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Networked Infomechanical Systems (NIMS) for Ambient Intelligence

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1. Introduction

Networked embedded sensor and actuator technology has developed over the last decade to now enable the vision of Ambient Intelligence. This will fundamentally advance our ability to monitor and control the physical world with applications for consumers, healthcare, the commercial enterprise, security, and for science and engineering in the natural environment. Significant progress has been made in the development of algorithms and complete systems for scalable, energy-aware networking, sensing, signal processing, and embedded computing. Now, new information technology, microelectronics, and sensor systems are being integrated and deployed in some of the first applications in critical environmental monitoring. This progress, however, reveals a new set of challenges. Specifically, distributed sensor networks have not yet acquired the essential capability to monitor and report their own spatiotemporally-dependent sensing uncertainty. Thus, while sensor networks may acquire information on events in the environment, these systems are not yet able to determine the probability that events may be undetected or determine how the combination of calibration error and unknown signal propagation characteristics may degrade the ability to fuse data across a distribution of sensors. For example, in virtually all important application areas, static sensor nodes are confronted with unknown and evolving obstacles to vision or acoustic signal propagation that severely limit the ability to characterize features of interest and introduce uncertainty. Most importantly, self-awareness of sensing uncertainty will be required, for in many applications it is only the sensor network that may be present in an environment and must be depended upon to report its true performance. It is important to note that since it is *physical* phenomena and evolving environmental structures that induce 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.

Figure 1. Networked Infomechanical Systems (NIMS) introduces a hierarchy of fixed and mobile sensing nodes and infrastructure enabling access to complex, three dimensional environments. NIMS mobility provides novel methods for establishing self-awareness of sensing uncertainty. Further, examples of new NIMS distributed services include node transport, physical sample acquisition, energy harvesting and delivery, wireless network relay functions, and many others.

This Technical Report describes a broad new research thrust, Networked Infomechanical Systems (NIMS), that provides networked nodes exploiting infrastructure-supported mobility for autonomous operations and physical reconfiguration. As shown in Figure 1, NIMS infrastructure and mobility allow nodes to explore complex, full three-dimensional environments. This also enables active reduction of uncertainty through physical reconfiguration of sensing nodes and infrastructures. NIMS adds a unique capability for acquisition and transport of physical samples (for example of water or atmosphere) thereby providing methods for detection and analysis of trace components that are not detectable by conventional in situ sensors. System operating lifetime is extended by NIMS infrastructure that provides energy harvesting (for example of solar energy) and energy distribution. Finally, NIMS mobility and aerial deployment provides networking resources that may be located and oriented to optimize wireless links for mobile and fixed node systems.

The remainder of this Technical Report begins in Section 2 with a description of the challenge problem of sensing uncertainty that inevitably appears in complex environments. The NIMS sensor diversity capability is discussed next with its benefits for reducing sensing uncertainty, enabling adaptive sensor fusion, and extending rate-distortion, bandwidth and energy limits in distributed sensor networks. NIMS applications are also described for natural environmental science and civil (built environment) monitoring. Section 3 introduces sensing diversity and its information theoretic foundations. Sensing diversity reduces sensing uncertainty by exploiting the ability to introduce new sensor systems and to reconfigure sensor networks through robotic mobility. Section 3 then continues with description of the fusion-based detection and localization enabled by NIMS.

The development of NIMS introduces essential new tiers in the distributed sensing architecture. These new tiers permit sensing, sampling, and logistics for transport of nodes, physical samples, energy, and data. The NIMS system hierarchy combines static and mobile sensor nodes, and physically reconfigurable infrastructure that provide sustainable mobility in large, complex three-dimensional spaces. This System Ecology and its attributes are described in Section 4 along with the methods of Coordinate Mobility that exploit the System Ecology for self-aware sensing and sampling.

Finally, this Technical Report concludes with a description of a NIMS Ambient Intelligence application with a system deployment in natural environment monitoring.

2. Self-Awareness for Sensing Networks

2.1. The Sensing Uncertainty Problem

Early work in the development of distributed sensor networks has demonstrated feasibility for low power, compact, sensor nodes and wireless sensor networks.[1-5] Scalable and energy-aware networking for densely distributed sensor nodes has been developed.[6-7] In addition, cooperative signal processing methods have been demonstrated.[8-9] Now, a multidisciplinary, international research community is addressing the broad spectrum of information theory, information technology, and fundamental sensing principles, to enable Ambient Intelligence for many applications.

> Together, the requirements for sensing fidelity and autonomous operation create the urgent need for a new distributed sensor attribute, *self-awareness*. Self-awareness provides a sensor network with the means to autonomously determine its *sensing-uncertainty*. The autonomous nature of this self-aware operation is essential. Specifically, many emerging applications for distributed sensor networks require that sensor networks acquire and return data that are critical to users and society. For example, the sensor network may supply information required to guide natural environment protection or physical security. Of course, human operators and other system may not be present at all locations and times in order to provide assurance of proper information acquisition. Thus, scalable, reliable operation demands that the distributed sensor network be self-aware and autonomously probe, report, and optimize its own uncertainty.

Distributed sensor networks provide the critical data source for Ambient Intelligence. Past research has demonstrated feasible operation of sensor networks. However, the value of this data source for Ambient Intelligence depends on ensuring its *fidelity* for acquiring information on physical phenomena. There are many limitations contributing to degraded measurement fidelity in sensor networks; some examples can be provided to illustrate. First, since phenomena under investigation are, in typical applications, inherently unpredictable, then the required density of measurement sampling and sampling rate required to achieve low distortion measurement is temporally and spatially variable and may be unknown. Further, since the development of phenomena and the evolution of the environment are unpredictable, then the propagation of sensor signals is also unpredictable. To illustrate, normal urban traffic patterns, or changes in natural environments, may introduce unexpected obstacles to vision sensors, sharply reducing sensing fidelity. Similarly, changes in foliage patterns or atmospheric conditions affect acoustic propagation.

The unpredictability of arrival of events and the appearance of environmental obstacles to sensing limit sensing fidelity. This, in turn, also limits the capability of sensor data fusion methods that rely on many sensor inputs to test a hypothesis regarding the presence and behavior of phenomena and signal sources in the environment. It is most important to note, however, that it is a fundamental goal for distributed sensor networks to enable *autonomous* monitoring of the physical environment and to acquire information about the evolution of events.

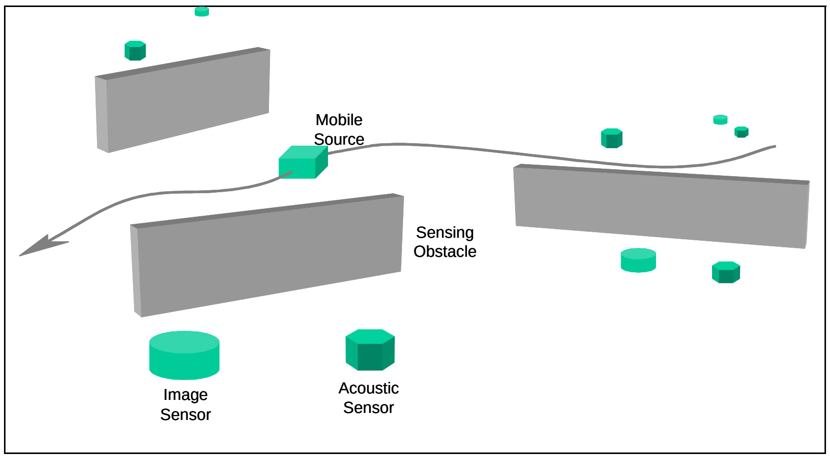

Figure 2. Environments inherently present obstacles to sensing, as shown here for distributed imaging and acoustic sensors. Unpredictable source motion leads to obscuration of the source from sensors.

