

# Towards a debugging system for sensor networks

By Nithya Ramanathan<sup>\*†</sup>, Eddie Kohler and Deborah Estrin

*Due to their resource constraints and tight physical coupling, sensor networks afford limited visibility into an application's behavior. As a result it is often difficult to debug issues that arise during development and deployment. Existing techniques for fault management focus on fault tolerance or detection; before we can detect anomalous behavior in sensor networks, we need first to identify what simple metrics can be used to infer system health and correct behavior. We propose metrics and events that enable system health inferences, and present a preliminary design of Sympathy, a debugging tool for pre- and post-deployment sensor networks. Sympathy will contain mechanisms for collecting system performance metrics with minimal memory overhead; mechanisms for recognizing application-defined events based on these metrics; and a system for collecting events in their spatiotemporal context. The Sympathy system will help programmers draw correlations between seemingly unrelated, distributed events, and produce graphs that highlight those correlations. As an example, we describe how we used a preliminary version of Sympathy to help debug a complex application, Tiny Diffusion. Copyright © 2005 John Wiley & Sons, Ltd.*

## Introduction

Sensor networks—networks of small, resource-constrained wireless devices embedded in a dynamic physical environment—have led to new algorithms, protocols, and operating system designs.<sup>1,2</sup> In sensor networks, interactions between sensor hardware, protocols, and environmental characteristics are hard to predict, making application design an iterative process between debugging and deployment.<sup>3</sup> For

example, owing to flaky or variable link connectivity, post-deployment environments can present unexpected combinations of inputs, or stimulate untested control paths in routing and transport code, uncovering new bugs and necessitating different application designs. Furthermore, because sensor networks are at an early stage of development, debugging needs are more fundamental than for the Internet (e.g., rebooting a router often solves issues seen in the Internet, but rebooting a node rarely fixes a bug in a sensor network).

<sup>1</sup> Nithya Ramanathan ■■

Eddie Kohler ■■

Deborah Estrin ■■

Department of Computer Science, UCLA, Los Angeles, California, USA

<sup>\*</sup>Correspondence to: N. Ramanathan, Department of Computer Science, UCLA, Los Angeles, CA 90025, USA.

<sup>†</sup>E-mail: nithya@cs.ucla.edu

## —Why Do We Need New Debugging Tools?—

We distinguish *debugging* from performance analysis and fault tolerance, and define debugging as *the process of root-causing a high-level failure*. This is an iterative process that begins by detecting a fault, isolating it, and then root-causing it—which often results in the identification of another fault, starting another iteration of this debugging loop. This process differs from traditional fault tolerance methods that aim to provide user-level transparency to system failures. Sensor network users do not primarily need fault tolerance; it is more important to know when and where a failure is occurring and have tools that will enhance visibility and aid in detecting, root-causing and fixing the fault causing the failure.

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Sensor networks are difficult to debug primarily owing to lack of visibility into the nodes and the dearth of effective debugging tools. Nodes' limited memory, communication, network and power resources prevent them from freely storing and transmitting debugging information, as this quickly depletes energy and network lifetime. As a result, once a sensor network is deployed, visibility into the network drops dramatically.

Envision deploying a dynamically taskable environmental monitoring sensor network, and not receiving queried data at the sink. Is this data loss caused by a mote tasking failure, failed sensors that are not returning samples, or packet loss along the path? Without more information, this failure is virtually impossible to track down and debug. With better tools and more observations, we may determine that data is not reaching the sink due to wildly varying link qualities at an individual or group of nodes. However, we cannot stop here as this still does not elucidate a fix: we must perform another iteration and determine why the link qualities are changing. This could lead to uncovering yet another fault which would

result in another iteration in the debugging process. All these iterations must often take place in the field, where visibility is lowest, since environmental conditions may trigger bugs.

Sensor networks are not only hard to debug due to the lack of visibility; they contain bugs characteristic of both distributed, embedded *and* wireless systems, which are notoriously hard to detect and root-cause. Such bugs can be multicausal and timing-sensitive; often they are triggered by ephemeral events such as race conditions, asynchronous changes in distributed state, and interactions with the physical environment, making them hard to reproduce. Failures can also be caused by the *interactions between* nodes, regardless of whether independent nodes and modules are functioning correctly. A final hurdle in debugging is having too much information, which can be as ineffective as not enough information; this is especially true for a system that may scale to hundreds or thousands of nodes. These issues are not solved by removing power and memory constraints, and also occur during pre-deployment debugging (debugging that occurs during simulation and emulation).

