netstumbler, a software utility for low-level interface access to a mobile terminal's RSS values, was used to gather the radio RSS data from the WLAN wireless terminal [39]. Time-averaging was performed over 30 seconds for all collected RSS values to remove time-variant noise.

Radiolocation is performed with measurements from the WAPs of the university's public access WLAN that is configured to maximize network coverage at minimum cost and is not optimized for localization accuracy. Although private WAPs, which can be readily identified by their SSIDs, could potentially provide additional information that can be used for improved estimation, they are not a reliable source of data because private WAPs could be moved or shut off at any time. In addition, the public access WAP antennas are fixed to the ceilings giving them superior area coverage. The university has installed four WAPs for the public WLAN on every floor of the building.

Each floor has dimensions of 65.5 m by 33.5 m and includes more than 40 rooms. The experiments were conducted in the public conference rooms and hallways. The total size of these restricted areas sums to 336 m^2. Network access from the other areas, such as offices, are more likely to be done via wired LAN, as opposed to WLAN, so radio location is currently less critical in these areas.

TABLE I
COMPARISON OF KERNEL WIDTH CALCULATIONS

Number of WAPs	h_v from Validation Set	h_v from Cross-Validation
3	2.1	1.4
4	1.8	1.6
5	2.2	1.9
6	2.3	2.3
7	2.3	2.3
8	2.3	2.4
9	2.6	2.6
10	2.8	2.8
11	2.9	3.0
12	2.8	3.1

The survey database of the ECS sixth floor includes 261 survey point locations, while the survey database of the ECS fifth floor contains 200 survey point locations. For all surveyed points on both floors, more than 35 unique WAPs from the university WLAN were visible to the mobile terminal, with a minimum of 12 WAPs being visible at all survey points. Except where otherwise noted, radio location was performed with measurements from 12 WAPs.

A comparison of the best h_v values obtained from the two training set method and the cross-validation approach are presented in Table I. This table lists the optimal h_v value for when location is performed using only a given number of measuring WAPs. In many cases, both approaches provide identical values and in cases where they are not identical, the kernel widths are very close. This verifies that the cross-validation may be used to obtain good kernel widths without the requirement of an extra survey set.

A. Accuracy with Noise Removal

To find the values of h_v, d, and σ^2 for the radio location algorithm and noise removal algorithms, cross-validation was performed. The parameter values obtained from the cross-validation process were used for noise removal and then localization was performed on an independent test set of over 400 points for each floor to evaluate the localization accuracy. For each floor, the test sets are collected on multiple days with the minimum time between survey set and dataset collection being two weeks with some dataset points collected up to three months after the survey set data collection. The test sets' locations are uniformly distributed over the public areas on each floor. In order to determine the best distribution of survey points for a survey set, two point sets were used as survey sets and the resulting localization accuracy compared. In the first set, the location points were collected in a uniform straight-line fashion. In the second set, the locations were collected in clusters clusters of four points. The point locations for each type of survey set for the fifth floor are plotted in Figure 2. The uniform survey set contains 215 points spaced at 70 cm apart. The clustered survey set has 208 points. Points inside of a cluster are spaced at 60 to 70 cm apart and the approximate distance between clusters is 120 cm. In both cases, the RSS values were averaged for 30 seconds at each survey point to remove time varying noise. To show the advantage of the noise removal, radio location was also performed on a survey set which had only time filtering noise removal performed on it.

The results of the radio location experiments are summarized in Table II. It can be seen that the time averaging noise removal technique provides an improvement in radio location accuracy. This improvement is about 16% (193.3 cm from 236.1 cm) when using the clustered survey set on the fifth floor and 11 % (248 cm from 280 cm) on the sixth floor. It is also noted that the clustered survey set provides accuracy improvements to the uniform set even when no spatial filtering is performed. This is because the Parzen window estimator includes some spatial filtering already by from the weighted averaging performed in the location estimate calculations. The lower accuracy on the sixth floor is due to the presence of large meeting rooms in the test area. Large open spaces have a lower density of significant RSS features over the location domain compared to hallways so the accuracy of pattern recognition based radio location is lower in these areas. The test sets' points are uniformly distributed over the floor so the uniform survey set points are a better match to the test sets' point distributions, the gain in accuracy for the clustered survey set is provided by the superior noise removal.

A more thorough comparison of radio location accuracy for the fifth floor is obtained from the plot the cumulative distribution function (CDF) of the distance between the true terminal location and the estimated terminal location in Figure 3. This plot shows the probability that the distance error is below the specified value on the x-axis. This plot shows that the estimated location is within 400 cm of the true location for the noise-reduced clustered survey set about 90 % of the time but without the noise reduction the distance increases to 450 cm and this distance is 500 cm for the uniform survey set. It is clearly seen that the spatial domain filter improves the localization accuracy. It is also seen that survey points in clusters provide superior accuracy to a uniform distributed survey set locations.

