Sixth Annual IEEE International Conference on Pervasive Computing and Communications

Exploiting Environmental Properties for Wireless Localization and Location Aware Applications

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***Abstract*— Wireless sensor networks monitor phenomena that vary over the spatial region the sensor network covers. The sensor readings may also be dual-used for additional purposes. In this paper we propose to use the inherent spatial variability in physical phenomena to support localization and position verification. We first present the problem of localization using general spatial information fields, and then propose a theory for exploiting this spatial variability for localization. Our Spatio-Correlation Weighting Mechanism (SCWM) uses spatial relationships of measured physical phenomena to determine an appropriate subset of environmental parameters for better location accuracy. We next present the $Flex-EP$ algorithm, which supports our theoretical model for performing localization. Finally, we provide an experimental evaluation of our approach by using a collection of physical phenomena measured across one hundred locations inside a building. Our results provide strong evidence of the viability of using general sensor readings for location applications.**

I. INTRODUCTION

The rapid advancements in sensor technologies are leading to a future where sensors will become pervasively deployed. Although the data associated with such sensor readings might be intended to drive specific applications, e.g. the remote monitoring of temperature, this wealth of data may also be dual-used for additional purposes. In particular, since the purpose of a sensor network is to provide sampling of a physical phenomena across a wide geographic/spatial distance, the close link between sensor data and location may assist applications involving localization and position verification. In this paper, we propose the use of spatially varying environmental properties to support localization, without requiring the deployment of a localization infrastructure and additional access points (or landmarks). Specifically, we examine the use of physical properties, such as temperature and ambient acoustic/RF energy, and whether their inherent spatial variability may be used to localize the position of a mobile entity.

Each physical parameter has unique spatial characteristics relative to the environment. For computational cost savings, it is desirable to find the most efficient subset of environmental properties that captures spatial variability. We propose a scheme, Spatio-Correlation Weighting Mechanism (SCWM), which can guide parameter selection for localization. Using SCWM, we can compare any subset of parameters and determine the parameter combination with the strongest discriminative characteristics needed for localization. We further developed an algorithm, called $Flex-EP$, which utilizes the parameter subset obtained from SCWM to determine a user's position based on it's environmental readings.

To validate our techniques, we collected an array of environmental parameters at one hundred locations in a real building environment. Using these data, we found that SCWM is highly effective in evaluating and selecting the parameter subset with the highest discriminative power. Further, we observed that the environmental parameters have localizing capability. Moreover, by using environmental readings plus the Received Signal Strength (RSS) from one access point, we can achieve qualitatively the same performance as traditional localization schemes employing RSS with at least four access points or landmarks [1]. Further, under the assistance of additional environmental parameters, the localization performance can be refined and improved over traditional approaches.

The remainder of this paper is organized as follows. In Section II, we provide an overview of our problem. We then formulate the theoretical model of exploiting environmental properties for localization and propose SCWM in Section III. In Section IV we present our $Flex-EP$ algorithm and its variations. Section V shows our experimental methodology and our evaluation results. We then move onto placing our work in the context of related research in Section

0-7695-3113-X/08 $25.00 © 2008 IEEE
DOI 10.1109/PERCOM.2008.65

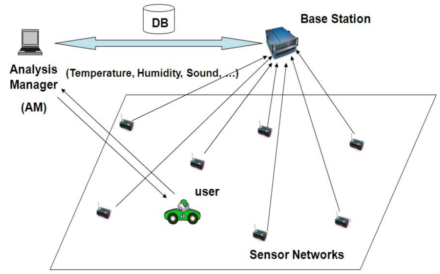


Fig. 1. Using environmental properties for spatial determination

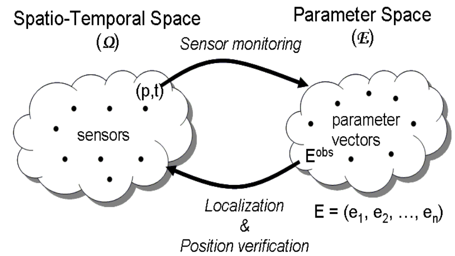


Fig. 2. Theoretical model: physical domain vs. environmental properties domain

VI. Finally, we conclude the paper in Section VII.

II. Problem Overview

Our proposed model for using environmental readings for localization and position verification is built upon an existing wireless sensor networks, as shown in Figure 1. In the area of interest, sensors are deployed to perform environmental monitoring. Sensors periodically report environmental readings back to Base Stations. For instance, temperature, humidity, and ambient acoustic energy are common environmental parameters under constant monitoring. The reported environmental information is stored in a database in real time for retrieval by the upper level applications. A management entity containing data processing and analysis capabilities, namely the *Analysis Manager(AM)*, calculates a user's location. The *AM* can be combined with the base station or operate alone in a centralized manner or running with multiple distributed instances when under performance demand. If the *AM* is operating by itself, the *AM* should be able to access the environmental readings stored in the database shown in Figure 1.