These characteristics of sensor networks motivate the need for a debugging tool that can enhance visibility while preserving resources, non-intrusively observe the network, and provide contextual information for failures; in addition, the tool must transition seamlessly between both pre- and post-deployment environments. Furthermore, the tool must extract debugging information from a running system without introducing the probing effect (alteration of normal behavior due to instrumentation). Standard debugging approaches that only provide passive infrastructure, such as running a debugger or continual logging, fall short for sensor networks; this will be discussed further under 'Current State of the Art'.

## —Debugging Goals—

An ideal debugging system may:

1. Detect a problem or unusual behavior by monitoring simple system metrics.
2. Aid in debugging the problem by collecting 'useful' information to provide context.
3. Proactively verify a hypothesis by injecting tests and go back to step 1 as needed.
4. Notify the user.

5. Fully debug the problem.
6. Finally, attempt to repair the problem.

This paper presents a preliminary design and evaluation of *Sympathy*, a debugging tool for pre- and post-deployment sensor networks that is designed to address the first three steps listed above. Our goal is to identify metrics that serve as accurate indicators of system health in order to determine what is needed for an autonomous system to monitor itself. *Sympathy*'s primary goals are to enhance a user's confidence in the system and aid in debugging. *Sympathy* will consist of mechanisms for collecting system performance *metrics* with minimal memory overhead; mechanisms for recognizing application-defined *events* based on these metrics; and a system for collecting events in their *spatiotemporal context*. We define a *metric* as directly observable system state based on externally visible behavior, and an *event* as a notable change in state of a metric. The key, then, is to define what a *notable change* is, and thereby determine when events are important to note. The *Sympathy* system will help programmers draw correlations by collecting distributed, time-stamped events. *Sympathy* will impose minimum storage requirements on each mote, be non-intrusive with respect to the protocol and timing of the application, and monitor events within a sensor node as well as interactions between nodes.

Our current contribution is a preliminary design and implementation of a tool that can be used for pre-deployment debugging, an initial analysis of metrics useful for debugging, and the role of a debugging tool in the entire design process. Using *Sympathy* we have begun to distill the important metrics, events, and generic correlators that indicate system health and help find bugs quickly, and to transmit this data in ways that minimize energy consumption and probing effects. We found that by logging specific metrics and events, a system can perceive potential issues and enable quick discovery of their root cause.

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*Sympathy*'s approach of correlating seemingly unrelated events has proven useful in detecting and debugging failures involving interactions between multiple nodes. To continue our previous example, imagine our sink stops getting data only from nodes A and B, and all data routed to the sink passes through node X. A system that reports that both node A *and* node B stopped sending data at approximately the same time, that node C *still* considers both nodes to be neighbors, and that link quality to node X from the previous hop suddenly dropped helps a user to isolate potential causes. In this scenario, the user can speculate that nodes A and B are probably still alive and that the dropped data is more likely due to the link to node X. All of these conclusions can be drawn simply by identifying correlated events based on nodes' neighbor lists. However, log files containing megabytes of unrelated data make it difficult to find and correlate events, especially those that are seemingly unrelated at first glance.

It is important to note that *Sympathy* entails user participation; it is not meant to be a generic bug-finder or 'black-box' technique. During pre-deployment, *Sympathy* is most effective once initial bugs have been fixed, and the harder-to-find coding and algorithmic bugs remain. *Sympathy* employs both traditional network management metrics and indicators of system health (e.g., route flapping and packet loss) in conjunction with sensor network-specific metrics and events (e.g., neighbor-list changes and next-hop selections), chosen as a result of sensor networks' unpredictable and highly varying links.

The *Sympathy* tool is new—we have used it so far only in simulation and emulation. Nevertheless, our experiences have been positive enough to validate the approach. Eventually, *Sympathy* will be part of a system that can aid in debugging sensor networks both pre- and post-deployment. Below we present a useful case study that demonstrates our current contributions by showing how *Sympathy* was used to debug a failure in Tiny Diffusion.<sup>4</sup>

## Current State of the Art

Standard debugging and fault detection approaches are often based on the assumption that all nodes: (1) are accessible, either by a human system administrator or another node with reli-

able connectivity; (2) have unlimited power; and (3) fail due to local causes, as opposed to interactions between several nodes. Furthermore, these techniques assume there is minimal cost associated with continually transmitting debug information to a centralized server. Such techniques fall short for sensor networks, which contain bugs characteristic of distributed, embedded, and wireless systems, and which need algorithms that minimize power, processing, and memory usage.