To illustrate these principles of *sensing self-awareness*, consider Figure 2. Here a mobile source moves through an environment, producing an acoustic signal detectable by acoustic sensors and also presenting a visible signature for image sensors. However, obstacles in the environment (natural foliage in a natural environment, mobile or static objects or structures in an urban environment) lead to fundamental *distortion* in measurements. Specifically, the motion of the mobile source may not be observed by occluded image sensors and signals emitted by mobile acoustic sources may be attenuated and distorted with an unpredictable nature as a result of propagation through distributed obstacles.

It is most important to note that the sensor systems do not presently possess the means to rapidly and accurately determine the presence of obstacles. An obstacle to sensing may not be detectable (for example by an acoustic sensor) and may not be interpreted properly by local analysis of images. Of course, a sensor network may hypothesize the presence of obstacles based on an observation of few or no detectable sources. However, verification of this hypothesis itself requires that a reliable model exist for the expected arrival of sources and that these sources arrive so frequently that a model for obstacle presence may be rapidly derived. This is clearly not a reliable and general solution to this most important problem.

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2.2. NIMS Infrastructure-Enabled Mobility for Sensing Self-Awareness

It is clear that sensing uncertainty is perhaps the primary concern in distributed sensor networks since it limits the acquisition of high-fidelity environmental information and it is this, after all, that motivates distributed sensor deployment. It is also clear that physical reconfiguration achieved through proper forms of mobility may be required to circumvent sensing obstacles (as will be discussed further in Section 4.1). However, here are conditions on the form of mobility that can enhance the full set of distributed sensing operational capabilities. For example, in addition to providing diverse location and perspective and providing navigation through complex environments, it is also essential that mobility methods be predictable and precise. Specifically, the mobility mechanism must *reduce* system-wide spatio-temporal uncertainty as opposed to increasing uncertainty as a result of errors or limitations in motion or navigation. As will be seen, this generally requires the introduction of an *infrastructure*.

The requirements for sensor mobility control for applications in environment monitoring are as follows: 1) Sensor mobility must permit a wide range of location and viewing perspectives. This requires the ability to change separation between sources and sensors over a wide range and choose a wide range of viewing or sensing perspectives. In the natural environment, this will require overhead viewing perspective. 2) Sensor mobility must be precise so that sensor location uncertainty does not degrade sensing uncertainty yet further. 3) Sensor mobility must accommodate complex terrain and surfaces that may incompatible with surface vehicle navigation (or may themselves be disturbed by vehicle passage). 4) Sensor mobility must also be sustainable in that energy requirements and the rate of system degradation must be low. At the same time, the impact of mobility on the environment (for example acoustic noise or powerplant exhaust emissions) must be minimized. 5) Finally, the sensor mobility system must also permit logistics for motion and delivery of components that may include physical samples, energy sources, replacement nodes, and other subsystems.

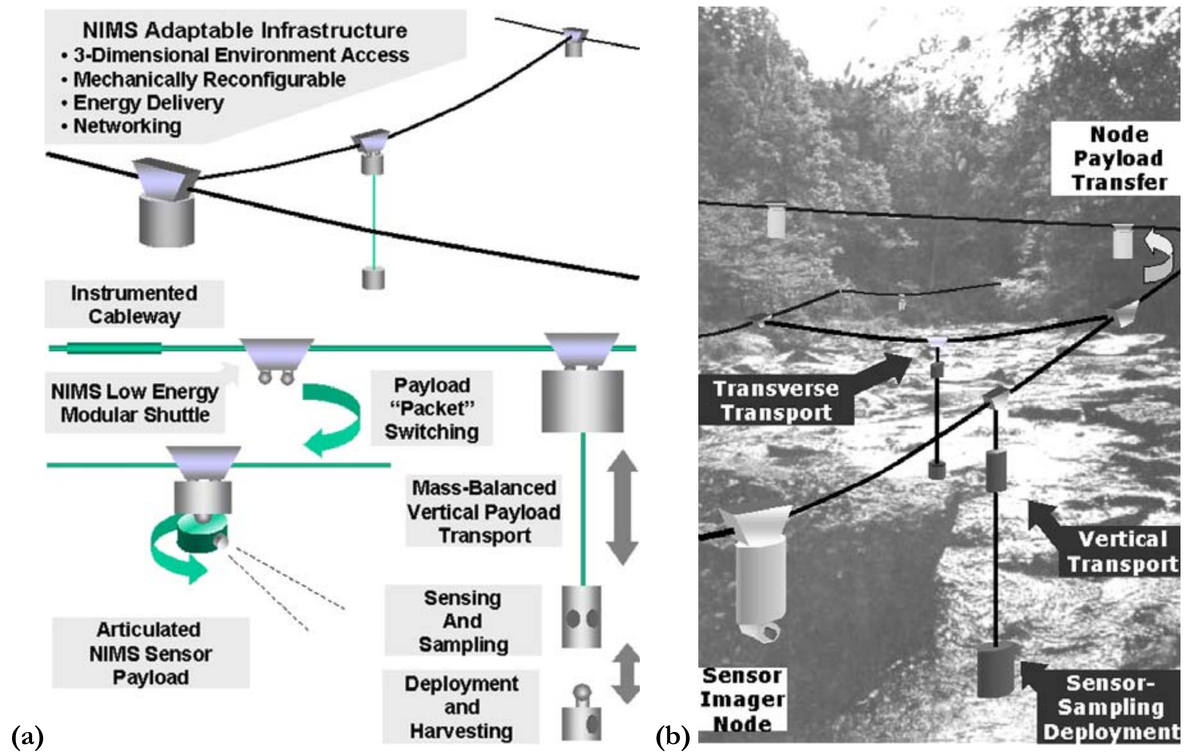

Figure 3. (a) NIMS Systems include fixed and mobile nodes along with instrumented and adaptable infrastructure. NIMS nodes may be fixed to the infrastructure, may move on the infrastructure, or be delivered to locations and recovered by other nodes. (b) A schematic view of a NIMS deployment in a riparian stream environment with distributed sensing, sampling, and node transport

The addition of an infrastructure immediately addresses the above requirements in a way that would not be possible with other robotic forms. While many infrastructure types are anticipated, the "cableway" infrastructure discussed previously and discussed further below provides an example that meets these requirements, and is compatible with a broad range of environmental science applications. Further, it requires small logistics cost for deployment (that is a deployment cost no greater than deploying fixed sensors at elevation). The cableway infrastructure will be discussed with reference to the above requirements. 1) First, the cableway permits a wide range of location and viewing perspectives by allowing aerial suspension of nodes that may themselves probe a three-dimensional volume, as shown in Figure 3a. 2) The cableway provides precise sensor mobility. 3) Also, the cableway system allows sensor nodes to negotiate complex terrain. 4) The cableway system also enables sustainable operation. Energy requirements for mobility are modest and may be made vanishingly small when transport velocity is low and mass-balancing is employed to reduce gravity-work. 5) Finally, the cableway system provides a means to acquire physical samples and deploy sampling systems. It also permits low energy transport of massive payloads (if required) and permits the implementation of logistics for energy, node, and sample transport.

2.3. NIMS Sensing, Sampling, and Applications

The NIMS architecture of fixed and mobile devices and infrastructure enables an expanded set of new applications for distributed sensing and monitoring that were beyond the scope of fixed sensors alone. These exploit the capabilities summarized in Table 1 of Sensing Diversity, Fusion Based Identification and Localization, and Distributed Physical Sampling. These methods will be further described in Section 3.

NIMS Sensing and Sampling Methods	
Sensing Diversity	Sensing Diversity methods exploit mobility to select and distribute available sensing resources to both map sensing uncertainty in space and time and then adaptively reduce this uncertainty.
Fusion Based Identification and Localization	NIMS mobility and the diverse resources available to infrastructure-supported nodes enable a large, multidimensional solution space for optimizing the cooperative identification and localization or sources.
Distributed Physical Sampling	NIMS mobility enables the acquisition of *in situ physical samples* for identification and localization of phenomena by sensitive and accurate *ex situ* methods based on, for example, laboratory analysis.

Table 1. Networked Infomechanical Systems, with its precise and sustainable aerial mobility and reconfiguration capability, enables a series of new capabilities for distributed sensing and sampling.

