Adaptive Sampling for Environmental Robotics

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Abstract— The capabilities and distributed nature of networked sensors are uniquely suited to the characterization of distributed phenomena in the natural environment. However, environmental characterization by fixed distributed sensors encounters challenges in complex environments. In this paper we describe *Networked Infomechanical Systems (NIMS)*, a new distributed, robotic sensor methodology developed for applications including characterization of environmental structure and phenomena. NIMS exploits deployed infrastructure that provides the benefits of precise motion, aerial suspension, and low energy sustainable operations in complex environments. NIMS nodes may explore a three-dimensional environment and enable the deployment of sensor nodes at diverse locations and viewing perspectives. NIMS characterization of phenomena in a three dimensional space must now consider the selection of sensor sampling points in both time and space. Thus, we introduce a new approach of mobile node adaptive sampling with the objective of minimizing error between the actual and reconstructed spatiotemporal behavior of environmental variables while minimizing required motion. In this approach, the NIMS node first explores as an agent, gathering a statistical description of phenomena using a *nested stratified random sampling* approach. By iteratively increasing sampling resolution, guided adaptively by the measurement results themselves, this NIMS sampling enables reconstruction of phenomena with a systematic method for balancing accuracy with sampling resource cost in time and motion. This adaptive sampling method is described analytically and also tested with simulated environmental data. Experimental evaluations of adaptive sampling algorithms have also been completed. Specifically, NIMS experimental systems have been developed for monitoring of spatiotemporal variation of atmospheric climate phenomena. A NIMS system has been deployed at a field biology station to map phenomena in a 50m width and 50m span transect in a forest environment. In addition, deployments have occurred in testbed environments allowing additional detailed characterization of sampling algorithms. Environmental variable mapping of temperature, humidity, and solar illumination have been acquired and used to evaluate the adaptive sampling methods reported here. These new methods have been shown to provide a significant advance for efficient mapping of spatially distributed phenomena by NIMS environmental robotics.

Keywords-component; Networked Infomechanical Systems (NIMS); Environmental Robotics, Sensor Networks; Adaptive Sampling; Statistics and Geostatistics.
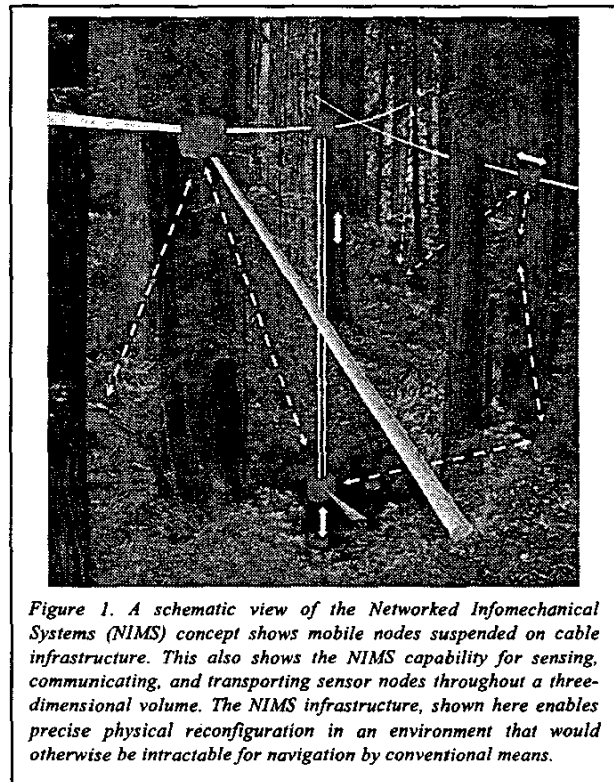
Figure 1. A schematic view of the Networked Infomechanical Systems (NIMS) concept shows mobile nodes suspended on cable infrastructure. This also shows the NIMS capability for sensing, communicating, and transporting sensor nodes throughout a three-dimensional volume. The NIMS infrastructure, shown here enables precise physical reconfiguration in an environment that would otherwise be intractable for navigation by conventional means.

I. INTRODUCTION AND MOTIVATION

Autonomous and comprehensive environmental monitoring robotics presents severe challenges for detection, location, and tracking of phenomena in the midst of unpredictably evolving environmental characteristics. Since phenomena may appear as single or multiple events and may migrate within the environment, it is required that sensing be spatiotemporally distributed. Also, in order to extract desired information regarding phenomena, it is generally required that multiple sensor modalities be brought to bear at the same point in space and time. Further, the reconstruction of phenomena from sensor sampling requires knowledge of the sensing channel propagation characteristics. Even more importantly, the presence of obstacles to sensing may entirely obscure events.