A user, when it wants to get its position, first sends a query to *AM*. After receiving the request, *AM* asks the user to provide environmental readings observed at that time by the user. By running localization algorithms using environmental properties, AM then compares the user's readings to the environmental data (provided by sensors) stored in the database and estimates the user's location.

The traditional approach for localization involves deploying enough landmarks with known positions to assist in localization. However, we note that sometimes there may not sufficient landmarks in the area of interest, e.g. due to cost limitations or environmental constraints (e.g. insufficient power outlets). Further, for certain applications, such as position verification in Spatial Access Control [2], [3], very high accuracy of location results is not needed, so additional landmarks would be wasteful. Thus it is desirable to find alternative strategies that can use available information, such as environmental properties from sensor networks supporting pervasive computing applications, to augment location services without requiring the infrastructure of additional landmarks.

III. Theoretical Approach

In this section, we present the theoretical underpinnings behind using environmental properties for localization. We first propose a generalized measurement model, and then provide rules to evaluate each parameter's localizing capability. Finally, we present mechanisms for parameter selection to assist in localization and position verification.

A. A Generalized Measurement Model

In order to quantify the effectiveness of using physical phenomena for localization and position verification, we need to derive the theoretical formulation of this problem.

Let $E = (e_1, e_2, ..., e_n)$ denote the vector of environmental properties that are monitored by the sensors, where e_i is the value of the i_{th} environmental parameter. These parameters have the property that they are recorded in the spatio-temporal domain, which means that they may vary with location and time. Thus the value of the parameter vector at position p and time t can be expressed as:

$$E_{p,t} = \left[\begin{array}{ccccc} e_1(p,t), & e_2(p,t), & \ldots, & e_n(p,t) \end{array}\right]. \quad (1)$$

Here p is a spatial position, which can be one-, two-, or three-dimensional. In this study, we focus on p in a two-dimensional space. More generally speaking, p can represent a point (x, y) or a region. Let $\Omega = P \times T$ be the spatio-temporal region [2] that we are interested in, and $\mathbf{E}$ be the domain of environmental parameter values, then there exists a mapping $f : \Omega \longrightarrow \mathbf{E}$ that takes the physical position p and maps it to an environmental parameter reading $E_{p,t}$ as presented in Figure 2. $f(p, t) = E_{p,t}$ represents the environmental readings recorded at the spatio-temporal location (p, t). The inverse mapping from

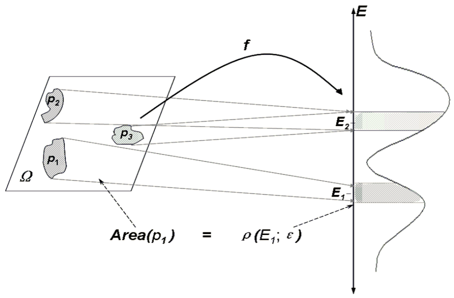


Fig. 3. Function f induces a probability density function ρ in measurement domain $\mathbf{E}$.

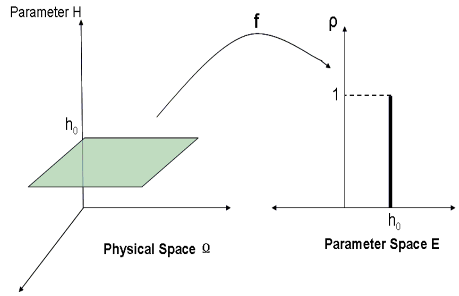


Fig. 4. An illustration of a "bad" environmental parameter that does not contribute to localization.

$\mathbf{E}$ to Ω enables localization and position verification from environmental properties.

At a fixed time t, the function $f_t(x,y) = f(x,y,t)$ induces a probability density function ρ on $\mathbf{E}$. We further define the function $\rho(E;\varepsilon)$ to be the probability of having value $f_t(x,y) \in (E;\varepsilon)$ as presented in Figure 3, when a position (x,y) is chosen randomly from an uniform distribution from $X \times Y$. Here $(E;\varepsilon)$ denotes the ε-ball around E. Note that $\rho(E;\varepsilon)$ is the integral of the probability density function over the region $(E;\varepsilon)$.

Given an environment measurement reading E, in order to find out the corresponding physical position, we want to find the region $p \subset \Omega$ such that $(E;\varepsilon) \subseteq \mathbf{E}$ is mapped back to p. In other words, we want to find the inverse mapping $p = f_t^{-1}(E;\varepsilon) = \{(x,y) : f(x,y) \in (E;\varepsilon)\}$.

Usually Ω has finite area, and we can normalize it to have $Area(\Omega) \stackrel{\triangle}{=} 1$. Then we can get the following claim:

Claim: $Area(p) = \rho(E;\varepsilon)$.