2.3.1. Natural Environmental Monitoring

Ambient Intelligence has been extended to the natural environment with distributed sensing deployments for fundamental science investigations of phenomena including global change, and for providing the data required for environmental stewardship. The application of NIMS to natural environment monitoring provides a means to reach the full three-dimensional region where the ecosystem exists. This application exploits sensing diversity that addresses the biocomplexity of the natural environment and its obstacles to sensing. Further this application relies on effective identification and localization. Finally, in addition to sensing, NIMS also provides essential sampling capability for the many investigations relying on laboratory analysis of chemical and biological phenomena for which no in situ sensors are available.

NIMS applications also include monitoring of environmental resources with example applications to efficient and safe use of agricultural land, harvesting of coastal resources, management of effluent, and collection of consumer water resources. All of these applications require monitoring by sensing and sampling of complex, dynamic terrestrial and marine environments. NIMS sensing and sampling will provide the unique capability of precise deployment and recovery of sensor systems in harsh aquatic environments. Also, NIMS physical sampling, driven by algorithms based on regular, triggered, or model-based sampling trajectories will allow for acquisition and processing of samples containing critical dissolved and suspended agents for which compact sensing systems do not yet exist. Sample-based measurements of aquatic resources may include monitoring of nutrients (nitrates) and biological pathogens. This also includes monitoring the effect of ecosystem dynamics (estuary flow, currents, tides, wave action, UV radiation) on the origin and fate of these agents.

2.3.2. Public Safety and Emergency Response

Physical safety and security includes a vast range of applications that have been supported by distributed sensors. With new concerns regarding public health and safety, monitoring in urban environments is now critical. Monitoring methods are required that provide high fidelity sensing in complex environments and that may rapidly adapt to emergency. For example, in the event of fire or structural collapse, highly mobile and sustainable sensing systems are required for accurately assessing damage and directing assistance where required. The urban environment presents a high spatial density of obstacles to imaging and sensing. In the event of structural collapse, new obstacles will appear and may create environments that are unsafe for emergency responders.

The NIMS capability for self-awareness of sensing uncertainty brings substantial new value to this application area. Specifically, as remote systems are deployed in environments, it may be that no manual observation of the environment is otherwise available (since no personnel may be present or because the environment may become unsafe for personnel presence). Thus, if environmental events cause sensing systems to be degraded (for example an environmental change introduces a new obstruction to an image sensor) then the NIMS principles of sensor diversity and coordinated mobility will be essential to recover system reliability.

NIMS capability may be deployed in place, integrated with structures, or may be rapidly deployed in response to events. For example, unconstrained robotic systems (ground-based or aerial vehicles) may deploy NIMS infrastructure to provide a means for sustainable, intensive monitoring of a disaster environment with a diverse array of sensing and sampling devices.

3. Networked Infomechanical Systems (NIMS): Enabling Self-Awareness

3.1. Information Theoretic Foundations

Fixed sensor networks inevitably confront sensing uncertainty due to inherent and evolving environmental evolution and the presence of distortion-inducing obstacles. This is manifested as an uncertainty in the support of a hypothesis derived from distributed sensor data. For example, this may result in a reduced detection probability, an identification fault, a tracking error, or a misestimate of the population of individual sources.

We can first consider the problem of detection, identification, and localization of sources by observation of an environment with a distributed sensor network. First, consider N types of individual sensors, $\mathbf{s}_k$, in the environment. Their location will be described by a manifold, M(t), with locations $\mathbf{x}_k$ and time, t. In typical applications of fixed, distributed sensors, these locations will be on the surface in the environment, or perhaps attached to natural or artificial structures that may or may not be under investigation themselves. Now, the set of sources (passive or active objects of interest) appear at locations **y** in a volume V, with location distribution p(y(t)) at time t. Sensors will yield an observation set, Z, from one or more sensors. This set will generally form a time series or sequence of images.

The nature of propagation from a source to a sensor will, clearly, determine the limits to sensing fidelity. Of course, it is this propagation, not the properties of sensors elements or sampling characteristics that set the strictest limits on sensing fidelity. Further, propagation characteristics may include frequency and phase dependent transfer functions as well as interference and noise. For imaging sensors, obstacles in the line-of-vision as well as confusion in background images combine to complicate propagation. The coupling between a sensor and its environment lends another important propagation consideration. For example, the coupling between a ground-deployed seismic sensor and the surface introduces an additional transfer function that must be included in source characterization.

Observations, therefore, depend on propagation gains G(**x**,**y**,t) between sensors at **x** and sources **y** at a time t. Models for propagation gains may be either deterministic or based on the propagation loss statistics of the inhomogeneous medium with respect to different sensing modes. For example, in imaging a 3-dimensional obstruction model is required. It is clearly elevation dependent and thus different parts of the sensor deployment manifold have different loss values, and these values themselves will be time-dependent as the environment evolves.

Together, these contributions to sensing uncertainty have been present in distributed sensing and are well-known in specific applications. Normally, complex site survey, preparation of the environment (for example the creation of a massive pier for a seismic sensor or the clearing of foliage for imaging sensors), and manual effort are devoted to each sensor. However, distributed sensor networks are planned for rapid deployment directly in unprepared, complex environments and will confront sensing uncertainty to a degree not reached for previous, isolated sensor deployments. As will be discussed, there is a new pathway, based on NIMS, for addressing these fundamental problems.

3.2. NIMS Sensor Diversity

NIMS *sensor diversity* methods exploit NIMS mobility and physical reconfiguration to combine diverse sensing types, diverse sensor locations, and perspectives for applications including 1) Reducing fundamental sensing uncertainty, 2) Enabling an actively optimized form of sensor data fusion, 3) Extension of rate-distortion limits, and, 4) Extension of energy and bandwidth constraints.

3.2.1. Reducing Sensing Uncertainty with Sensor Diversity

Sensing uncertainty in a conventional fixed sensor network arises due to the unknown and unpredictable characteristics of G(**x**,**y**,t). As was noted previously, since the arrival of events are unpredictable, and since obstacles to sensing may themselves be passive (and not detectable by sensors) then the fixed sensor network may generally never *determine* or *reduce* its uncertainty. However, self-awareness of sensing uncertainty can be obtained through sensor diversity. To illustrate, consider Figure 4. Note that for this example, increasing the density of sensors deployed on the surface has negligible impact on sensing uncertainty if, as is often the case, the density of obstacles is similar or even greater than that of sources. An example is that of imaging sensors deployed at a low level (the understory) of a forest environment. Here, experimental observations show that obstacle densities limit line-of-site viewing segments to distances of only one to several meters. Thus, high probability detection of sources via imaging (should this be required to support a scientific investigation) requires an extremely high sensor deployment density.

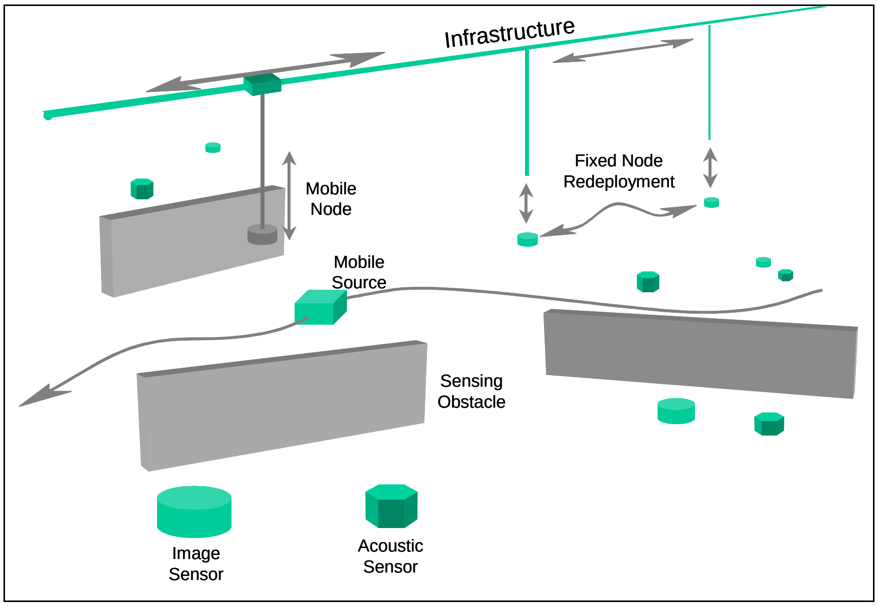

Figure 4. As shown in Figure 2, mobile sources propagate through the environment and are generally not observable by fixed distributed sensors deployed at the surface. However, the introduction of Networked Infomechanical Systems (NIMS) mobile devices permits nodes to be physically relocated at optimized locations and with optimal viewing perspectives. In addition, the presence of many source events may also lead to the physical redeployment of a fixed node to an optimized location and viewing perspective.