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This paper describes a new capability, Networked Infomechanical Systems (NIMS) combining distributed networked sensing with infrastructure-enabled mobility. NIMS enables active physical reconfiguration of a diverse spatiotemporal distribution of sensor nodes in three dimensional environments. NIMS infrastructure enables high precision and reliable mobility to locate sensor nodes as required to both calibrate and configure sensor distributions to the points of minimum sensing uncertainty. However, this new capability is accompanied by many challenges, including the problem of optimizing spatiotemporal sensor sampling to reduce resource costs while recovering the most accurate reconstruction of environmental phenomena. New algorithms with analytical, simulation and experimental results with NIMS systems will be presented here. Finally, the broad range of capabilities and applications of NIMS for environmental monitoring will also be discussed.

Distributed sensor networks have demonstrated feasibility for environmental monitoring [1-3]. However, experimental and theoretical investigation of the monitoring capability determined from the deployment of these early sensor networks has revealed the challenge of **sensing uncertainty**. The problem of sensing uncertainty is inherent to environmental monitoring since it is uncharacterized. Unexpected physical phenomena and evolving environmental structures induce uncertainty in the coupling between signal sources and sensors. Further, since *physical phenomena* are the source of *uncertainty*, then *physical adaptation* of a sensor network (for example, through robotic mobility) may provide the only practical method for detection and reduction of uncertainty. However, while mobility is required, there are constraints on the form of mobility that can provide the required benefits for environmental monitoring.

The structural complexity of natural environments and the nature of phenomena to be studied create a unique set of requirements for sensor node mobility. These include: 1) Mobility must permit a wide range of location and viewing perspectives within the space of large three-dimensional environments. This requires the capability to *adjust location to adapt range* between signal sources and sensors. This also requires the capability to choose viewing or sensing perspectives to enable image acquisition, for example, in the midst of obstacles. In typical natural environments, the proper viewing perspectives may be reached only with an overhead, aerial perspective and may not be accessible to surface-borne robots. 2) Mobility methods must also *provide predictable and accurate sensor location and perspective.* Specifically, in order to reduce spatiotemporal uncertainty, it is essential to avoid navigation errors or limitations that would, in the case of conventional methods, increase uncertainty. 3) Sensor mobility must also *access complex terrain* and surface regions that may be incompatible with conventional surface vehicle navigation (or may represent regions where surface vehicle passage may disturb the environment in an undesired fashion). 4) Sensor mobility must also be *sustainable* since environmental events may evolve slowly or be infrequent, yet still require constant exploration and vigilance in order for detection. 5) The sensor mobility system must provide a means for enabling a logistics capability for *transport of sensor nodes, energy, and physical samples* (for example of atmosphere or water resources). 6)

Finally, the mobile sensor environmental monitoring system must also support *reliable network access to spatially dispersed*, mobile nodes operating in complex environments. This networked capability is required to enable the accurate coordination of sensing assets for characterization of the many phenomena that are best investigated by the simultaneous application of multiple sensor devices.

NIMS technology, shown in Figure 1, addresses the environmental monitoring requirements above in a way that would not be directly possible with other robotic forms. Here, a "cableway" infrastructure is shown. While many infrastructure types are adapted for specific applications, the general purpose cableway system satisfies requirements for a broad class of environmental monitoring requirements while introducing only limited deployment logistics and planning cost. The cableway enables 1) elevated, aerial viewing perspective, 2) accurate, reproducible motion, 3) long range mobility in complex terrain, 4) low energy motion for sustainable operation, 5) logistics capability with energy transport via the cable systems, and 6) node elevation for enhancing wireless link budget relative to surface-distributed nodes [4]. Finally, the need for high fidelity monitoring of large environments will require the simultaneous operation of multiple NIMS nodes that exploit the infrastructure for communication and coordination [5].

NIMS applications to environmental monitoring range from fundamental science objectives to public health and safety. Examples include natural environment monitoring with requirements for characterization of the atmosphere for photosynthetic gas flux, time-lapse imaging of plant growth and animal behavior, and sampling of water resources. NIMS physical sampling capabilities offer a dramatic advance for these applications by providing a means to automate the programmable acquisition of atmospheric gas and water for later characterization of trace concentrations. NIMS may also be deployed over waterways including river and wetland systems. Here NIMS offers a distributed means for monitoring of atmosphere, water, and subsurface sediment all in response to events or model-driven schedules. NIMS devices are applicable as well to civil infrastructures for monitoring and inspection. In this example, NIMS devices may be deployed for condition monitoring as well as being held in reserve and deployed rapidly upon demand in response to emergencies and failures.