Proof:

$$\begin{aligned} \rho(E;\varepsilon) &= \int_{(x,y):f(x,y)\in(E;\varepsilon)} \frac{1}{Area(\Omega)} \cdot dxdy \\ &= \frac{Area(p)}{Area(\Omega)} = Area(p). \end{aligned}$$

Further, we note that, in order to localize a user in a two-dimensional space, simply using a single environmental parameter is generally not sufficient. Note that a position p in a two-dimensional space belongs to $\mathbb{R}^2$, while a single environmental parameter e_i belongs to $\mathbb{R}$. Generally, using multiple environmental parameters is desirable for localization and position verification. However, using all the available environmental parameters for localization may result in high computational complexity. We would like to choose subsets of parameters that consist of enough parameters to provide reasonable localization accuracy.

B. Parameter Evaluation

Different parameters have different characteristics in describing the environment in terms of value changes across various physical locations and different time periods. For certain parameters, the values may vary largely across different locations. The physical phenomena reported by these kind of parameters can be utilized to distinguish location differences. We define such parameters to have large *discriminative power*. On the other hand, the values of some parameters may vary little within the area of interest. Figure 4 is an illustration of a parameter H belonging to this category. It has the same value h_0 throughout the physical region, thus, in the parameter space $\mathbf{E}$, $\rho(h_0) = 1$. These kind of parameters do not have the capability to distinguish physical variability and thus cannot contribute to better localization accuracy.

Further, it is important to choose a parameter subset so that the combination of the parameters in the subset have enough discriminative power to support localization. Carelessly choosing a parameter subset may even result in localization errors as shown in Figure 3, where two far-away regions p_2 and p_3 in the physical space have the same environmental readings $(E_2;\varepsilon)$. The inverse mapping would result in $f_t^{-1}(E_2;\varepsilon) = p_2 \bigcup p_3$. This indicates that the subset of parameters in this case is not sufficient in describing the physical variability and causes failure in localization.

C. Parameter Selection

Next, we will develop a series of approaches to help select environmental parameters, that when combined, have greater capability for localization and position verification.

1) Parameter dispersion: Conceptually, for an environmental parameter e_i, the more disperse the values are, the better the discriminative power is for this parameter. In statistics, there are several ways to measure dispersion of a parameter, such as *range*, *variance*, *standard deviation* and *average absolute deviation*.

However, none of these measurements are complete, since no matter which above statistical dispersion methods we use, they only look at the data itself and neglect the spatial relationships between the data and the physical environment. For example, if the data readings from two different environmental parameters have the same distribution, their dispersions are about the same. However they may result in very different accuracy if used for localization. Suppose both of them have a subset of readings with the same value, but for one parameter, the same-value readings are clustered, while for the other parameter, the same-value readings are scattered among the region. The latter parameter will generate larger errors when applied in localization than the former parameter, according to our analysis in Section III-B.

Further, we found that the cross-parameter relationship, e.g. covariance, does not heavily contribute to localizing capability. Instead, the spatial relationship dominates localization accuracy. This leads us to look for metrics that take into consideration of the spatial correlation when evaluating an environmental parameter, in addition to the parameter dispersion.

2) Data Normalization: Different from the traditional localization methods [1], [4], the data sources in our problem are from different kinds of environmental parameters, such as temperature, humidity, ambient acoustic energy, and etc. Different environmental parameters have different units and different range of values. For example, in our experiments the temperature readings range from 65.2F to 77.3F, whereas Received Signal Strength values range from -59.8dBm to -99dBm. In order to choose a subset of environmental parameters working together for localization purpose, we need to compare and calculate the contribution of each parameter directly. Currently we take an un-biased approach, i.e., we normalize the data using the classical statistical approach, $e_i^{norm} = (e_i - \mu_i)/\sigma_i$, where μ_i and σ_i are the mean and standard deviation of the parameter e_i. We then work with the normalized data e_i^{norm} for the rest of our study.

3) Spatio-Correlation Weighting Mechanism (SCWM): The important factor that we need to take into consideration when performing parameter selection is to analyze how far away two positions can be in the physical domain $\mathbf{P}$, given a distance in the environmental-parameter domain $\mathbf{E}$. The SCWM calculates a sum $W(K)$ of pairwise weighted distances in $\mathbf{P}$, which gives larger weight to similar parameter readings in $\mathbf{E}$ and smaller weight to more different parameter readings. If we define K to represent a set of parameter indices chosen to form the parameter subset, the $W(K)$ is defined as follows:

$$\begin{aligned} W(K) &= \sum_{p_i, p_j, i \neq j} w_{i,j} \cdot d_{i,j} \\ &= \sum_{p_i, p_j, i \neq j} w_{i,j} \cdot \|p_i - p_j\|^2 \qquad (2) \\ with\ w_{i,j} &= \frac{1}{1 + \tau \cdot \|e_{k \in K}(p_i) - e_{k \in K}(p_j)\|^2} \end{aligned}$$

where τ is a scaling factor. We call $w_{i,j}$ the *parameter weight*, which takes values from $(0, 1]$. The computational complexity does not dramatically increase with the number of parameters in a parameter subset when using SCWM for parameter selection.