Sensor diversity, however, introduces methods for determination and reduction of sensing uncertainty through, deployment, operation, and re-deployment of sensors that provide diverse detection methods and perspectives.

An illustrative example is shown in Figure 4. Here we observe that sensing obstacles obscure the mobile source from the view of fixed sensors. However, the introduction of sensor diversity through use of sensor nodes that are mobile and supported by (in this example) an overhead infrastructure offers a reduction in sensing uncertainty by placing image sensors in optimal locations and affording optimal viewing perspectives.

Sensor diversity itself depends on NIMS for providing viewing perspective and enabling precise mobility. NIMS, in this example, itself depends on infrastructure for both the support of nodes and the ability to move and replace nodes. Note that in contrast to conventional mobility systems, the NIMS infrastructure provides a high degree of certainty associated with motion and orientation, as required to reduce uncertainty.

3.2.2. Exploiting Sensor Diversity by Active Fusion

The advantages of sensor diversity and an example of its implementation are provided in an *active sensor fusion* method that seeks to optimize sensing uncertainty for each component contributing to the derived hypothesis. This can be applied to the source identification problem. Here an optimization criterion is to select the largest likelihood $p(\mathbf{s_k}|Z(\mathbf{x},\mathbf{y},t))$ according to a fusion rule over the set of sensor locations **x** (each within **M**), over the ensemble **y** of locally relevant source positions (within V), at some time t, subject to a global cost constraint for placing sensors at the best locations, and the propagation model, G.

Note that again, in contrast to conventional approaches, the location of sensors, **x**, may be actively adjusted in optimization. Of course, there is a cost for this sensor re-location. However, the cost constraint above can further include the energy cost of re-location as well as the cost processing data and communicating decisions to the end user. When a fidelity constraint (e.g., identification probability and latency) is added, this is then a network rate-distortion problem, with distributed lossy source coding and possibly cooperative communication. In other variations, sources may actually follow some trajectory, each node may follow a distinct trajectory (possibly responsive to the source), and the fusion rules/optimality criteria can be varied. While not always the best approach, the Bayes criterion is particularly interesting, since optimal fusion among multiple sensors for detection problems amounts to a maximization of mutual information [10,11]. It thus applies to sensors of widely diverse types (e.g., imagers and acoustic), with the main problems being determination of prior probabilities and the specific signal conditioning that leads to conversion of observations into sufficiently good approximations of the likelihoods with reasonable complexity. More generally one can form weighted sums of (quantized) log-likelihoods for other optimization criteria.

While many versions of these problems are being studied in the context of static sensor networks [8,9], NIMS dramatically transforms the available solution space. Rather than sensors remaining at static locations constraining the network to the sensing performance first observed at deployment time, the manifold of permitted locations is much larger and more topologically complex. In addition, the cost of moving nodes among positions is relatively low. Therefore, nodes can be redeployed to take advantage of better knowledge of p(y) or G acquired through sustained observations, or with actual changes in the source and obstruction distributions (e.g. with season). Further, the larger manifold of permitted positions enables choice of positions with lower obstruction, thereby allowing improved detection probabilities or lower communication energy costs between the static nodes and the infrastructure. The ability to reposition static nodes and also have nodes that sense while moving provides greater scope for investigation of adaptive algorithms. This allows, for example, a direct implementation of iterative optimization algorithms.

3.2.3. Extending Rate-Distortion Limits

Another example illustrating the benefits of sensor diversity achieved by NIMS mobility is the network rate-distortion problem. For the Gaussian n-helper problem, a main sensor X_0 and n helpers X_1, X_2, … X_n observe a Gaussian source and then fuse their information while minimizing the set of transmission rates $\{R_0, R_1, \ldots, R_n\}$ subject to a distortion (fidelity) constraint D. The resulting rate-distortion region is bounded by [11]:

$$R_0(D) \geq \frac{1}{2}\log^{+}\left\{\frac{\sigma_0^2}{D}\left[\prod_{k=1}^{n}(1-\rho_{0k}^2+\rho_{0k}^2 2^{-2R_k}\right]\right\}$$

where ρ_{0k} is the correlation between observations at sensors 0 and k. As usual, $\log^+(x) = \max\{\log(x), 0\}$. For static networks, the sensor positions are fixed and the adaptation choices are limited to determining which nodes will participate in fusing information and at what rates. In the context of NIMS, on a local scale one can additionally ask for a given node deployment, manifold M, propagation model G and source distribution p(y) where the next node should be placed to minimize the expected rate, over the ensemble of source positions (or trajectories). Similar questions can be posed in terms of communication cost, rate savings that would be realized by repositioning some or all of the sensors X_n, or some combination of these quantities. The solution may serve for example as the iteration in a greedy deployment algorithm, possibly supplemented by occasional redeployment steps. Alternatively, this question may be asked in terms of specific estimates of source locations for tracking of a mobile source as it traverses the volume V, and based on the model of source motion and the constraints on node mobility how the nodes should be marshaled in a neighboring region. A global planning problem is to consider detection probabilities for nodes with given location distributions within a manifold M, and assess detection probabilities according to some fusion rule given G and p(y) (e.g., over the ensemble of locations). Then variations in M and node density may be considered to determine whether the average detection probability improves to meet the desired performance level.

3.2.4. Extending Energy and Bandwidth Limits

The NIMS infrastructure also dramatically changes the energy and bandwidth constraints for these optimizations so as to radically transform the solutions. Thus, while in static sensor networks energy constraints dictate intense processing at sources with careful management of observation duty cycles [12], in NIMS, the nodes connected to the cable network may have no such constraints, enabling a rich set of design trades that exploit the asymmetry between different classes of observers. The nodes and infrastructure may also be laid out to allow for lower energy ground to air links (single hop) or with a small number of hops between any given node and the infrastructure to mitigate scalability [13-16] and energy consumption issues. NIMS also allows local signal processing and sensing to be augmented with new resources, leading to a far less uniform distribution of resources throughout the sensing volume V (slowly varying with time), to achieve a given level of observation fidelity. That is, resources can be adaptively matched to actual conditions.

3.3. NIMS Fusion-Based, Detection, Identification and Localization

Fusion-based detection, identification, and localization of sources through cooperative algorithms operating over distributed nodes are fundamentally limited in the event of sensing uncertainty. Typical distributed sensor applications expose sensing elements to a variable, uncertain sensing environment, and with potentially uncertain sensor calibration. This fundamentally degrades the performance of essential cooperative algorithms that must be relied upon for the essential function of fusion-based information acquisition regarding sources. NIMS self-awareness and sensor diversity through physical reconfiguration directly addresses this most important and long-standing problem.