A series of new challenges accompany the development and application of NIMS for environmental monitoring. A primary example lies in the accurate reconstruction of distributed environmental phenomena, including, for example the measurement of microclimate dynamics. Here, the accurate determination of space- and time-dependent variables of temperature, water vapor concentration, and solar illumination within the complex environment is essential to the investigation of global change phenomena [6]. These variables must be sampled in a vast three-dimensional volume while both spatial and temporal variations are unknown and initially are unpredictable. Thus, while NIMS capabilities offer the ability to explore large volumes, it is now required that sampling strategies be properly devised such that the density of sampling points is dynamically and autonomously adjusted using information derived from sensor systems. This requires a

combination of new sampling algorithms, coordinated mobility, and proper dynamic selection of sensor assets. In some applications, this will also require the coordination of multiple sensor nodes. Objectives for optimization may include the accurate reconstruction of variable distribution or may include the optimization of accuracy associated with a variable set derived from combined, distributed measurements.

II. RELATED WORK

Environmental robotic development has provided methods for mapping, localization, and sampling of phenomena. For example, environmental mapping by robotic systems includes the reconstruction of a spatial model of the robot's environment based on sensor samples. Here environmental mapping may be characterized as the presence of absence of objects that enable robot navigation and localization.[7-8] Map reconstruction relies on sensing with range finders, cameras, odometers, tactile sensors, inertial and direction sensors, and GPS. Environmental mapping remains a challenge, particularly in the presence of dynamic environments. Robotic mapping algorithms have relied primarily on *probabilistic* as opposed to *statistical* approaches. These approaches range from the Bayesian filter [9] to Kalman filter [10], hidden Markov model [11], to Bayesian network. These methods apply to mapping unknown environments with known robotic localization or localization with known environments. The Simultaneous Localization and Mapping (SLAM) approach is intended to achieve both mapping and localization without prior knowledge of either.[12]
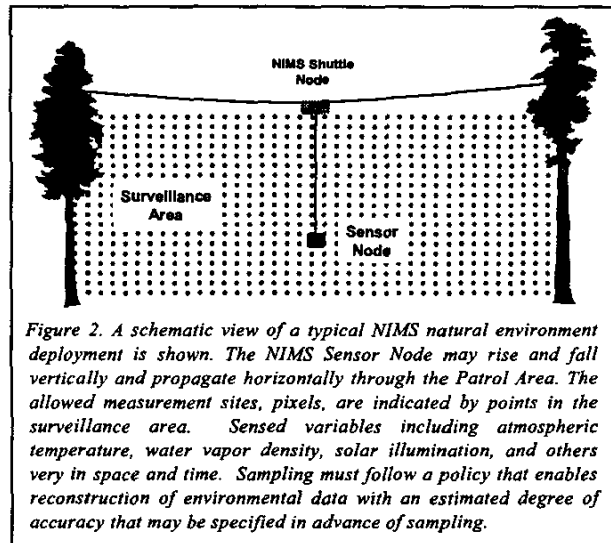
Geostatistics provides analysis methods for determination of spatial variation and interpolation of sampled data to obtain reconstructions (maps) of phenomena. These techniques have been long used in science disciplines such soil analysis, [13] weather mapping, [14] atmospheric science, [15] contamination studies, and geology.

Also in the field of sensor networks, research has yielded methods for determination of spatio-temporal variable distribution and efficient field estimation for fixed sensing points.[16,17]

This NIMS investigation is focused on the problem of spatiotemporal sampling of *dynamic* and *unpredictable* environmental phenomena in three-dimensional spaces. This requires that sampling be responsive to not only spatial variation, as in Geostatistics methods, but, also to unpredictable temporal variations. The exploitation of NIMS infrastructure enables precise robotic localization, removing an uncertainty from the reconstruction problem. This, in turn, will enable introduction of new sampling capabilities with coordinated mobility of individual or multiple nodes.

III. ROBOTS AS STATISTICAL AGENTS

The NIMS sensor node motion is limited by mechanical means to a minimum resolvable unit, referred to here as a pixel, indicated schematically in Figure 2. Pixels represent the upper bound on spatial sampling frequency. Exhaustive sampling of the environment at all pixels may generally be prohibitively expensive in time and resource cost. Indeed, for many

Figure 2. A schematic view of a typical NIMS natural environment deployment is shown. The NIMS Sensor Node may rise and fall vertically and propagate horizontally through the Patrol Area. The allowed measurement sites, pixels, are indicated by points in the surveillance area. Sensed variables including atmospheric temperature, water vapor density, solar illumination, and others very in space and time. Sampling must follow a policy that enables reconstruction of environmental data with an estimated degree of accuracy that may be specified in advance of sampling.

examples, an attempt to sample at highest spatial resolution may result in an unacceptable latency with respect to visiting environmental regions, resulting in errors in the reconstruction of dynamically varying environmental phenomena.

