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Abstract

Distributed embedded sensor networks are now being successfully deployed in environmental monitoring of natural phenomena as well as for applications in commerce and physical security. Distributed architectures have been developed for cooperative detection, scalable data transport, and other capabilities and services. However, the complexity of environmental phenomena has introduced a new set of challenges related to sensing uncertainty associated with the unpredictable presence of obstacles to sensing that appear in the environment. These obstacles may dramatically reduce the effectiveness of distributed monitoring. Thus, a new distributed, embedded, computing attribute, self-awareness, must be developed and provided to distributed sensor systems. Self-awareness must provide the ability for a deployed system to autonomously detect and reduce its own sensing uncertainty. The physical constraints encountered by sensing require physical reconfiguration for detection and reduction of sensing uncertainty. Networked Infomechanical Systems (NIMS) consisting of distributed, embedded computing systems provides autonomous physical configuration through controlled mobility. The requirements that lead to NIMS, the implementation of NIMS technology, and its first applications are discussed here.

1. Introduction

Distributed embedded sensor and actuator technology has developed over the last decade to now enable the vision of pervasive monitoring of environments.[1-4] Rapid progress has lead to system deployments in applications ranging from natural ecosystem to security monitoring. The next generations of applications are expected to direct distributed networked sensor technology to many of our most urgent international societal problems including the stewardship of natural resources and protection of public health.

As distributed embedded sensor technology has appeared, the first challenges confronting their successful deployment have been addressed. This has included development of energy-aware architectures for long lived, unattended operations and scalable networking for pervasive deployment.[5,6] Also, distributed algorithms enabling cooperative detection by networked embedded sensors have been developed.[7,8] However, as embedded sensors have been deployed in environments, a new set of problems associated with their most essential information return capability has emerged.

One of the most important challenges include sensing uncertainty that arises from the unpredictable and time-variable nature of obstacles to sensing. Sensing uncertainty degrades the performance of event detection and the capability for sensor data fusion for event characterization.

This paper describes the Networked Infomechanical Systems (NIMS) concept that combines distributed embedded computing with mechanical actuation to enable systems that are self-aware of their own sensing uncertainty. This is achieved by allowing the distributed sensor network to 1) determine sensing uncertainty by mobile spatiotemporal mapping of environmental variables and signal propagation, and 2) exploit the new principle of sensor diversity to adjust the location, perspective, deployment density and type of sensor systems to actively reduce uncertainty.

2. Sensing Uncertainty and Requirements for Self-Aware Distributed Operation

Distributed embedded sensors are intended to acquire information regarding signal sources and events associated with these sources in the environment. However, the conventional methods for characterizing and localizing sources and events are fundamentally hindered by the unknown and unpredictable nature of complex environments.

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For example, as shown in Figure 1, vision systems encounter obstacles to viewing that obscure sources (objects) in an unpredictable fashion. Or as another example, acoustic sensing systems face the challenge that acoustic signal propagation is distorted in the presence of environmental structures. Of course, this implies that large uncertainty will accompany attempts to localize or characterize sources by single sensor nodes or by distributed sensor nodes combined via fusion methods.

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 characterized with degraded fidelity or actually completely undetected. Also, conventional distributed sensors may not determine how the combination of calibration error and unknown signal propagation characteristics may degrade the ability to fuse data across a distribution of sensor nodes. This is, of course, a serious limitation for many critical applications of distributed sensors.

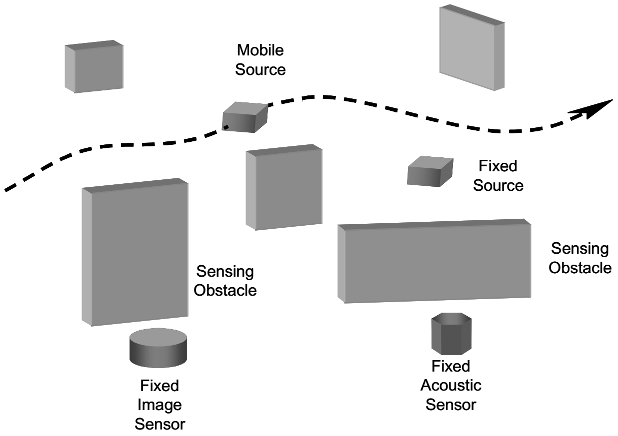


Figure 1. Distributed sensors encounter naturally occurring obstacles to signal propagation that introduce sensing uncertainty in the detection and characterization of fixed and mobile sources.