V. CONCLUSION

In this paper, a distance-averaging noise removal filter that decreases the effect of multipath propagation noise on the survey RSS measurements collected for indoor radio location purposes has been presented. Noise reduction for two distinct geometries used in data collection of survey points was examined. The results presented in this paper show that the location accuracy improved by 16% when the noise reduction filter is used These results indicate that survey data collection in clusters of points allow a survey set to better characterize the RSS in an indoor environment when the spatial domain noise removal filter is used. Future work will investigate the number of points in each cluster for optimal noise removal and the required geometry of the cluster locations needed to obtain the highest localization accuracy.

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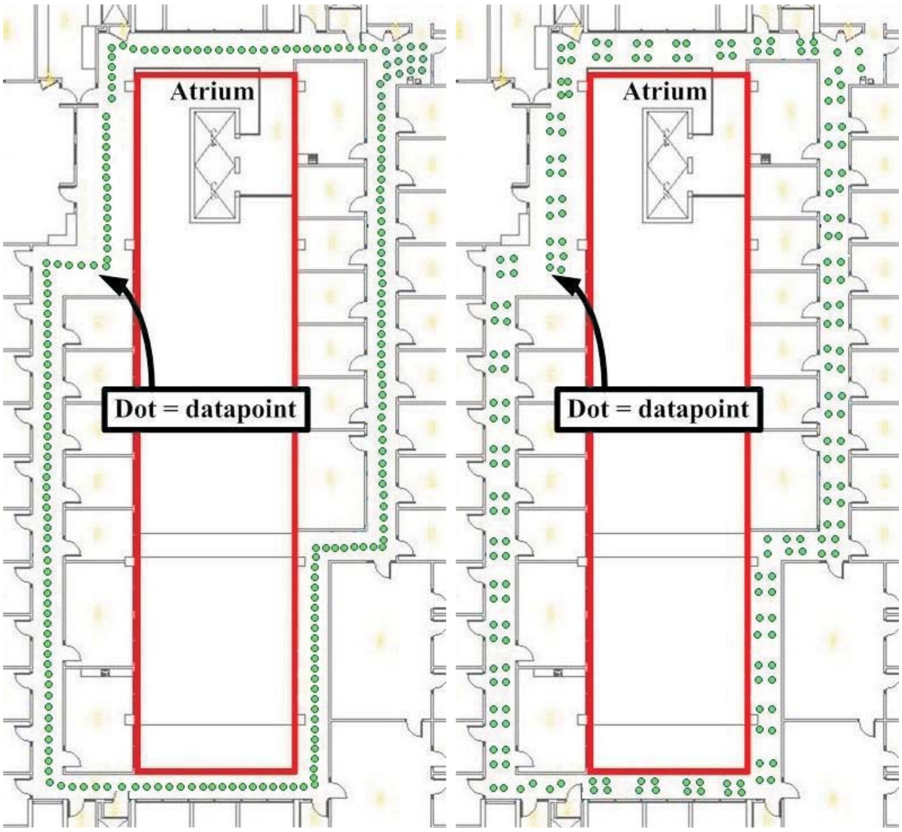
TABLE II
RADIOLOCATION ACCURACY SUMMARY

	Normal Survey Set		Filtered Survey Set			
	h_v	RMSE	h_v	d	σ^2	RMSE
Fifth Floor Uniform Survey	4.3	250.5 cm	3.6	1000 cm	0.28	236.1 cm
Fifth Floor Clustered Survey	5.1	229.1 cm	3.5	550 cm	0.2	193.3 cm
Sixth Floor Clustered Survey	3.2	280 cm	3.4	850 cm	0.24	248 cm



(a) Uniform Survey Set (b) Clustered Survey Set

Fig. 2. Survey Set Comparisons

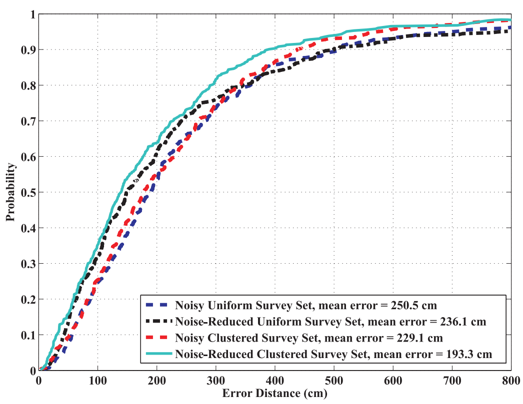


Fig. 3. Localization Accuracy Comparison

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