Thus, the development of a NIMS sampling policy is required in order to minimize reconstruction error for a set of finite resources in node mobility. Our approach assigns the NIMS nodes to operate as "statistical agents" that are commissioned to acquire data regarding variable distributions by appropriately scheduled exploration. This approach is intended to apply to environmental conditions where no prior knowledge exists regarding variable distribution. However, it is also intended to be applicable to instances where domain knowledge may be applied to superimpose rules that focus exploration and sampling (for example, to those regions estimated by domain knowledge to require the highest spatiotemporal sampling rate).

In the following discussion, we review choices of sampling policies, including our proposed policy, for reconstruction of a map of environmental variables. Note that this map may be composed of a single variable such as the sensor attributes the robot carries (i.e. temperature, humidity, gas composition, or others) or it may be a more complex utility function such as a map of the correlation between the variables themselves (for example the correlation of atmospheric gas composition and temperature) or correlation between images collected in multiple spectral bands.

The following important assumptions focus our initial our analysis:

1. The reconstruction of a spatiotemporal map of dynamic phenomena using a single robotic element inherently implies a contention between spatial and temporal fidelity and system coverage. This robotic sampling system is intended to determine its own sampling distribution based only on its measurement results. However, we consider the limit where the rate of change of phenomena is low to the extent that it may be considered static during the time required for the NIMS

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system to complete its sampling cycle over those points determined to be visited by the sampling policy. In the limit where the sampling policy and phenomena characteristics result in sparse sampling, then this approximation is valid. However, examples will be explored and new approaches will be required that exploit multiple robotic NIMS nodes to reconstruct maps of rapidly evolving phenomena in large spaces.

2. Analysis assumes that the NIMS infrastructure enables robotic sensor localization at a degree of accuracy such that motion contributed negligible sensing uncertainty. (This is readily achieved with present NIMS architectures that exploit odometer measurements for motion along fixed cables.)

3. For the present investigation, it is further assumed that no sensing errors are present and that the phenomena understudy are spatiotemporally continuous. While these assumptions are broadly applicable, in the future, these assumptions will be lifted. Specifically, NIMS will be applied to *in situ calibration* of sensors and instruments, the detection of sensing uncertainty, and the adaptation of the NIMS system to enhance sensing performance.

IV. SAMPLING POLICY

Adaptive sampling policies investigated in the past include:

A. Uniform (Regular or Grid) Sampling

Uniform sampling methods acquire measurements at uniform intervals. The primary disadvantage of this method is, of course, high resource cost since in order to achieve adequate sampling density at those regions requiring greatest density, the sampling density must be uniformly high everywhere. Secondarily, the lack or randomization in sampling introduces a potential error in sampling of periodic phenomena.

B. Random Sampling

The random sampling procedure assures that each element in the pixel population has an equal chance of being selected. As for uniform sampling, resource cost is potentially prohibitive and may lead to loss of temporal fidelity.

C. Stratified Random Sampling

This adaptive method is well-suited to sampling in the presence of *environmental heterogeneity*. Here, the environment is partitioned into strata in which statistical characteristics of environmental variables are determined. Random sampling may occur in each stratum. This method offers the benefit that adequate sampling density is applied to those strata for which estimation error is high. However, at the same time, those strata not requiring high density sampling are not over-sampled at high resource cost.

D. Nested Stratified Random Sampling

This adaptive method uses the stratified random sampling approach but bases sampling density on the variance of measured variables within each stratum. This method continues the stratification process and creates a hierarchical tree of strata. It has been applied to soil analysis with up to a
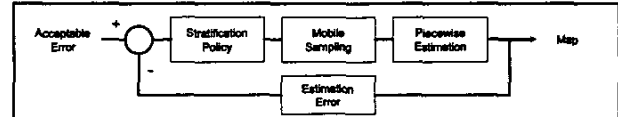

Figure 3. The NIMS sampling policy described here is intended to produce a map of an environmental variable with a specified maximum acceptable error between the reconstructed (computed) map and estimated actual phenomena. Adaptation of the Stratification Policy determines the rate and location of Mobile Sampling, in response to an estimated error level.

seven stratification stages.[18-19] Disadvantages of nested stratified sampling have appeared in fixed sensor deployments where the requirements on stratification may vary, rendering the stratification sub-optimal. However, for NIMS environmental monitoring, the sampling policy may be continuously adapted to follow evolving requirements.