Figure 5 illustrates how SCWM helps to choose the parameter subset with the highest discriminative power. We describe three typical scenarios during SCWM calculation. The first scenario is shown with position pair p_2 and p_3. The two positions are close to each other and they have similar parameter readings. The contribution of the parameter weight $w_{2,3}$ is large, close to 1. But the resulting $(w_{2,3} \cdot d_{2,3})$ is small because $d_{2,3}$ is very small. Next, position pair p_1 and p_4 is farther away from each other and their parameter readings are very different. In this case, the contribution of the $w_{1,4}$ is very small and much less than 1. The above two scenarios satisfy the theory requirements of better location accuracy described in Section III-B. Finally, we look at a poor scenario with position pairs $\{p_1, p_3\}$, and $\{p_1, p_2\}$. Their parameter readings are the same or very similar, but they are farther away from each other. The contribution of the parameter weight is large, especially for $w_{1,3}$ which reaches its maximum, equaling to 1. Both $(w_{1,3} \cdot d_{1,3})$ and $(w_{1,2} \cdot d_{1,2})$ are also large because of the distances are farther away.

For a fixed number of parameters, SCWM calculates all the pairwise weighted distances over all the possible combination of parameters. The parameter subset with most of its readings following the patterns described in the first two scenarios will result in the final value of $W(K)$ to be small. While the parameter subset having most of readings similar to the third scenario we presented, the calculated value of $W(K)$ will be large. The parameter subset that results in the minimum value of $W(K)$ is the optimal parameter combination that contains the

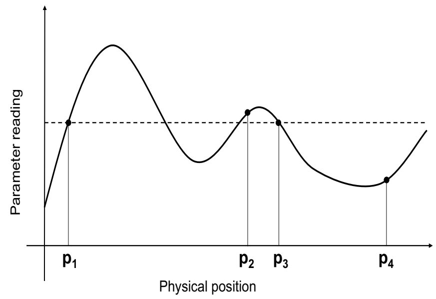


Fig. 5. Three scenarios under SCWM calculation: (1) position pair $\{p_2, p_3\}$; (2) position pair $\{p_1, p_4\}$; (3) position pairs $\{p_1, p_3\}$ and $\{p_1, p_2\}$. The relationship is: $(w_{1,3} \cdot d_{1,3}) > (w_{1,2} \cdot d_{1,2}) >> (w_{1,4} \cdot d_{1,4})$ and $(w_{2,3} \cdot d_{2,3})$.

highest discriminative power for performing localization. SCWM can sort all the possible combination of parameters under a fixed size parameter subset in the descending order from the highest discriminative power to the lowest discriminative power for localization. In Section V, we present experimental results utilizing SCWM.

IV. Algorithm Model

A. Basic Approach

To evaluate the viability of using environmental parameters for localization and position verification, especially the effectiveness of SCWM for parameter subset evaluation and selection, we developed the *Flexibly choosing Environmental Parameter* ($Flex-EP$) algorithm. $Flex-EP$ finds the minimum distance between the user and the sensor network in the domain of environmental parameters based on the observed readings E^{obs} reported by the user and the information recorded by the sensor network, which is stored in the database, as shown in Figure 1. $Flex-EP$ reports the position of the closest sensor as the location estimate of the user. Figure 6 presents the pseudo-code that implements $Flex-EP$.

B. Algorithm Variations

In addition, we developed variants of $FLEX-EP$ algorithm. $FLEX-EP-Avg$ chooses the top k closest sensors to the user and returns the centroid of k locations, with $k > 1$. Another variant of $FLEX-EP$ is to build an Interpolated Map Grid (IMG) over the region of interest. Building an environmental IMG is similar to surface fitting and derives more environmental parameter readings across the area of interest that would be similar to the reported ones. Thus the $FLEX-EP-Grid$ algorithm uses the interpolated sensor readings and determines either the closest sensor or the "interpolated" sensor to the user.

input $E^{obs}_{subset}(p,t)$
output
min dist in the parameter domain
closest sensor position in the physical domain
initialize
$minDist = maxNum$
$sensorPosition = empty$

loop through information reported by sensors
  for each set of information from a sensor **begin**
    $dist = \|E^{obs}_{subset}(p,t) - E^{sensor}_{subset}(p,t)\|$

    if $dist < minDist$
    then $minDist = dist$ and $sensorPosition = sensor$
  end for
end loop
return $minDist, \ sensorPosition$