For distributed sensor networks, source identification involves an interaction of layered suites of signal processing algorithms, networking algorithms, and distributed database access. The generic optimization problem is to maximize the mutual information subject to resource constraints (for example, energy reserves and number of nodes in the volume, V). In static networks, the energy constraints dictate layered processing, with low energy operations at the bottom level operating with constant vigilance, and higher levels operating episodically as detection thresholds are met or activation signals from other nodes are received. Similarly, nodes whenever possible process information to avoid communication; such as cooperative fusion of (approximate) likelihoods among a subnetwork of nodes, and then, only if necessary, exchange raw data for coherent combining. Data is queued based on its likelihood of being needed in a later query from a neighbor or remote observer. Node density can be adjusted to reduce the likelihood of more than one target being in the regard of a sensor so that expensive cooperative source separation algorithms can be avoided, with some balance against node cost. These problems individually and collectively are the subject of many interesting research efforts.[18-21]

Note however that distributed fixed sensors are constrained to the limited locations and orientations X, and fixed energy resources that are provided at time of deployment—both planned based on knowledge of p(y) and G at deployment time. However, the environment provides unscheduled, surprising events that are distributed in space and time and may not be compatible with the mix of deployed sensors or other critical aspects of their deployment. While the group of nodes that participates in fusion in response to an event may adapt, the performance may not be adequate unless the initial deployment will greatly overprovision resources in the environment; that is, node densities and energy reserves corresponding to worst case conditions throughout the entire volume, V.

All of the design considerations for fixed networks play a role in NIMS, but mobility and the far greater resources available to nodes connected to or serviced by the infrastructure allow for a far broader source identification solution space. This is illustrated by the example in Figure 4. Here, the path of a mobile source is not detectable by sensors that are obstructed from viewing this source. The obstruction may be an obstacle to viewing by imaging sensors (for example foliage in an natural environment), an obstacle to acoustic propagation, or may also be a source of interference for a chemical sensor and or an ecosystem event that separates a chemical sensor from its medium to be sensed (e.g., change in water level). Sensor diversity addresses these problems: if optimal fusion of information from the resources deployed in a set of positions X is not sufficient to meet detection or identification performance criteria, then NIMS will allow resources to be re-deployed automatically. Self-aware operation results from this approach through algorithms that use diverse sensor types and perspectives to continuously perform measurements of sensing performance to ensure that adequate sensing coverage exists for establishing a high probability for detection of events.

The (Bayes) data fusion problem in this context is to adapt the fusion rules to maximize the probability of selecting the most likely hypothesis based on the prior information and the set of observations. Consider the recursive estimation of log-likelihood functions for a single sensor:

$$\ln p_S(s \mid Z^r) = \ln p_S(s \mid Z^{r-1}) + \ln\left[\frac{p_Z(z(r) \mid s)}{p_Z(z(r) \mid Z^{r-1})}\right]$$

where S is the set of hypotheses, z(r) is the observation taken at time r and Z^i is the set of observations up to time i. Taking expectations on both sides, this equation may be interpreted as stating that the posterior information is equal to the prior information (to time r-1) plus the information obtained from the current observation. Data fusion is obtained by replacing the last term by a sum of the log-likelihoods over the set of sensors [11]. A variety of weighting strategies are possible, resulting in a broad set of fusion algorithms. Unfortunately, there may be considerable initial uncertainties in the propagation environment, the hypothesis priors, and the calibration of the sensors, all of which make the choice of effective fusion rules difficult.

With NIMS, the ability to deploy a wide variety of devices makes the fusion problem (and subsequent identification problems) both richer and paradoxically more tractable through the ability to reduce these uncertainties. Consider for example the problem of autonomous in situ calibration. Calibration is described by the above equation, where now the hypotheses are known with near-certainty, and the objective remains to determine the log-likelihood function given a test observation set (a standard) whose priors will generally not match those of the environment to be sensed. In the fusion context, the reliability of the measurements of individual sensors can be gauged according to how the likelihoods they report compare to the known hypotheses. With NIMS, it is possible to obtain the standards in several new ways. The shuttle network can actually create events: broadcast sound patterns, present a visible target for detection by imaging sensors, and introduce a seismic signal to calibrate acoustic, imaging, or seismic sensors, respectively. This enables the distributed determination of G. It may also transport an instrument that has been calibrated off-line into a region and measure the test events to precisely determine G and also measurement errors of instruments in its vicinity. Alternatively, samples can be collected and analyzed off-line, with the results compared to elements in the field. Based upon the model for instrument drift, an interpolation function can be applied to adjust measurements made in between calibration events.

Note further that there is no essential difference between determination of G and the basic update required for adaptive data fusion. In both instances, observations reduce the uncertainties and can serve as one step in a recursive update of the log-likelihood function. However, when observing natural phenomena, there will be decision uncertainty so that less weight will be assigned in updating according to the degree of that uncertainty. Further, in dealing with heterogeneous sensing modes or instruments with different accuracies (or calibration confidence) again not every observation will be accorded the same level of reliability. Indeed, unreliable sensors can be detected based on the extent their reported likelihoods match the weighted group consensus. New instruments can be brought into a region in which there is insufficient consensus or progress in reducing measurement uncertainties. Consequently, within the same simple mathematical framework it is possible with NIMS to explore in situ automated calibration, reliability, and adaptive data fusion.

Consider for example the following localization algorithm. Nodes with arrays can estimate direction of arrival (DOA) for a source. It is desired to use the minimum number of such nodes to achieve a given accuracy. One way to proceed is to incrementally add nodes that lead to maximum reduction in the uncertainty following fusion [22,23]. It may be shown that given our current estimate of p(y) based on the sensors making observations, the potential for reduction of uncertainty is the entropy of the predicted DOA minus the entropy of the estimator. Our initial experimental results show great promise for static networks. This basic approach can be extended in NIMS: if the available nodes cannot produce sufficient accuracy, then additional resources can be brought to bear, or nodes moved to more advantageous positions, e.g., using a gradient search algorithm guided by uncertainty reduction. Further, the principle extends to other data fusion problems, provided the appropriate pre-processing can be accomplished to produce an estimate of the marginal reduction in uncertainty.

3.4. NIMS Distributed Physical Sampling

A limitation of the contribution of distributed sensors and even sensing diversity to information acquisition includes the limitations of fundamental sensing elements. A primary goal of enabling scalable deployment of distributed sensors has been that individual elements be compact and low in mass (to reduce the logistics cost of deployment) and to present low energy demands. Of course, it is also required that sensing elements provide reliability with adequate sensitivity (noise-equivalent signal spectral density) in the environment of interest. However, many environmental characterization problems involving chemical sensing (solid, liquid, or gas phase) confront the need for detection of trace elements within interfering media. In addition, these sensor systems may require subsystems for management of media flow and filtering. Also, in the event that trace element detection or isotopic analysis is required for an investigation, then compact sensors may not be available and laboratory-scale spectrometers may be needed. Taken together, these fundamental measurement requirements may limit the capability of conventional distributed sensor networks since the fundamental measurement may not be possible with distributed, compact sensors. However, again NIMS sensor diversity may be applied, but, now with physical sampling capability.

NIMS infrastructure enabled mobility provides another high precision method with the ability to acquire physical samples (solid, liquid, or gas phase) from the environment for transport to centralized assets for analysis. As shown in Figure 5, this includes the ability to acquire a compact sample and in addition to re-provision sensors that may require entire replacement or replacement of materiel required for operations. In addition, the NIMS infrastructure can enable the accurate recover, re-calibration and replacement of sensor systems. The NIMS infrastructure effectively enables a distributed sensor to consist of two components, a remote forward area sampler, and a fixed base and possibly centralized, analysis system.