V. ROBOTIC ADAPTIVE SAMPLING

A. NIMS Sampling Policy

We developed a Nested Stratified Sampling method for NIMS as a "divide and conquer" algorithm (shown in Figure 3) that defines a sampling "tree" where individual strata occupy leaves on this tree. Here,
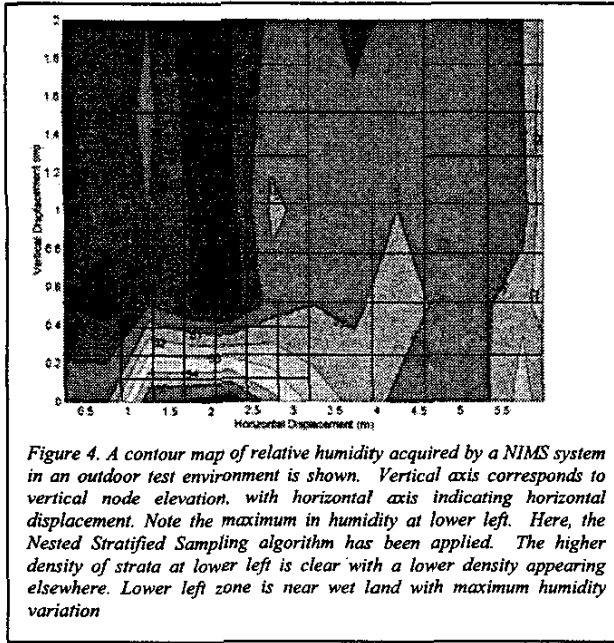
- First the complete surveillance area under investigation, is stratified into a number of strata, m.

- Then, environmental variables are sampled in each strata with a number of samples proportional to the area of the strata with:

(1)
$$\rho = \alpha_r P_S$$

(2)
$$\mu = \sqrt{P_S / \rho} = 1 / \sqrt{\alpha_r}$$

Where, ρ is the number of sampling points in the current stratum, μ is the mean of vertical and horizontal step size in terms of pixels, P_s is the number of pixels in the current stratum and α_r is a design parameter with the stratum rank indicated by r. In practice parameter α_r may be selected based on domain knowledge and have a linear relation with α_{r-1}.

- Then, data is acquired in the current strata using (2). The variance of these data are computed and, if the variance is found to exceed a threshold value, stratification is again performed to produce reduced area strata with an equivalent number of sample points.

- Iteration of this process continues until variance falls below a desired threshold.

- A stratum is regarded as fully mapped when the variance of each leaf of this stratum tree is observed to fall below threshold. This process continues until the entire region has been sampled with a stratum rank

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Figure 4. A contour map of relative humidity acquired by a NIMS system in an outdoor test environment is shown. Vertical axis corresponds to vertical node elevation. with horizontal axis indicating horizontal displacement. Note the maximum in humidity at lower left. Here, the Nested Stratified Sampling algorithm has been applied. The higher density of strata at lower left is clear with a lower density appearing elsewhere. Lower left zone is near wet land with maximum humidity variation

Figure 5. The variogram of the data set of Figure 4 is shown in the upper panel. The lower panel displays the quad-level tree. Lower rank regions of the tree correspond to high variance zones while higher rank regions correspond to low variance zones. Leaf zones may show different areas and but their variance falls below a certain threshold. The leaves can be used to create a contour map of the environment. The tree also gives and estimation on the upper bound of the variogram value at each rankl depending on the number of leaves node at that rank..

B. Maximum and Minimum Sampling Point

If we define location of a stratum inside the tree as the rank, r, of that stratum then the population of pixels in each of the strata is:

$$(3) \qquad P_S = N_{pixels} / m^r$$

$$(4) \qquad P_S = (A / A_{pixel}) / m^r$$

Where P_S is the number of pixels in the current stratum, N_{pixels} is the total number of the pixels in the surveillance area, A is the surveillance area, A_{pixel} is the size of each pixel and m is degree of stratification. The maximum depth of the stratification tree is:

$$(5) \qquad d_{Tree} = Log_m^{(A / A_{pixel})}$$

Since at each step we effectively α_r the sampled point then the maximum number of sampling point is:

$$(6) \qquad S_{max} = N_{pixels} \sum_{r=1}^{r=d_{tree}} \alpha_r$$

Where, S_{max} is the maximum bound on the number of sampling points in the extreme case of a complete random system. A complete random system is a system for which in the limit of the smallest indivisible strata ($n_{pixels} < m$) the variance of values of all neighboring pixels exceeds the threshold variance). The minimum number of sampling points is:
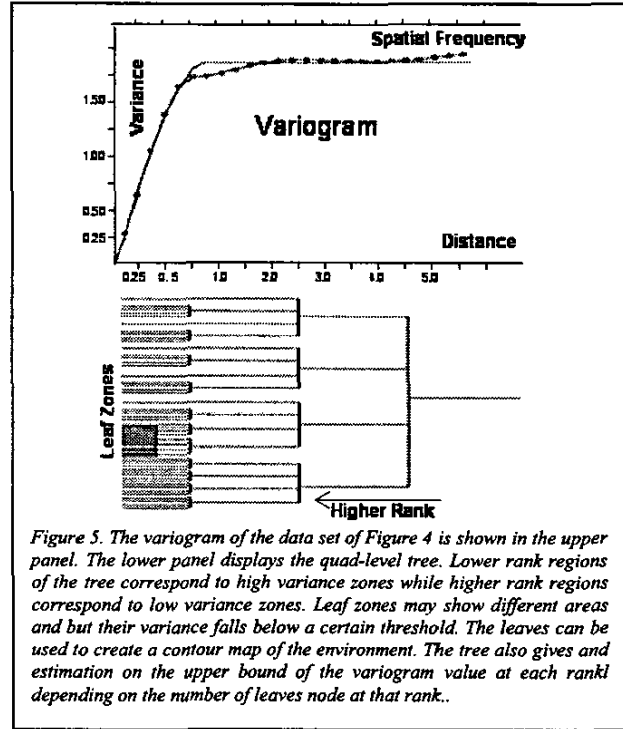
$$(7) \qquad S_{min} = N_{pixels} \alpha_1$$