Sensing uncertainty appears as a result of obstacles to signal propagation, but, may also appear as a result of interfering signals or to limitations in sensing elements. For example, in detection of compounds and materials in media (for example, detection of chemical or biological contamination of water) other compounds or materials may distort sensing results. Or, mobility of sources to be detected (for example, changes in the pattern of flow) all may result in uncertainty.

Coupled with the problem of sensing uncertainty is the challenge for calibration. Sensor system calibration depends on sensor deployment location and perspective. Calibration of detection also depends on detailed knowledge of environmental structure and signal propagation, all of which may be unknown at the time that the distributed sensor network is designed and deployed.

The traditional method for verification and optimization of sensing performance has relied on methods where operators manually reconfigure sensor systems. However, this is clearly not practical for remote systems and is not a scalable approach. In summary, a primary distributed embedded computing requirement is the capability for the remote, unattended, sensor network to detect its own uncertainty, report this to users, and also find means to reduce uncertainty.

3. Self-Aware Distributed Embedded Systems

The primary goal for self-aware distributed systems operation is to reduce the uncertainty with respect to a hypothesis regarding events in the environment (for example the arrival of a source and its characteristics). This is accomplished by gathering evidence from distributed sensors. Evidence may be fused using, for example the Bayes method. Here we wish 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 acquired from sensors. [10] As an example, we may 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. This is interpreted as stating that the posterior information is equal to the prior information (to time r-1) along with 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.

Now, a variety of fusion weighting strategies are possible, resulting in a broad set of fusion algorithms. However, the physical environment renders this challenging since the nature of sensing signal channels and the presence of obstacles are unknown.

3.1. Reducing Sensing Uncertainty

The nature of the sensing uncertainty challenge to distributed sensing inspires its solution: *physical obstacles to sensing must be matched with physical reconfiguration of distributed sensors.*

It has recently been proposed that the introduction of low complexity, constrained mobility with limited span motion over limited dimensions will enable reduction in sensing uncertainty.[9] Specifically, for a broad class of physical phenomena where sensing uncertainty results from the presence of obstacles, then motion enables distributed sensors to circumvent obstacles. This hypothesis has been theoretically and experimentally investigated. Results indicate that indeed low complexity mobility may lead to a dramatic reduction in sensing uncertainty for typical natural environments.[9]

3.2. Controlled Mobility Methods for Distributed Sensing

The goal for reducing sensing uncertainty in complex environments requires a controlled mobility method with a number of novel attributes that will be discussed here.

First, it is required that the mobility mechanism provide reconfiguration of sensors does not itself introduce new uncertainty. For example, many robotic forms face an uncertainty with respect to their ability to navigate through complex environments in a long term, sustainable fashion. Thus, their motion may actually increase uncertainty.

Second, controlled mobility must be sustainable in operating at low energy. It also must operate without disturbing the environment in question.

Third, this mobility system must operate in a full three-dimensional environment and must be suspended in an aerial fashion.

Conventional mobility methods do not meet one or more of these requirements. For example, wheeled and tracked robotic vehicles only access the surface and may not view the full three-dimensional space that generally requires an overhead perspective. Also, such vehicles encounter uncertainty in navigation.

Aerial and wheeled vehicles also require large energy reservoirs and may not be sustained in place over years of operation, for example.

However, by embracing the progress of robotics and introducing infrastructure that supports mobility, then a controlled mobility method is possible where large mass may be moved precisely in an aerial fashion within three dimensional environments at low energy.