Fig. 6. The Flex-EP algorithm

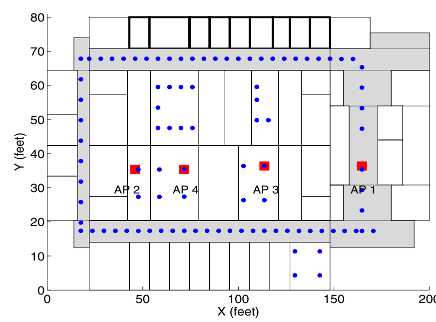


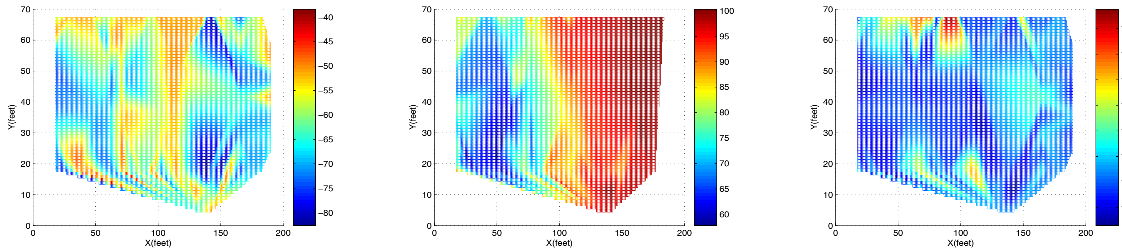
Fig. 7. Layout of the experimental floor

V. Experimental Evaluation

In this section we present our experimental evaluation results. We first describe our experimental methodology. We then examine the dispersion of individual parameters and the process of choosing parameter subsets utilizing SCWM. We next evaluate the effectiveness of our approach in using environmental properties for location estimation and verification. Finally, we show that our mechanism can refine results from conventional localization schemes.

A. Experimental Setup

In order to study the effectiveness of using environmental properties for localization and position verification, we have conducted experiments on the 3rd floor of the Computer Science building at Rutgers University, as shown in Figure 7. For over one hundred locations on the floor, shown as small blue dots, we collected environmental readings at these locations over a one-week period of time. This simulated the setup of a sensor network with over one hundred sensors deployed.



(a)Max 2.435GHz Wi-Spy (b)RSS from AP2 (c)Ambient noise (daytime)

Fig. 8. Sample data maps of individual environmental parameters

The environmental parameters that we studied are temperature, humidity, ambient noise, spectrum energy, and Received Signal Strength (RSS) from an 802.15.4 (ZigBee) network with four Access Points (AP) deployed across the floor. The access points are implemented using Telosb motes. To simulate a scenario where only one base station is available in the area of interest, we will choose only one RSS reading (in dBm) when forming the parameter subset. Further, we used a Wi-Spy spectrum analyzer [5] to record the spectrum energy at each location. It records the signal amplitude (in dBm) versus the frequency from 2.400GHz to 2.485GHz. At each testing location, we picked two frequencies 2.435GHz and 2.465GHz and calculated their maximum and average amplitude respectively over the recording period. Note that the RSS is the received signal from a beacon packet, while the spectrum energy is the ambient RF energy corresponding to a specific frequency range.

For ambient noise, our intuition is that the behavior of the parameter can vary largely during daytime and night time. Thus we collected readings of ambient noise (in dB) for both day and night. Moreover, we measured the humidity (in percentage) using a digital hygrometer and temperature (in Fahrenheit) using a thermometer respectively at each location. Table I is a summary of the parameters and the devices that we used to conduct experiments.

Parameter		**Index**	**Measuring Device**
Temperature		1	Thermometer
Humidity		2	Digital hygrometer
Ambient Noise	Daytime	3	Microphone and Dell laptop
	Night time	4	
Spectrum Energy	2.435GHz Max	5	Wi-Spy Spectrum Analyzer
	2.465GHz Max	6	
	2.435GHz Avg	7	
	2.465GHz Avg	8	
Received Signal Strength (RSS)	AP 1	9	Telosb motes and Dell laptop
	AP 2	10	
	AP 3	11	
	AP 4	12	

TABLE I

SUMMARY OF ENVIRONMENTAL PARAMETER MEASUREMENT

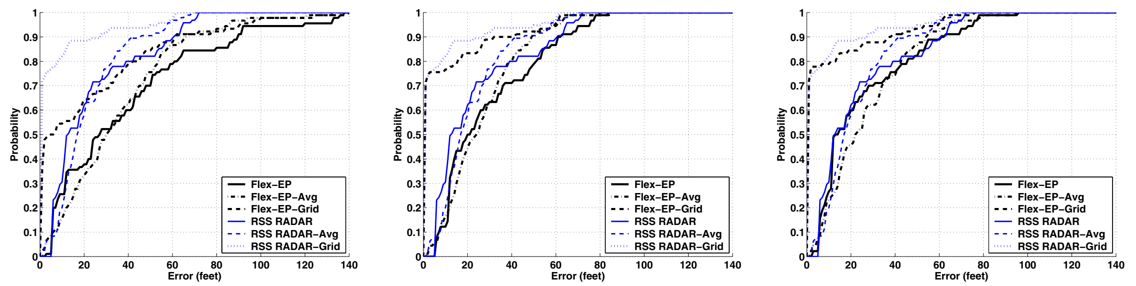
Parameters and Their Variance			
Temperature	**Humidity**	**Ambient noise** daytime	**Ambient noise** night time
4.15	9.3	0.01	0.0012
Spectrum energy			
2.435GHz Max	2.465GHz Max	2.435GHz Avg	2.465GHz Avg
84.36	88.21	2.09	0.08
Received Signal Strength (RSS)			
AP1	AP2	AP3	AP4
211.63	136.65	123.31	127.27