S_{min} and S_{max} show the minimum and maximum bound on the number of sampling points. Note that performance of adaptive sampling policy in the worst case is equal to a simple random sampling with S_{max} samples of the population. In this case the penalty of the adaptive sampling policy is (d_{tree}-1) additional sampling sweeps. In general, the number of sampling points is equal:

$$(8) \qquad S = N_{pixels} \sum_{l=1}^{l=d_{tree}} [(A_l / A) \sum_{q=1}^{q=r_l} \alpha_q]$$

Where, S is the number of sampling points over all leaf stratums. Leaf stratums are stratified sections for which variance is below the variance threshold and hence has not been stratified further. A_l is the size of the leaf stratum and r_l is its rank in the tree.

C. Error Estimation

This system ultimately converges to produce a piecewise estimated map of the environment within each stratified block, represented by the mean of that stratum and its variance.

Our Estimation of the environmental variable map is then represented by:

$$(9) \qquad \hat{M}_{x,y} = \hat{Z}_L(x, y) \qquad\qquad x, y \in L$$

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Where $\hat{M}_{x,y}$ is map estimation at point x,y and $\hat{Z}_L(x,y)$ is the estimation of the average of highest rank stratum (leaf stratum) that contains point x,y. The mean square root error of this estimation of map is then equal to:

$$(10) \qquad \hat{\delta} = \sum_{i=1}^{X_p}\sum_{j=1}^{Y_p}(z_{i,j} - \hat{Z}_L(i,j))$$

Where, $\hat{\delta}$ is the map estimation error, X_p and Y_p are the maximum number of pixels in X and Y axis, $z_{i,j}$ is the sampling pixel at point i,j and $\hat{Z}_L(i,j)$ is the average value of the leaf stratum that the pixel belongs to it.

In practice a more sophisticated spatial mapping technique, for example, that of Kriging[20] may be readily used here leading to reduced estimation error in specific applications.

D. Convergence Properties

Convergence condition of this sampling algorithm depends on the spatial distribution of data. There are existing techniques for specification of sampling characteristics for environments. One such tool that has received much attention is the *variogram* [21]. The variogram reveals the randomness and structured aspects of the spatial dispersion of a given variable. The variogram is a plot of the average square difference between the values of a spatial variable at pairs of points separated by a lag distance versus the lag itself (Figure 5). The *empirical variogram* γ (h) is calculated as

$$(11) \qquad \gamma(h) = \frac{1}{2N(h)}\sum_{i=1}^{N(h)}[y(x_i) - y(x_i + h)^2]$$

where h is the lag (in pixels) over which γ (semivariance) is measured, N is the number of observations used in the estimate of $\gamma(h)$, and y is the value of the variable of interest at the spatial position x_i. The value $y(x_i + h)$ is the variable value at lag h from x. This calculation is then repeated for different intervals of h. The empirical variogram describes the overall spatial pattern of sample data.

This adaptive sampling approach is sensitive to variogram value and adapts sampling density of the phenomenon in accordance with variance. It samples the environment at high lag values and based on variance of the information, stratifies the environment leading to lower lag distances and provides an estimate of the variance at these less lower lag distances. In practice, for most phenomena, the variogram monotonically decreases from higher lag distance toward lower lag distance. In those cases this sampling approach converges toward a stratified tree.

There are some rare cases in which the variogram of a phenomenon may exhibit temporal fluctuation or periodicity. Spatial periodicity may occur in the environment (for example as a result of cultivation and land management. In such cases the variogram displays a local minimum point near the variance