4. NIMS System Ecology

4.1. NIMS System Ecology

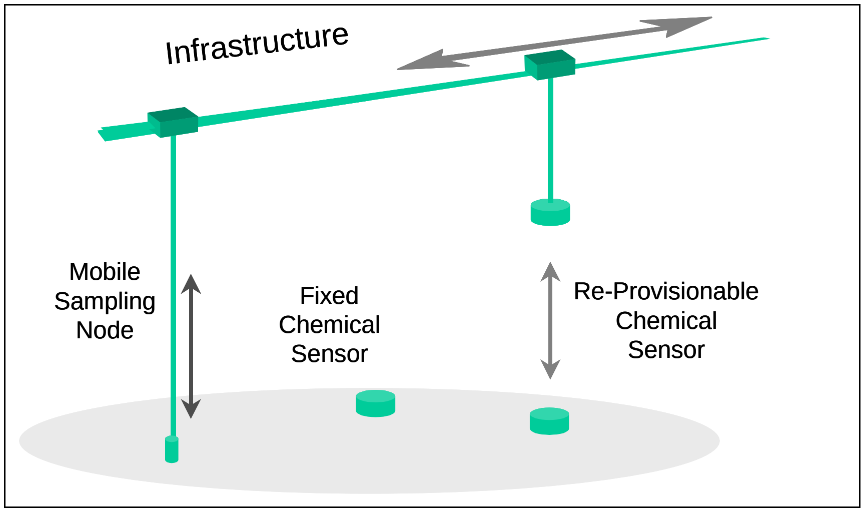

Figure 5. In addition to physical sensing, NIMS enables physical sampling where mobile devices may acquire samples according to an event-driven or scheduled algorithm and convey samples to centralized sample analysis facilities (that may include remote laboratory analysis). NIMS also permits re-provisioning of in situ sensors that may be otherwise limited by a short operating lifetime in the medium.

The central requirements for self-awareness has motivated the development of sensor diversity and coordinated mobility. It is clear that physical reconfiguration (or a very high three-dimensional, volume density of deployed static sensor nodes) is required for enabling autonomous measurement and active reduction of sensing uncertainty in complex environments. Further, it is also clear that to achieve the sustainable, precise, and capable sensing and sampling needed, infrastructure-enabled mobility is required. However, to achieve the ability to adapt to varying environments, and to scale to large deployments, an architecture is required that properly combines the advantages of fixed and mobile nodes and infrastructure. In particular, it is important to introduce hierarchy to enable scalability with the assets requiring the largest resource costs being sparsely distributed and yet supporting a high spatial density of less capable nodes. Further, this hierarchy of node architecture tiers must include standardized interfaces and methods for cooperation between tiers in order to exploit hierarchy in favor of scalable, sustainable, robust and high performance operations. Specific applications may favor a larger distribution of elements in a specific tier and self-aware, self-adapting systems will adjust their own distribution to optimize application-specific resource costs and benefits.

The hierarchy of fixed and mobile nodes tiers along with interaction among tiers, forming a System Ecology, as shown in Table 2. Here, the resources exchanged between tiers along with system architecture define the System Ecology. These resources include data, samples, nodes assets, and energy. In some cases, resources are extracted from the environment (for example, sensor data, physical material samples, and solar energy) and in other cases these are supplied at the time of deployment.

The lowest System Ecology level includes untethered fixed nodes, such as wireless sensor networks that can be precisely and autonomously deployed and maintained by NIMS for study of phenomena at appropriate spatial scales. The next level consists of tethered fixed assets such as wired suspension networks, mobility drive mechanisms, gateways (for energy and communications), position beacons, storage depots, and chemical analysis engines. Together, the three levels in this info-mechanical network provide a means for generating and transporting energy and information, where information may be in the form of bits or physical samples.

NIMS operation algorithms confront the challenges of rapid spatio-temporal formation of teams (linking multiple tiers) that enhance sensing and sampling capability by autonomously allocating appropriate tasks and roles. This is related to previous progress in homogeneous [33] and to a lesser extent, heterogeneous teams [34] for agents and robotics. NIMS, however, departs from previous development by including a System Ecology, organized hierarchically, with a diversity of communication pathways and sensing assets. NIMS operation also depended on a multi-objective optimization, (engaging all ecology dimensions), spatially distributed, and operates over a wide range of temporal scales (for example, defined by the speed of data transport and the speed of mechanical transport).

	Sensing Fidelity Dimension	Energy Efficiency Dimension	Spatial Coverage Dimension	Temporal Coverage Dimension
Mobile Node Tier	Adaptive Topology and Perspective	Enable Low Energy Transport and Communications	Enable Both Sensing and Sampling in 3-D	Enable Long Term Sustainability
Connected Fixed Node Tier	Optimal, Precise Deployment of Nodes	Enable Energy Production and Delivery Logistics	Enable Optimized Node Location and Sensing Perspective in 3-D	Continuous, In Situ Sensing-Sampling
Untethered Fixed Nodes Tiers	Localized Sensing and Sampling Capability	Event Detection and Guidance for Mobile Assets	Access to Non-Navigable Areas	Continuous Low Energy Vigilance

Table 2. The NIMS System Ecology includes Fixed and Mobile Node and Infrastructure Tiers to enable the adaptation required to optimize the Dimensions of sensing fidelity, energy efficiency, and reach the largest spatio-temporal coverage. In this Table, the benefits contributed by each tier to these sensing dimensions are listed.

The System Ecology opens a complex design space that enables adaptation to application demands. For example, the relative demands of spatial sampling density and physical configuration latency both contribute to determining the required rate-distortion operating point. By exploiting the System Ecology, both at design-time and run-time, therefore, the distribution of static and mobile sensors with varying operation range may be selected to match evolving environmental and application demands. For example, at the cost of increased measurement latency, a slowly moving mobile sensor node may explore a region of space with a high sampling point density and at the cost of only few mobile assets. Alternatively, at the cost of node resources, static or mobile nodes may be relocated and remain resident at locations that best benefit the sensing task. Such adaptations may evolve in time and space.

Finally, the System Ecology may include both infrastructure-supported nodes of primary focus in this Technical Report, as well as unsupported and freely moving surface-bound or aerial robotic systems that further augment monitoring capability.

4.2. Reactive and Proactive Coordinated Mobility

Sensor diversity enables a method for determining and reducing sensing uncertainty. Now, since sensing uncertainty arises from limitations associated with *physical* configuration of sensor network nodes, then *physical reconfiguration* in the form of articulation, mobility, and the distribution of new sensing assets is *required* for reducing uncertainty. However, this then creates the requirements for systems that combine sensor diversity based self-awareness to enable *coordinated mobility* for measurement of sensing uncertainty and methods for effecting its reduction.

The relocation of sensing assets may be in rapid response to a triggering event that results from physical phenomena directly or model-based analysis of phenomena. This exploits progress in multi-robot operations,[24-25] however, with the new features of NIMS constrained and precise mobility. This is enabled by *reactive coordinated mobility*. However, the NIMS system many also *proactively* probe the sensor network environment to determine the spatio-temporal regions where sensing uncertainty is expected to be large. This forms a *proactive coordinated mobility operating regime.*

A domain specific application applies to the problem of detection of mobile objects (sources) in natural environments. For example, acoustic sensors may typically be deployed in environments where acoustic propagation is highly variable with source-sensor range, terrain foliage, and meteorological conditions. Yet, it is at the same time required that detection of sources remain effective throughout these variations. Figure 6 illustrates an example where acoustic sensors are able to detect that sources have moved through their area, however, due to obstacles to sensing, these acoustic sensors are not able to support detection of an important large aggregation of sources. A combination of both event detection and an awareness of sensing uncertainty level produce a trigger for *reactive coordinated mobility* of mobile sensors and redeployment of nodes. Figure 6 illustrates that coordinated mobility enables a potentially drastic advance in performance by optimizing sensor population and position with both mobile nodes (imaging devices with powerful viewing perspective) and redeployed sensors. In this example, a static node acts as a trigger and the system is able to physically relocate sensing assets to acquire data at higher resolution and diversity at the trigger location.

Examples of *proactive coordinated mobility* include those where mobile nodes may analyze historical data (obtained via sensor diversity algorithms) and realize that particular areas are mapped with less certainty, causing them to revisit those areas at higher frequency until they are better mapped. Another reason for opportunistic motion is exploration, where in the absence of triggers from the static sensors on the ground, the mobile nodes proactively explore their configuration space, to detect phenomena of interest. For example, it is a general occurrence that in situ sensors may not successfully detect features of interest (i.e. acoustic sensors may not detect sound sources or chemical sensors may not detect compounds for which they are sensitive.) However, of course, it cannot be concluded by the system that the lack of sensor signals means that no sources are present – they may simply be occluded by current environment conditions or be unexpected with respect to initial sensor deployment. Thus, proactive exploration of the sensing space is *essential* for establishing performance. Here, *proactive coordinated mobility* provides a constant background probing of system performance and at the same time surveying for unanticipated events and sources. Without this, the distributed sensor system may detect, at best, only those sources that were expected prior to deployment.