TABLE II

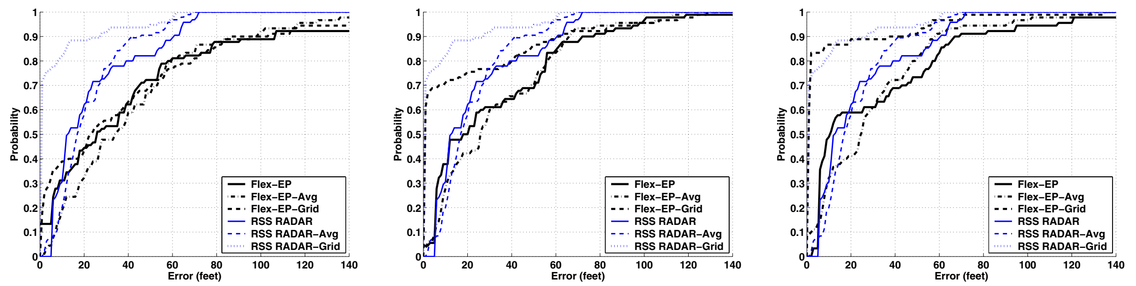
RESULTS OF SINGLE-PARAMETER DISPERSION

B. Evaluation of Individual Parameters

We first study the dispersion of individual environmental parameters through parameter variance. Table II presents the results of the variance for each individual parameter. We found that the maximum value of the spectrum energy and the RSS have larger variance across the area of interest, while the average value of the spectrum energy, temperature, humidity, and ambient noise do not vary much across the experimental floor. Both daytime and night time readings of ambient noise have smaller variance compared to other environmental parameters. For the rest of the paper, we will use the ambient noise data collected at night time. The sample maps of spectrum energy at 2.435GHz, RSS from AP2, and ambient noise are shown in Figure 8. The irregular shape of signal maps is due to the limitation of our data collection. We can see that the sample readings of ambient noise do not change much in the whole floor, while both the maximum values of spectrum samples at 2.435GHz and the RSS readings from AP2 present large variance indicating high discriminative power to describe the uniqueness of each location in the floor.



(a) two parameters (good): index 4, 12 (b) three parameters (good): index 4, 6, 12 (c) four parameters (good): index 1, 4, 6, 10



(d) two parameters (bad): index 2, 7 (e) three parameters (bad): index 1, 2, 8 (f) four parameters (bad): index 1, 2, 4, 7

Fig. 9. Comparison of localization errors using Cumulative Distribution Function (CDF)

C. Effectiveness of Parameter Selection

In this section, we present the results of parameter selection using SCWM. We then evaluate the effectiveness of SCWM by comparing the Cumulative Distribution Function (CDF) of localization errors under different sizes of parameter subsets with traditional localization methods.

Table III presents the results of $W(K)$ calculated from SCWM with the size of K equal to 1, 2, 3, 4, and 5 respectively. We have shown a representative subset of parameters in Table III with "good" and "bad" indicating that the value of $W(K)$ is smaller or larger. As we described in Section III-C, the smaller the value of $W(K)$ for a parameter subset, the higher the discriminative power the parameter subset has. From our experimental results, we found that the parameter subset containing all the RSS parameters will result in the minimum value of $W(K)$. This is because the parameters of RSS readings have the largest variance, according to the results in Section V-B, plus also have high spatial correlation based on signal propagation to distance [6], and thus can uniquely describe the physical variability across the experimental floor. However, in this study we focus on situations where there is no localization infrastructure available and we need to rely on the additional environmental properties to assist in localization and position verification. Thus, the parameter subsets displayed in Table III only involved one RSS parameter in the subset at the most.

# of Parameters in a subset	Evaluation	Parameters: in index	SCWM calculation
1	Good:	12	20641548.6
	Bad:	8	370356046.8
2	Good:	4, 12	595033.7
	Bad:	2, 7	23284151.1
3	Good:	4, 6, 12	140758.4
	Bad:	1, 2, 8	940833.1
4	Good:	1, 4, 6, 10	72365.1
	Bad:	1, 2, 4, 7	201856.6
5	Good:	1, 4, 5, 8, 12	55198.0
	Bad:	1, 2, 4, 7, 8	112585.6

TABLE III
EVALUATION OF SCWM WITH DIFFERENT SIZE OF PARAMETER SUBSETS

Based on the parameter selection results obtained from SCWM, we further conducted localization with these parameter subsets utilizing the $Flex-EP$ algorithm and its variants. In order to compare the performance of our approach, we need to compare with the performance benchmark in the current localization research. The traditional RADAR algorithm [1] and its corresponding variants are used for our comparison, which utilize the RSS readings collected from four APs in our ZigBee network.