4. Networked Infomechanical Systems (NIMS)

The NIMS method enables distributed self-awareness by providing the means for detection and reduction of sensing uncertainty through controlled mobility. This paper will describe a primary NIMS embodiment that includes mobile, aerial nodes moving on a cableway infrastructure that may be suspended in three-dimensional environments (see Figure 2). [11]

The NIMS cableway system permits controlled mobility in both horizontal and vertical directions that is energy efficient and precise. In contrast to wheeled or tracked vehicles that remain on the surface, NIMS may operate in a suspended fashion. Also, NIMS may be placed in many typical environments that are non-navigable by wheeled or tracked vehicles. Through this infrastructure-supported architecture, NIMS enables sensor diversity for adjusting and exploiting the sensor node population to reduce uncertainty in the 3-D environment.

4.1. Reducing Sensing Uncertainty with NIMS

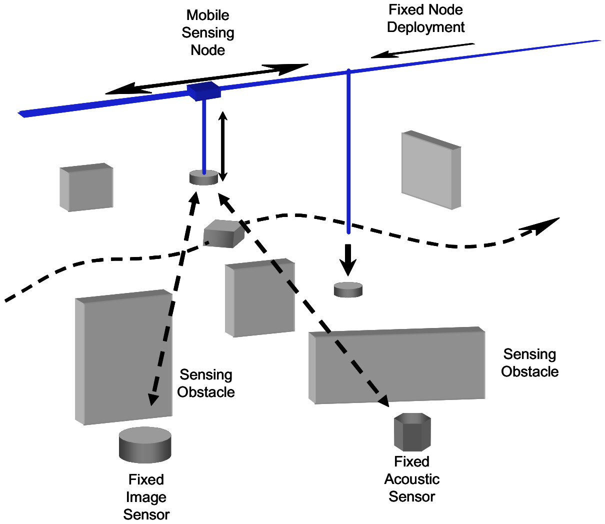


Figure 2. NIMS infrastructure permits mobile sensor nodes to precisely reconfigure to both probe and then reduce sensing uncertainty. NIMS distributed operations engage both mobile and fixed embedded sensor nodes.

Figure 2 illustrates the NIMS architecture consisting of fixed and mobile nodes along with supporting infrastructure. As will be described, NIMS provides not only the capability for reconfiguring mobile nodes, but also relocating fixed nodes into positions that are optimized within mobility system operating constraints.

As indicated in Figure 2, NIMS offers a means for detecting sensing uncertainty. For example, here the sensing obstacles that do not permit the fixed image and acoustic sensors to detect objects are, in fact, detected by the mobile node. Clearly, distributed algorithms that engage the mobile and fixed devices may be developed that would now inform the nodes as to their sensing uncertainty. Further, upon determining sensing uncertainty, this may be reduced by relocating fixed nodes.

4.2. NIMS Systems

As will be described in Section 4.3, a set of NIMS distributed services are now enabled. This includes sensing, adaptive sampling, networking, node transport, fixed node logistics, and energy harvesting and distribution. This is supported by NIMS systems that have been implemented as shown in Figure 3. Here, the NIMS systems are supported by cableway structures suspended within the environment. Anchoring of cableways may exploit environmental infrastructure, for example trees for operation in forest environments, river channels, or interior or exterior built infrastructure. Energy harvesting also exploits infrastructure where solar photovoltaic cells have been suspended from the infrastructure. Power distribution also exploits the cableway for transport of power to nodes.

Figure 3. The left-hand image shows a NIMS prototype node system. An imager appears above a package compartment containing embedded computing along with horizontal and vertical actuator components. The right-hand image displays a NIMS node deployed in a forest environment (here at a height of 50m above the forest floor). Suspended from the node is a sensor package that enables sampling of temperature and relative humidity climate variables with solar radiation intensity sensing.