While some sensor network faults, such as node failures and bad route selections, are similar to those seen in common distributed architectures such as the Internet, the approaches to detecting these failures are necessarily different owing to the embedded, wireless, and resource-constrained platform. Moreover, common sensor network failures, such as data not arriving at the sink, nodes not receiving tasking or query packets from a sink, or even performance-based issues such as nodes consuming too much power, are not as prominent in Internet debugging; and Internet debugging

may focus more on user latency, high availability, and application-level failures—issues not necessarily pertinent for sensor networks.

Current techniques for distributed systems can fall into the *debugging infrastructure/passive monitoring* and *fault detection* categories.

### —Infrastructure/Passive Monitoring—

Current debugging infrastructure and techniques include the use of passive monitoring, tracing programs, simulation, visualization tools, and debug log files. While simulations are useful, clearly they are not a replacement for debugging on the actual hardware; it is impossible to simulate real-time network dynamics, dynamic environments, and numerous timing, MAC, and hardware-related details.

Visualization tools are helpful for real-time debugging when running on actual hardware. Figure 1 is a screen capture of Emview, a visual-

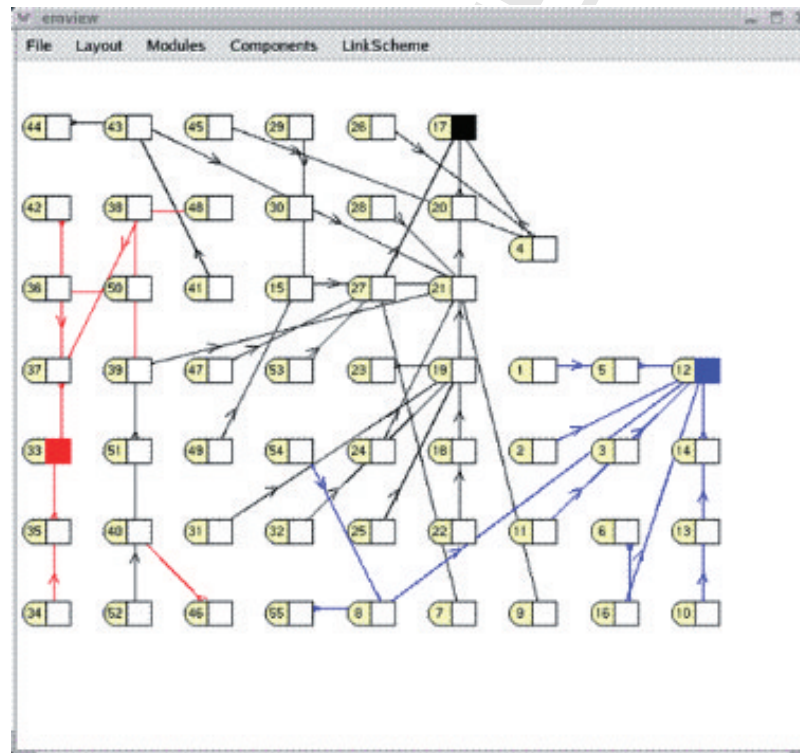


Figure 1. Screen capture of Emview, the visualizer available with Emstar.<sup>3</sup> This screen shows nodes, neighbor-list connectivity and link qualities associated with each link. The image changes in real time with changes in the network, capturing no historical context and performing no data analysis

1 izer tool designed for debugging distributed  
 2 embedded applications. However, visualizers  
 3 often don't highlight events that may indicate a  
 4 failure, nor are they meant to capture historical  
 5 context. For example, Emview-like visualizers  
 6 show *either* link quality *or* neighbor-level connect-  
 7 ivity; conflicts in these properties—a node that  
 8 has no neighbors despite relatively high-quality  
 9 links, for example—are difficult to see.

10 While log files can capture historical perspective  
 11 and context, they contain excessive and unfiltered  
 12 data that can obfuscate important events.

13 Tracing tools such as the Gnu Debugger (GDB)  
 14 are highly utilized in order to understand real-  
 15 time code dynamics, but such tools ignore the  
 16 platform constraints of sensor network nodes,  
 17 assuming that users can access a node through  
 18 some sort of shell in order to launch and run the  
 19 tool.

20 While traditional network management does  
 21 not specifically address characteristics specific to  
 22 sensor networks, such as low power and commu-  
 23 nication needs, there are many insights that we can  
 24 apply.