Figure 9 presents the CDFs of localization errors for $FLEX-EP$ with the size of the parameter subset set to 2, 3, and 4 respectively. The localization results using RADAR are presented in each figure as a comparison. Figures 9(a) and 9(d) are the results using two parameters in the parameter subset. The localization results when using *RSS from AP4* and *ambient sound* are better than using *humidity* and *2.435GHz Avg*. This is because the parameter, *RSS from AP4*, has large variance and better spatial correlation across the experimental floor. Thus, the parameter subset, {*RSS from AP4*, *ambient sound*}, has smaller SCWM value than the set of {*humidity*, *2.435GHz Avg*}. The performance of $Flex-EP$ using two parameters is not as good as the performance of RADAR.

Next, Figures 9(b) and 9(e) show the error CDFs when using three parameters in the parameter subset. We added one more parameter with high discriminative power, *2.465GHz Max*, into the "good" parameter set of two parameters shown in Figure 9(a). Figure 9(b) presents the results of using {*ambient sound*, *2.465GHz Max*, *RSS from AP4*}. Surprisingly, we found that when using two environmental parameters with high discriminative power (*2.465GHz Max* and *RSS from AP4*) and one parameter with low discriminative power (*ambient sound*), the performance of $Flex-EP$ is qualitatively similar to the performance of using traditional RADAR algorithms, which utilizes four RSS parameters. In Figure 9(e) each parameter in the parameter subset {*ambient sound*, *humidity*, *2.465GHz Avg*} has low discriminative power and results in a larger SCWM value as shown in Table III. Hence, the performance of our localization is not improved much.

Further, we examined the localization error CDFs when using four environmental parameters as presented in Figures 9(c) and 9(f). In Figure 9(c), we still use two environmental parameters containing high discriminative power, *2.465GHz Max* and *RSS from AP4*, while *ambient sound* and *temperature* do not vary much across the experimental site. Again, we observed the performance of $Flex-EP$ is about the same as the RADAR and its variants. Moreover, under the assistance of two environmental parameters with low discriminative power, the performance is slightly improved over the three-parameter subset case as shown in Figure 9(b).

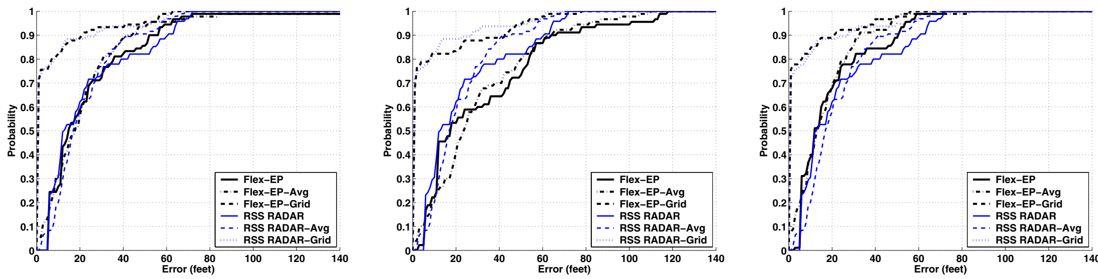
These results demonstrate that our SCWM consistently predicts the performance of parameter subsets, and further indicate that choosing two environmental parameters containing high discriminative power is enough to produce comparable performance to the traditional localization approaches employing RSS with at least four access points. On the other hand, as shown in Figure 9(f), simply adding environmental parameters with low discriminative power into a parameter subset does not significantly improve the localization performance. Since when using RSS for localization, the performance across a broad spectrum of algorithms was found to be about the same [4], we conclude that our approach of utilizing $SCWM$ for parameter selection and $Flex-EP$ for localization can achieve similar performance to a broad array of traditional localization algorithms. The similar performance is very encouraging as it indicates utilizing environmental properties can effectively determine the position of a user and can further assist in applications involving location and position verification.

D. Refining Localization

In a four-parameter subset, we further increased the number of parameters with high discriminative power to three by adding one more RSS parameter into the parameter subset. Figure 10(a) presents the corresponding error CDFs. We found that by utilizing three parameters with high discriminative power in a four-parameter subset, the localization performance is further refined and is almost exactly the same as the performance of RADAR algorithms.

Further, we explored the parameter subset with five parameters. Figures 10(b) and 10(c) show the localization error CDFs utilizing five parameters. The parameter subset in Figure 10(b) still contains only two parameters with high discriminative power (*2.435GHz Max* and *RSS from AP4*), the same as the four-parameter case in Figure 9(c), and three other parameters with low discriminative power (*temperature*, *ambient noise*, and *2.465GHz Avg*). We observed that the localization capability is about the same as in Figure 9(c) for the four-parameter case. This is in line with our previous observation, adding more environmental parameters with low discriminative power does not help much in improving the localization performance.