The underlying problem in coordinated mobility for any distributed actuated system is the selection of actions at the individual node level such that the entire system performance is optimized, or at least improved. Typically performance is measured using a task-specific objective function (give example from one of our applications here). This underlying action selection problem is widely studied in the mobile robotics community. Approaches fall broadly under one of two sets of algorithms: those that minimize spatial interference [26] (e.g. avoid collisions between nodes at junctions), and those that focus on task allocation [27-29] which dynamically assign nodes to tasks. Each of the two problems (interference and task allocation) exist for both regimes (proactive and reactive) in which NIMS operates.

4.3. Coordinated Mobility Examples: Sampling

An example illustrating NIMS reactive coordinated mobility is referred to as *sampling*. An example of proactive coordinated mobility is referred to as *exploration*. The exploration operating regime enables the detection and mapping of obstacles to sensing.

Consider the sampling problem where samples are acquired at k source locations $s_1, s_2, \ldots s_k$. The mobile nodes are at locations x(t). Assume there are N mobile nodes, with locations $x_1(t)$, $x_2(t)$, .. $x_N(t)$ and Q nodes on the ground with locations $h_1(t)$, $h_2(t)$, .. $h_Q(t)$. While the NIMS nodes are autonomously mobile, the sensors on the ground are not (however, they may be deployed up by the mobile nodes and relocated as well). The sensors generate observations Z(X,H,Y,t), where Y is the set of source locations.

In a simple version of sampling, the sensors on the ground are pre-deployed at fixed locations, and we can solve for X such that $p(s_k|Z)$ is maximized subject to visibility constraints, G. These constraints express knowledge about the map of the environment. Informally put, this asks the following question – 'What are good vantage points for the mobile sensors in response to a trigger from a sensor on the ground?' For small values of k (few sources), the corresponding task-allocation problem (assigning action(s) to a few mobile nodes), and the interference problem (avoiding mobile node contention for use of infrastructure) by central planning. For small values of k (k <<N) both of these problems can be successfully solved using a central planner, and re-planning is relatively low in computational burden. At medium values of k (k ~ N), a hybrid technique may solve the problem. The NIMS system may be decomposed into a collection of clusters. Each cluster will have some mobile nodes and some fixed nodes as members. $p(\mathbf{s_k}|Z)$ is then approximated by the product of terms depending on the configurations of the clusters instead of individual nodes. A central planner will handle the task-allocation and interference problems across clusters, whereas within each cluster,

reactive techniques will be used to address these problems. At values of k larger than N, synoptic sampling by re-positioning mobile nodes alone, is impossible - a somewhat more complex version of sampling is needed where the sensors on the ground are repositioned by the mobile nodes, followed by a repositioning of the mobile nodes themselves.

This latter version of the sampling problem requires us to solve for H *and* X such that p($\mathbf{s}_k$|Z) is maximized subject to the visibility constraints G. Informally put – 'where should the ground sensors be deployed *and* where should the mobile sensors position themselves?' In this regime the conditional probability of sampling at locations $\mathbf{s}_k$ can be factorized into the probability of sampling conditioned on the positions of the mobile nodes, and the probability of sampling conditioned on the positions of the nodes on the ground. This enables a solution for the configurations of the mobile and ground nodes separately. The task allocation problem for assigning mobile nodes to fixed ground nodes using reactive techniques will follow a greedy assignment, and planner-based techniques will optimize the sum of the distances traveled by the mobile nodes.

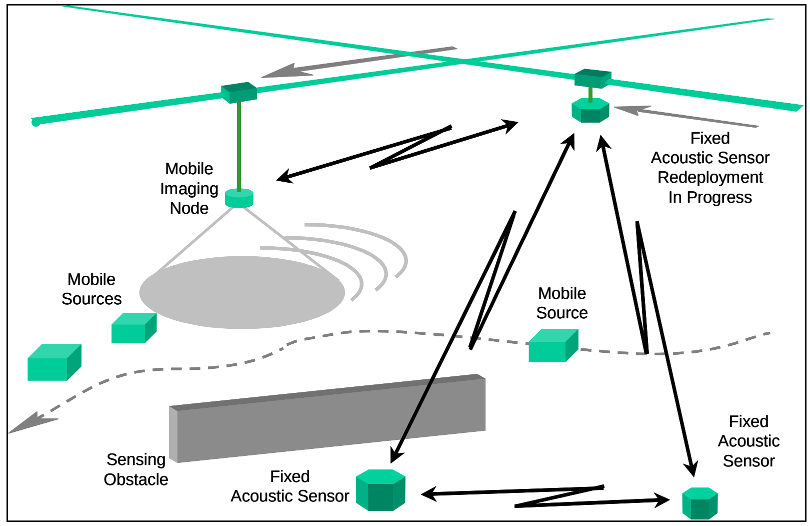

Figure 6. An application example illustrates the aggregation of mobile objects (sources) at a location. In this typical example, fixed acoustic sensors are able to detect motion of some sources, but due to obstacles, are not able to detect the aggregated source population. However, their combination of event detection and awareness of their sensing uncertainty enables a trigger of coordinated mobility where the fixed and mobile elements collaborate on both detection of souces and redeployment of nodes. Coordination includes redeployment of nodes on more than one infrastructure element.

4.4. Coordinated Mobility Examples: Exploration

We now consider a second problem, exploration: an example of the proactive regime. In particular, consider the case where the mobile nodes explore the environment opportunistically to build a map of the environment. The mobile nodes identify the locations of obstacles in the environment to update the visibility constraints G. Formally, this is the problem of minimizing uncertainty in G given the observations Z. This problem has been studied in vision [30] (given the camera pose, estimate the poses of feature points) and robotics [31] (build a map of the environment given the location of the robot(s)). A completely distributed, greedy solution to the problem would be for each mobile node to update G individually. This is likely to lead to suboptimal task allocation (node visits to each area would overlap) and possibly high interference. A hybrid, cluster-based approach could mitigate the sub-optimal allocation to a certain extent, but interference problems would still have to be solved reactively. Another approach will be to embed the 'rules of the road' into the NIMS infrastructure itself, so that spatial contention between nodes would be reduced. However, given that this regime does not necessarily require as fast a response as the pull regime, it may be possible to rely on centralized planning to a large extent. We observe that this version of the problem where nodes explore opportunistically to build a map of the environment is made significantly harder if all the nodes positions are not known precisely. This, more general, problem is that of simultaneously localizing nodes and mapping the environment, and is known to be very difficult to solve in large part due to issues in dataassociation[32]. Incremental but approximate solutions exist [32], which interleave the estimation of node locations with map estimations. These approaches interleave the two estimation problems by maximizing the probability of the node locations and map conditioned on the sensor readings. The most likely map that maximizes this conditional is used to estimate locations. This process is repeated until convergence. We propose to focus primarily on the mapping problem. We will solve the localization problem to a high degree of accuracy for mobile nodes [33] by imaging known GPS locations on the ground. Once locations (and hence visibility constraints) are known, maps may be constructed accurately.

5. NIMS for Environmental Ambient Intelligence

Figure 7 shows an image of a NIMS prototype system developed for forest environment monitoring. Its objective is the monitoring of critical parameters, including complex microclimate dynamics and also the spatiotemporally dynamic light environment that affect plant physiology and in particular, photosynthetic production by plants. The NIMS node also includes capability for imaging of the forest ecosystem. The NIMS node and its cable may be suspended between trees (or other structure). In addition to horizontal transport, vertical node transport is included as well. Thus, the NIMS system may access nearly the entire volume of a transect defined by a plane between two trees

NIMS Node Classes	
NIMS node and infrastructure appear in four classes defined by the nature of infrastructure and nodes reconfigurability and mobility. These are listed below.	
NIMS Class I	Systems composed of fixed infrastructure with fixed nodes supported by the infrastructure
NIMS Class II	Systems composed of fixed infrastructure (this may be fixed cableways or fixed rigid infrastructure) and mobile nodes that propagate on the infrastructure.
NIMS Class III	Systems composed of mobile infrastructure (this may include moving cableways to which nodes are attached).
NIMS Class IV	Systems composed of both mobile infrastructure and mobile nodes. An example of a Class IV system is shown in Figure 2a where two parallel cableways support NIMS nodes that themselves support a cable transverse relative to these parallel cables.