25 The simple network management protocol  
 26 (SNMP) implements a protocol to manage the  
 27 exchange of network statistics between a central-  
 28 ized server, the network management system  
 29 (NMS), and the agent nodes that record and trans-  
 30 mit the metrics. The NMS queries agents and  
 31 receives network statistics as well as asynchronous  
 32 events from agents and can set variables within  
 33 agents. Agents receive and store management  
 34 data, and can asynchronously signal events to the  
 35 NMS. SNMP focuses all processing at the NMS,  
 36 expecting nodes to continually transmit all metrics  
 37 back to this centralized server. This places an  
 38 undue load on sensor network nodes that must  
 39 minimize transmission in order to extend network  
 40 lifetime.

41 *Management by delegation*<sup>5</sup> begins to address this  
 42 issue of centralized processing of network statis-  
 43 tics by moving some of the responsibilities of  
 44 network management from a centralized server to  
 45 distributed nodes. This responsibility transfer is  
 46 done using mobile code: i.e., downloading scripts  
 47 that can perform management tasks or even  
 48 dynamic tasking to nodes. These scripts, or *delega-*  
 49 *tion agents*, empower individual nodes to take  
 50 action based on observed behavior, instead of con-  
 51 suming network bandwidth to convey metrics and

52 commands between the centralized server and the  
 53 nodes. The node is then able to monitor its own  
 54 behavior, detect any problems, diagnose these  
 55 issues, and even repair the problems.

56 Debugging tools designed for sensor networks  
 57 are in their nascent stages. Although no common  
 58 practices exist yet, Zhao *et al.*<sup>6,7</sup> make several rec-  
 59 ommendations for post-deployment debugging.  
 60 Zhao *et al.*<sup>6</sup> present an algorithm to continually  
 61 compute aggregates (sum, average, and count) of  
 62 loss rates, energy levels, and packet counts to aid  
 63 in debugging. Zhao *et al.*<sup>7</sup> argue that, while it is  
 64 important to continuously gather node state in  
 65 order to monitor the health of the network, it is not  
 66 feasible to do so for each node due to energy lim-  
 67 itations. The authors propose an energy-efficient  
 68 algorithm based on in-network aggregation. The  
 69 authors focused solely on the process of efficiently  
 70 transmitting collected metrics and do not specify  
 71 what metrics should be collected or how to process  
 72 this data.

73 There are several TinyOS-based tools that  
 74 support debugging. For example, SNMS is an  
 75 infrastructure to enable system monitoring and  
 76 fault detection.<sup>8</sup> This tool allows programmers to  
 77 export counters and statistics and record applica-  
 78 tion metrics. We have focused instead on deter-  
 79 mining the right metrics to export. With minimal  
 80 modification, we could leverage the infrastructure  
 81 provided by SNMS and replace Sympathy's  
 82 logging mechanism and application interface.

83 While debugging tools such as SNMP, SNMS,  
 84 and management by delegation provide monitor-  
 85 ing infrastructure, we could find no work that  
 86 examined or proposed specific metrics and data  
 87 analysis techniques specifically applicable for  
 88 sensor networks. Furthermore, Sympathy distin-  
 89 guishes itself from such passive data logging  
 90 approaches by proactively collecting only poten-  
 91 tially relevant events and their context, in order to  
 92 highlight failures and aid in isolating their causes.  
 93 In addition, Sympathy specifies generic low-level  
 94 metrics and events that specifically examine  
 95 *inter-node* dynamics in addition to internal node  
 96 metrics.

## —Fault Detection—

97  
 98  
 99  
 100  
 101 Another group of work related to Sympathy is  
 102 those tools that utilize models for fault detection.

1 These systems use models to infer internal state  
 2 based on externally visible statistics. Szewczyk  
 3 *et al.*<sup>9</sup> identify nodes that report sensor data  
 4 exceeding a static threshold as being close to  
 5 failure. This work utilizes a simple model to  
 6 specify expected values and infer the node health  
 7 when returned data does not match the model.

8 Model-based calibration techniques for sensor  
 9 networks are similar to, though more refined  
 10 than, the simple thresholding techniques used by  
 11 Szewczyk *et al.* Feng *et al.* define calibration as 'the  
 12 process of mapping raw sensor readings into  
 13 corrected values'.<sup>10</sup> While calibration takes the  
 14 process of fault detection one step further by  
 15 attempting to fix the values, Feng *et al.* use their  
 16 error model to interpret the sensor data and deter-  
 17 mine which sensors may be faulty.