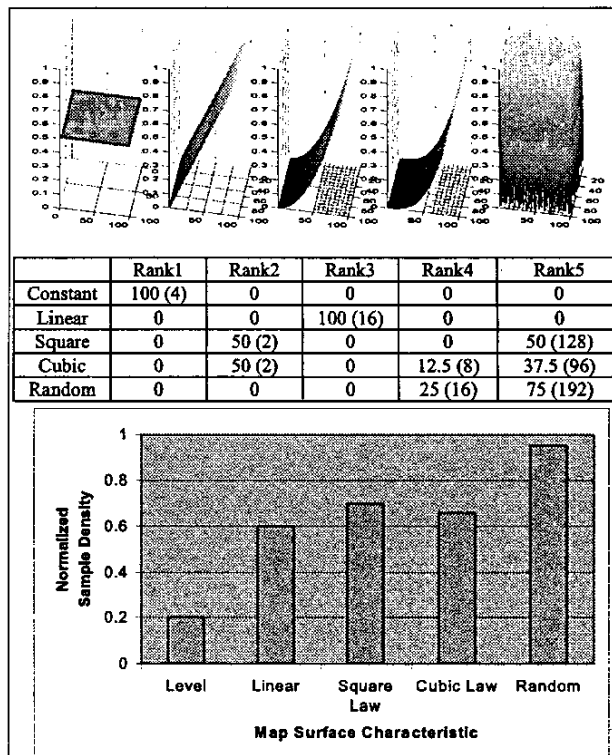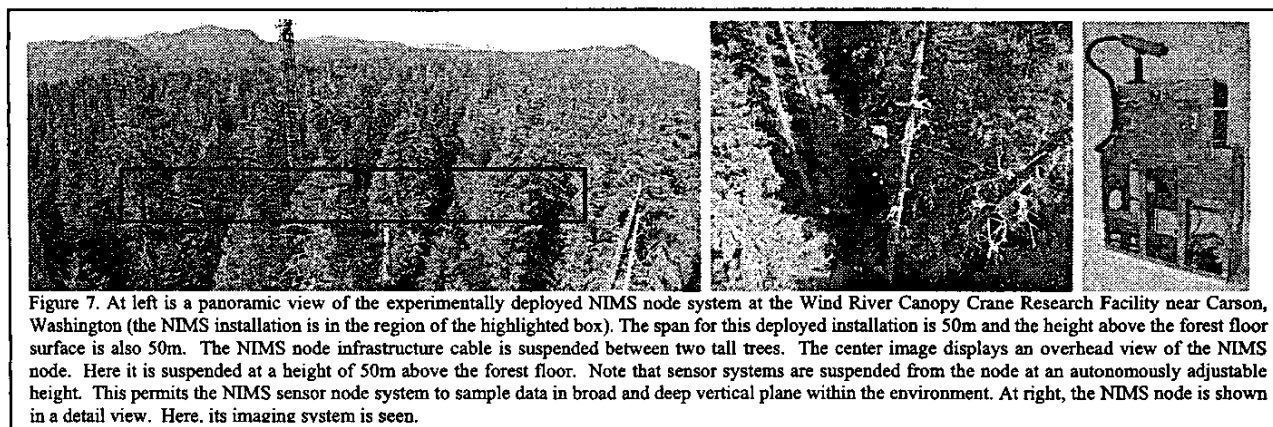|	Rank1	Rank2	Rank3	Rank4	Rank5
Constant	100 (4)	0	0	0	0
Linear	0	0	100 (16)	0	0
Square	0	50 (2)	0	0	50 (128)
Cubic	0	50 (2)	0	12.5 (8)	37.5 (96)
Random	0	0	0	25 (16)	75 (192)

Figure 6. The upper images display characteristic map surface topographies where the vertical axis represents an environmental variable value and the horizontal axes represent the spatial coordinates associated with NIMS node motion. From left: A level surface, linear, square, cubic and random surface are shown. The table shows the percentage of the area covered by different leaf ranks (leaf numbers) for each of those functions. It is clear that as non-linearity increases the stratification process shifts from low ranks leaves to higher rank leaves. The lower graph shows the dependence of sampling density on the characteristics for these typical surfaces. Here, sampling density is normalized with respect to the maximum sampling density of 2500 points for this system.

threshold, complicating the search for an optimal sampling solution. A method that may avoid the effects of such local minimum include the proactive exploration of continued stratification even after algorithm convergence is observed

E. Motion Policy

For this investigation, it is assumed that the NIMS node system has either been provided with an obstacle map (limiting its range of motion) or this obstacle map has been discovered through use of depth sensors.

The motion policy of the NIMS node is orthogonal to its sampling policy. A robot may support a wide range of sampling policies including the adaptive sampling policy in a raster scan fashion. In the case of the adaptive policy the sampling step size scales linearly with location in the sampling tree. Adding the assumption of the presence of any temporal variability during the map frame time, highlights the importance of a motion policy since this is required for minimizing distortion of measurements in distributed locations. The raster scanning method used for the experiments reported here follow a "comb" pattern, relying on vertical excursions of

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Figure 7. At left is a panoramic view of the experimentally deployed NIMS node system at the Wind River Canopy Crane Research Facility near Carson, Washington (the NIMS installation is in the region of the highlighted box). The span for this deployed installation is 50m and the height above the forest floor surface is also 50m. The NIMS node infrastructure cable is suspended between two tall trees. The center image displays an overhead view of the NIMS node. Here it is suspended at a height of 50m above the forest floor. Note that sensor systems are suspended from the node at an autonomously adjustable height. This permits the NIMS sensor node system to sample data in broad and deep vertical plane within the environment. At right, the NIMS node is shown in a detail view. Here, its imaging system is seen.

the NIMS measurement node over the entire measurement range followed by horizontal steps.