The NIMS embedded platform of Figure 3 includes a standard embedded computing system supporting the Linux operating system. The NIMS system must explore an entire transect plane and thus carries devices that provide both horizontal and vertical transport. The NIMS system shown in Figure 3 includes imaging systems supported by a node that propagates horizontally on the suspended cable and also supports a second embedded platform that is lowered and elevated under actuation supplied by the horizontal node. The embedded platforms in horizontal and vertical elements communicate over IEEE802.11 wireless links and also over links supporting “mote” platforms.[2] The NIMS system actuators include motor actuator systems and motor position encoders. Imager systems include pan, tilt, and zoom actuation. These actuators provide both horizontal and vertical transport control by operating wheel and spool systems directly on the NIMS cableways. Interfaces between application level software systems and sensor and actuator systems follow the Emstar architecture.[12]

4.3. NIMS Distributed Services

The presence of the NIMS hierarchy of system layers (fixed nodes, mobile nodes, and infrastructure) creates a requirement and opportunity for distributed computing that is dramatically more capable than that for any individual layer. This includes, for example, logistics for node transport, data transport, sensing uncertainty mapping, calibration, geolocation, and energy harvesting and delivery. Some of these distributed services will be particularly difficult to achieve without a NIMS infrastructure. The examples of energy and geolocation services will be presented and discussed here.

It is well-known that the limited lifetime of fixed sensor nodes results from their energy operating requirements and their lack of sustainable energy resources.[13] This limited lifetime severely impacts distributed monitoring applications that may require multi-year unattended operation. NIMS infrastructure and node hierarchy enables an energy logistics for all system elements. Here, NIMS systems may harvest solar energy and transport energy via the cable system and then use mobile elements to find and dock with fixed nodes for the purpose of transferring energy to fixed nodes. This provides the prospect of fixed nodes that may be densely distributed, operate in untethered fashion, and yet also operate indefinitely.

An additional severe challenge for fixed sensor nodes is the problem of geolocation. Sensor node location ushers in the most complicated problems associated with the generation and reception of ranging signals, synchronization, and communication, along with sensing uncertainty associated with ranging. In many environments, geolocation solutions for autonomous, unattended nodes do not yet exist. NIMS, however, offers an ability to optimize the location of a mobile element to geolocate a fixed node using optical landmark methods hosted by the mobile node and exploiting the precision for mobile node location on its precise infrastructure.[14] Thus, distributed systems that link fixed and mobile devices provide geolocation services for fixed devices that may otherwise not have been supplied with accurate location information.

Finally, as has been discussed, it may generally not be possible for fixed sensor networks to determine their own sensing uncertainty. However, distributed sensing uncertainty services and related calibration services again can be developed based on the coordination of nodes in multiple hierarchical tiers.

4.4. Challenges for Distributed Mobile Sensing

Challenges that face mobile sensing include the observation of transient and rapidly time varying phenomena. Mobile elements employed in tracking phenomena represent a resource that must be assigned to sensing tasks. However, as may be expected, phenomena will be encountered for which the exploration of the environment by mobile NIMS elements may require a speed of motion that is either unachievable, or may violate required rate-distortion limits associated with sampling dwell time physical limits. Thus, again distributed computing solutions opportunities exist for implementation of efficient observational methods that engage multiple hierarchical tiers.[15]