This prototype system includes an embedded processing platform (Linux operating system) and horizontal motion drive in a horizontally mobile Class II node. This node also includes a two-axis articulated image sensor. The NIMS node also carries a vertical transport mechanism for a vertically-suspended Class III NIMS node. This second node includes atmospheric temperature and relative humidity meteorological sensors along with an optical sensor for detection of downwelling photosynthetically active radiation (PAR). Wireless networking supports links between the Class II and Class III NIMS nodes, fixed nodes, and gateway access points to the Internet that are distributed in the environment. While developed for forest monitoring, it is clear that this NIMS system is applicable in many other environments and is also one application-specific example of a very large configuration space of NIMS architecture choices.

NIMS has recently been deployed in both test environments for fundamental algorithm and system research as well as in a natural environment, the Wind River Canopy Crane Research Facility in the Wind River Experimental Forest in Washington. A view of the NIMS node suspended in the forest environment is shown in Figure 7 and Figure 8 with both detail and panoramic views.

This system includes an embedded processing platform (Linux operating system) and horizontal motion drive in a horizontally mobile Class II node. This node also includes a two-axis articulated image sensor. The NIMS node also carries a vertical transport mechanism for a vertically-suspended Class III NIMS node. This second node includes atmospheric temperature and relative humidity meteorological sensors along with an optical sensor for detection of downwelling photosynthetically active radiation (PAR). Wireless networking supports links between the Class II and Class III NIMS nodes, fixed nodes, and gateway access points to the

Internet that are distributed in the environment. While developed for forest monitoring, it is clear that this NIMS system is applicable in many other environments and is also one application-specific example of a very large configuration space of NIMS architecture choices.

Figure 7. (Left Panel) A Class II NIMS Node system deployed in a forest environment. This node includes embedded computing, wireless networking, horizontal transport, image sensing. This node also supports a vertically suspended meteorological sensing Class III Node carrying atmospheric temperature, relative humidity, and photosynthetically active radiation (PAR) sensor devices. Wireless links provide access between the nodes and conventional wide area networks.

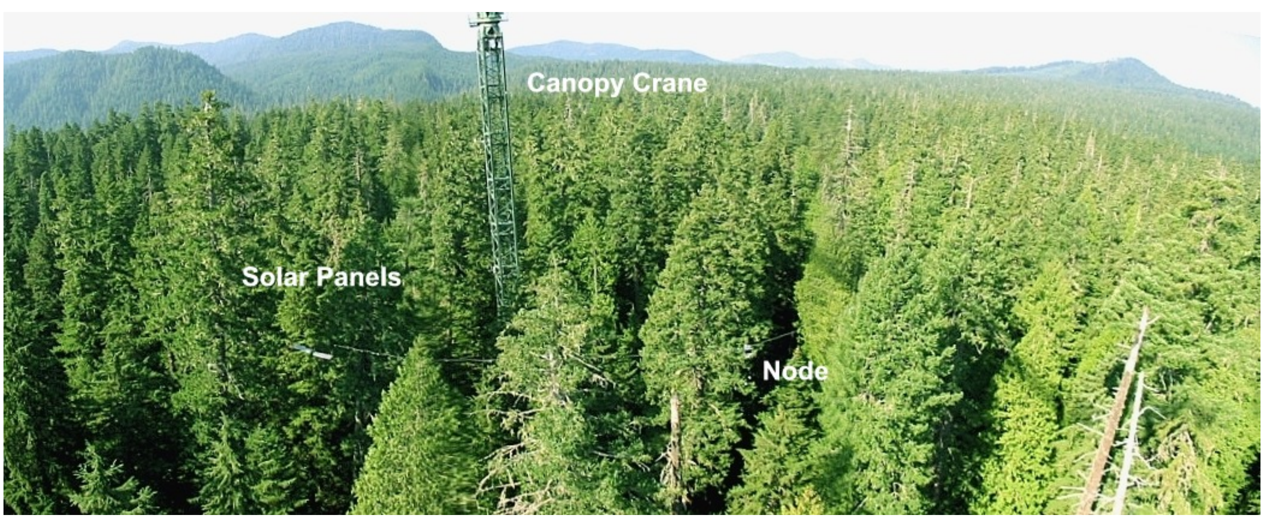

Figure 8. The NIMS node system is shown in a panoramic view. This system was deployed at the Wind River Canopy Crane Research natural forest facility.

6. Summary

The realization of Ambient Intelligence in many environments will require methods for mapping and reducing spatio-temporally varying sensing uncertainty. Sensing uncertainty results from the presence of unknown path loss in sensor signal propagation and unknown sensor system calibration. Obstacles to sensing, often the structures in the environment of interest, may occlude light or sound propagation or introduce. Uncertainty may enter detection of dissolved chemical agents in water, for example, due to changing currents. Clearly, sensing uncertainty is a general problem that will limit distributed sensor system performance in many applications by reducing the probability of detection and introducing distortion in fusion-based detection, identification, and localization.

After the deployment of a fixed sensor network, distortion or occlusion in the physical sensing channel will be ultimately manifested as sensing uncertainty. Since the sensing channel depends on physical properties of the environment and sensor elements, then in general, only a physical reconfiguration can change this distortion or occlusion. Thus, mobility and articulation of perspective are required to be present in some elements of distributed sensors networks. This mobility, however, must be precise (so as to not introduce further uncertainty relative to location), must probe 3-D spaces, and must also operate with sustainable characteristics to enable long-term operations.

The Networked Infomechanical Systems (NIMS) architecture has been introduced to provide these characteristics of precise navigation in complex 3-D environments with a low energy transport method. Now, to match the spatiotemporal variation of environments, the distributed sensor system must incorporate fixed and mobile devices along with systems that provide services, including transport of computation, communication, time synchronization, and transport of node systems and energy resources. The systematic implementation of architectures that match these requirements invokes the need for a complete System Ecology hierarchy of nodes and infrastructure. Now, development of Ambient Intelligence can access a vastly expanded design space to match environmental monitoring goals.

For autonomous Ambient Intelligence operations, the NIMS systems must itself autonomously explore the environment in an adaptive fashion to produce the required spatiotemporal map of sensing uncertainty. Sensor diversity algorithms are introduced to exploit many sensor types, sensing perspectives, and locations. Through coordinated mobility algorithms, fixed and mobile nodes may cooperate to proactively probe the environment to establish the uncertainty map and then adaptively adjust available sensing resources to reduce sensing uncertainty. In addition, coordinated mobility may respond also to events on demand. NIMS introduces a further mobility-enabled approach for environmental characterization with the ability for autonomous physical sampling of material in the environment – relaxing demands on sensing requirements and creating opportunities for sensitive trace analysis of components.

NIMS capabilities are matched to a broad range of Ambient Intelligence applications in natural, indoor, and urban environments. Applications for environmental science and public health and safety have been described. Another set of Ambient Intelligence NIMS applications may focus on indoor "built" environments with functionality intended to support individuals and groups to promote collaboration, productivity, and safety. These benefits may apply to healthcare clinics, to the workplace, to architectural and artistic and to entertainment environments. For example, the lighting, displays devices, and acoustics within a space may be dynamically modified to best benefit productivity or artistic goals. Personnel may exploit the electromechanical reconfigurability of NIMS technology also to support architectural features that modify structures in response to needs or environmental changes.

NIMS technology adds new dimensions to Ambient Intelligence by introducing an entire System ecology of distributed devices, infrastructures and autonomous systems. NIMS research is anticipated to enable many new applications with the ability to explore environments, actively optimize system performance, and also adapt environments to benefit users.

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