VI. SIMULATION RESULTS

Sampling efficiency in this approach depends on the nature of the variable map "surface". While this sampling method finds the minimum number of required sample points to achieve a desired accuracy in reconstructed data, the advantages of this approach are greatest for systems that display spatially localized variance. Of course, for environments displaying a high variance the density of sample points may always be high. This has been investigated in simulation.

We have evaluated sampling algorithm response to representative surface shapes. These include a 1) uniform, level surface, 2) a surface displaying a linear slope in height, 3) a surface displaying a square law characteristic, 4) a surface displaying a cubic law characteristic, 4) and a surface displaying a random surface height variation. In all these simulations the surveillance area was 100×100 pixels, the span of the signal was between zero and one and the threshold variance was 8% of the full span of the signal. This means that in our simulation, adaptive sampling policy guarantees a piecewise error estimation in which, estimated error bounded to the threshold variance. We have investigated the effect of increasing nonlinearity for the same error on the number of sampling points while estimation of error is bounded to variance threshold.

Figure 6 shows the effect of this map characteristic on the stratification process. As the map characteristic increases in order, as expected, the density of sampling points increases from 500 samples to 2375 samples in the case of random distribution. The maximum theoretical bound on number of samples in this case (based on equations 5 and 8 above) is 2500 for a simple random sampling policy.

VII. NIMS DEPLOYMENT

We have deployed a NIMS system for investigation of microclimate dynamics phenomena with measurement of atmospheric temperature, humidity, and solar illumination (measured in the Photosynthetically Active Radiation (PAR) spectral band. In addition to local deployments near our facilities an experimental deployment has also been completed at the Wind River Canopy Crane Research Facility [22] near Carson, Washington, located in the Wind River Experimental Forest. The NIMS deployment included a complete system with NIMS sensor nodes (carrying both vertical and horizontal mobility), solar cell energy harvesting with sustainable operation, batteries, power transfer system, and sensors including an imager and microclimate dynamics sensor systems. This node spanned a 50m wide transect that was 50m deep in a region between trees (Figure 7).

VIII. FUTURE WORK

Each of the many NIMS environmental robotics applications will rely on adaptive sampling methods that include those described here. Examples of future development include:

- Systems and algorithms that permit accurate reconstruction of data in the presence of rapid temporal variation of environmental variables.

- Methods combining mobile and fixed sensor nodes that may remain at a location or be adaptively relocated, on demand, by the NIMS system.

- Coordinated sampling algorithms linking multiple mobile and fixed devices. Here, the challenge of meeting sampling demands in space and time will be partially relaxed by the availability of multiple assets that may be properly distributed.

- Using more accurate piecewise linear tree estimation of a phenomena. Estimation of leaf area can be replaced by higher order estimators at each stratum [23] to increase sampling efficiency especially as nonlinearly of the phenomena increases.

- Finally, while the sampling method reported here relies on a proactive exploration of the environment (followed by the execution of an optimized sampling policy) other sampling methods will be developed that are reactive to events.

- These sampling methods and NIMS node systems are being prepared for further long term deployments (multiple seasons) and experimental investigations of

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environmental phenomena at the James San Jacinto Mountains Reserve.[24]

IX. CONCLUSION

In this paper, we have described the new Networked Infomechanical (NIMS) methodology that permits the intensive and extensive exploration of environments with mobile, robotic sensor systems. This environmental robotic technology has promising potential for monitoring of natural environments, urban environments, and indoor facilities. Its applications include scientific investigation, public health monitoring, characterization and tracking of environmental contamination and remediation progress, as well as applications in commerce. NIMS offers the unique characteristics of precise mobility in complex environments with low energy, sustainable transport.

A particularly important objective for NIMS monitoring is the spatiotemporal mapping of environmental variables. Here, the objective is to enable a reconstruction of environmental variables in a full three-dimensional space. This meets with the challenge of computing proper sampling density in order to minimize error in reconstruction.

This paper has described an adaptive sampling method that exploits the NIMS system to proactively explore the environment and simultaneously develop a spatially varying map of sampling density with the objective of allowing accurate variable map reconstruction. This, in turn, enables data reconstruction while minimizing required mobility, thereby reducing resource costs associated with investigation. An analytical description of this sampling method has been presented along with simulation results. Finally, experimental measurements confirm the applicability of this technique to environmental robotics applications including microclimate monitoring.

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