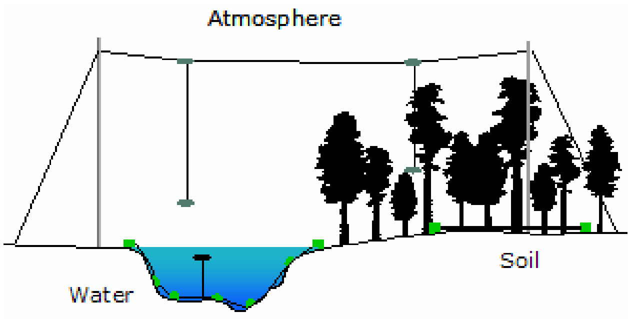


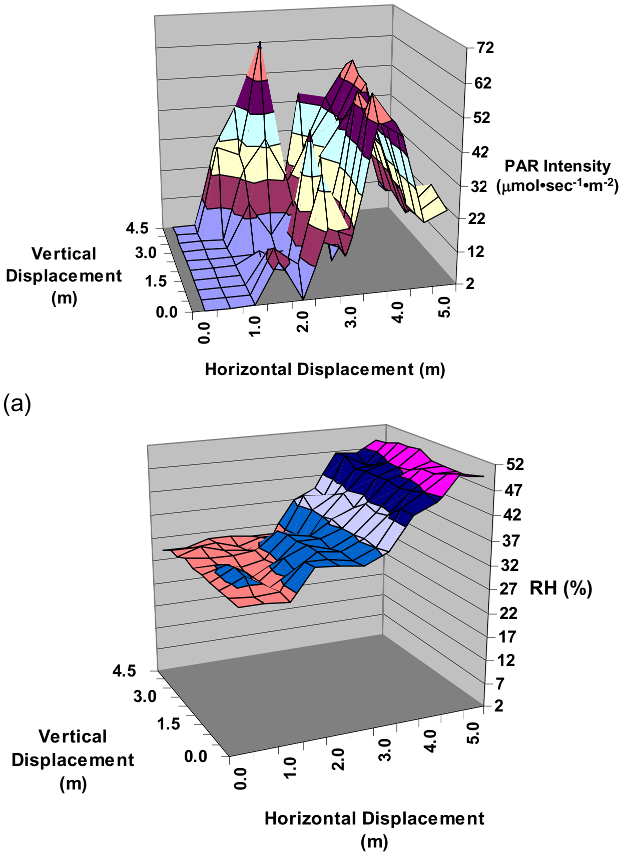
Figure 4. NIMS systems may be deployed in natural environments in terrestrial, marine, and atmospheric monitoring applications. This includes monitoring of atmospheric gases and their thermodynamic properties, investigation of water systems with chemical and biological probes, and monitoring of forest soil systems.

5. Applications

NIMS applications include many monitoring system requirements for natural and built environments. NIMS may be applied in terrestrial as well as marine systems. An illustrative example is that of investigation of fundamental atmosphere – forest canopy interaction.[16] Here, the scientific application goals are to characterize the fundamental flux of carbon, water, heat, and light in the forest canopy structure. This is an urgent scientific demand due to the dominant contribution of the forest canopy to global atmospheric phenomena. As indicated in Figure 4, NIMS systems may be deployed directly in the environment with a scale of motion that matches the environmental monitoring needs.

NIMS systems have been deployed in the field for monitoring of microclimate variables. Shown in Figure 3 is a deployment at the Wind River Canopy Crane Research Facility[17] and the James San Jacinto Mountains Reserve[18].

Typical examples of measurement results obtained in a forest transect are shown in Figure 5. Here, measurements of Photosynthetically Active Radiation (PAR) are shown for a planar NIMS transect. PAR intensity is plotted in vertical relief as a function of vertical and horizontal displacement. This provides a map of illumination with structure that reflects the forest canopy architecture.[16] Figure 5 shows water vapor concentration as relative humidity in the same region. This transect crossed a meadow area and stream with the stream lying at the right hand region of the horizontal displacement. Note that humidity is observed to rise at this location. The combination of these data are of use in understanding the spatiotemporal rate of photosynthesis, growth, and the influence of these variables on carbon flux in the environment. These NIMS results are in agreement with data obtained from fixed sensors, however, these reveal the spatial dependence of these phenomena for the first time.



(a)

(b)

Figure 5. Microclimate data acquired by the NIMS system. Photosynthetically Active Radiation (PAR) (a) and Relative Humidity (RH) (b) is shown as a function of vertical and horizontal displacement.

6. Summary

The continued progress in distributed sensing requires new methods that autonomously detect and reduce fundamental sensing uncertainty. NIMS technology introduces a new controlled mobility form for distributed embedded computing. This provides capability for relocating mobile and fixed sensing assets to improve sensing performance, introduce diverse new sensors, and reduce wireless link path loss. Distributed NIMS operation will provide an opportunity for future a future sensor network logistics where sensor nodes, energy, and environmental samples are autonomously transported to enable environmental monitoring and exploration.

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