Turning to examine Figure 10(c), which has three parameters (*2.435GHz Max*, *RSS from AP2*, and *RSS from AP3*) with high discriminative power in a five-parameter subset, interestingly, the localization performance using $Flex-EP$ methods has achieved up to 20% improvement compared to the traditional RADAR algorithms. In this case, only two RSS parameters are used, which means that under the assistance of other environmental parameters, only two access points are needed to achieve a better localization performance than the traditional localization algorithms employing RSS using at least four access points. This provides strong evidence that utilizing environmental properties for localization can both achieve similar performance to the traditional



(a) four parameters: index 1, 5, 10, 11 (b) five parameters: index 1, 4, 5, 8, 12 (c) five parameters: index 1, 4, 5, 10, 11

Fig. 10. Using environmental properties to refine localization results.

approaches, as well as refine the conventional localization results.

VI. Related Work

In this section, we first discuss research efforts in using spatio-temporal information in Wireless Sensor Networks (WSN). Then we overview the active research in wireless localization and describe the work that are mostly related to ours.

By utilizing the radio on sensor nodes, it is possible to invert the role of sensor networks, and allow sensor nodes to actuate the environment. [2] utilized sensor networks in an inverted fashion to facilitate new forms of access control that are based on whether a user is located at the right place at the right time. Moreover, [7] pointed out that sensor observations are highly correlated in the space domain. They proposed a theoretical framework to capture the spatial and temporal correlations in WSN and enable the development of efficient communication protocols in WSN utilizing these information. In this work, we explore the possibility of utilizing the physical phenomena monitored by WSN to assist in wireless localization and position verification.

Localization of nodes in WSN has become increasingly important because the location of sensors is a critical input to many high-level applications. The localization techniques can be categorized along several dimensions. Based on localization infrastructure, [8] used infrared methods and [9], [10] employed ultrasound to perform localization. Both of them need to deploy specialized infrastructure for localization. On the other hand, using RSS [1], [4], [11] is an attractive approach because it can reuse the existing wireless infrastructure. Dealing with ranging methodology, range-based algorithms involve distance estimation to landmarks using the measurement of various physical properties like RSS [1], [4], Time Of Arrival (TOA) [12] and Time Difference Of Arrival (TDOA) [9]. Range-free algorithms [13], [14] use coarser metrics to place bounds on candidate positions. Examining the strategy used to map a node to a location, lateration approaches [12], [14]–[16], use distances to landmarks, while angulation uses the angles from landmarks. Scene matching (or fingerprint matching) strategies [1], [4], [17], [18] use a function that maps observed radio properties to locations on a pre-constructed radio map or database. Finally, another dimension of classification extends to aggregate [13], [19] or singular algorithms.

The same type of physical properties is required to be used within each of the above methods to ensure the appropriate functioning of the mechanism. They have to be either infrared, ultrasound, RSS, angle, time, or hop count. Our work is unique in that we have proposed a generic localization approach by not restricting ourselves to only examine a single type of physical property. Instead, our method can incorporate all kinds of physical phenomena. The closest works to this paper are [1], [20]. [1] developed a localization mechanism measuring the minimum euclidean distance in the signal space, and only deals with the physical property of RSS. [20] proposed a GSM signal strength fingerprinting-based localization system to determine the current floor of a user. It addressed the problem that certain physical sources may not contribute to localization accuracy by developing a set of feature selection techniques. However, these feature selection techniques did not tract the performance of each possible combination in parameter subsets and might contain "bad" physical sources to start with. Also, [20] only deals with one type of physical property, the signal strength. By handling all kinds of physical properties, our work is broader than [1], [20], and our SCWM for parameter selection is more general than the feature selection approaches in [20]. In addition, our method is novel in that we utilize the existing deployment of sensor networks to assist in localization, rather than requiring the deployment of a localization infrastructure or additional access points (or landmarks) in the area of interest.

VII. Conclusion

In this work, we proposed to use the inherent spatial variability in physical phenomena recorded by sensor networks to support wireless localization and position verification. We formulated a theoretical measurement model for quantifying the localizing capability of environmental properties. We proposed a scheme to evaluate the environmental parameters' ability to capture the physical variability, the Spatio-Correlation Weighting Method (SCWM), which can find the optimal parameter subset with the highest discriminative power for localization for a given size of the parameter subset. Moreover, we developed the $Flex-EP$ algorithm to perform localization and position verification utilizing parameter subsets obtained from SCWM.

We evaluated our methods through experiments conducted in an office building where we collected various environmental parameters including temperature, humidity, ambient noise, spectrum energy, and RSS. We found that choosing two environmental parameters containing high discriminative power is enough to produce comparable performance to the traditional localization approaches employing RSS with at least four access points. By increasing the number of parameters with high discriminative power in a subset, we can further refine the localization accuracy and obtain better performance than conventional localization results. Thus, our experimental results provide strong evidence of the feasibility of utilizing environmental properties to assist in localization and the effectiveness of our approach by using SCWM and $Flex-EP$ algorithms.

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