18 Kiciman *et al.* collect low-level network metrics  
 19 and use statistical analysis in order to identify  
 20 application-level anomalous behavior.<sup>11</sup> This  
 21 approach solely focuses on identifying faults, and  
 22 is based on their stated assumption that identi-  
 23 fying a fault consumes a majority of the time  
 24 involved in handling a failure for Internet service  
 25 providers. The authors postulate that once a fault  
 26 has been detected, the fix involves simple tech-  
 27 niques such as rebooting a node. Rebooting can  
 28 work well for occasional transient faults on an  
 29 essentially solid infrastructure. It can help for  
 30 sensor networks as well (on networks that support  
 31 remote reboot), but most sensor network infra-  
 32 structure—network protocols, node operating  
 33 systems, and so forth—is still under active devel-  
 34 opment, and far from Internet-level stability and  
 35 robustness.

36 Fox *et al.* extend this idea to suggest using sta-  
 37 tistical learning techniques to identify anomalous  
 38 behavior.<sup>12</sup> Their first step in this process is to:  
 39 'Ensure the system is in a state in which it is mostly  
 40 doing the right thing most of the time, according  
 41 to simple and well-understood external indica-  
 42 tors.' However, these 'simple and well-understood  
 43 external indicators' do not exist for sensor net-  
 44 works. Before we can move on to apply increas-  
 45 ingly complex tools to monitoring sensor network  
 46 behavior, we must first identify such indicators.

47 Tools that analyze effects of configuration  
 48 changes and predict anomalous behavior come  
 49 close to the needs of sensor networks, but do not  
 50 often take into account interactions between  
 51 nodes, node constraints, and the unpredictable

communication of wireless radios. These tools  
 often assume perfect knowledge, expecting that  
 nodes can reliably and continuously transmit  
 system metrics to a server. This non-determinism  
 in the environment is a key difference, even  
 between pre-deployment and post-deployment  
 debugging of sensor networks, as will be  
 discussed below under 'Post-Deployment  
 Architecture'.

Ruan and Pai's DeBox system<sup>13</sup> motivated the  
 initial design of Sympathy and may be the most  
 similar to it. DeBox suggests that exposing  
 minimal internal state in real time to applications  
 affords better performance analysis and tuning  
 than passive profilers that provide information  
 post facto. This transparency allows applications  
 to get immediate feedback on the impacts of their  
 actions on kernel performance and behavior.  
 While Sympathy is not as concerned with perfor-  
 mance, and focuses on fault detection and debug-  
 ging, this approach of enhancing system visibility  
 and transparency by exposing minimal internal  
 state forms the basis of our work.

## Architecture

We propose a generalizable architecture, called  
 Sympathy, which continually monitors a network  
 while an application is running, enhances visibil-  
 ity by identifying and collecting generic, low-level  
 system metrics and events used to infer system  
 health, and highlights unexpected correlations  
 between these events in order to detect and help  
 debug failures. The second-tier goal is to inform  
 applications of events in case they can modify  
 their behavior. The design of Sympathy should be  
 considered preliminary; as we move to post-  
 deployment debugging, architectural details may  
 change.

Sympathy logs metrics as they change. These  
 metrics are directly collected from the application,  
 not independently calculated by Sympathy. We  
 aim to define a minimal set of metrics sufficient for  
 inferring system health and postulate that the list  
 in Table 1 fulfills this criterion.

The metrics are then analyzed to detect *events*,  
 which are essentially notable changes in the metric  
 state. Once the network has established initial  
 neighbor lists and routing configurations, any  
 occurrence of the events listed in Table 2 are con-  
 sidered notable.

Metric name	Metric description
Neighbor lists	List of neighbors. Neighbors are identified by ID.
Link ingress/egress	Link quality from and to each neighbor. Link quality is calculated as a delivery rates between 0 (100% loss) and 100 (100% delivery).
Byte counts	The number of bytes transmitted and received by this node.
Next hop (Routing table)	The next hop chosen by this node.
Path loss (Routing table)	Whole-path loss rates calculated over an entire path from a node to the sink, using pair-wise link qualities at each hop. Each node calculates a separate path loss for each (next hop, sink) pair in its routing table, then chooses the next hop with the lowest path loss. Path loss is the inverse of link quality: lower values mean lower packet loss and thus provide better quality of delivery.

Table 1. Metrics gathered at each time step

Event name	Description	Metrics used to recognize event
Missing node	No node reports a node $n$ as a neighbor. Logs $n$	All neighbor lists
Isolated node	Node $n$ has no neighbors. Logs $n$	$n$ 's neighbor list
Route change	$n$ 's next hop changes at least once. Logs the previous and current next hop, the associated path loss for the top two choices for next hop, and the number of gradient messages received in this round	$n$ 's routing table information
Neighbor list change	Node $n_2$ joins or is dropped from $n_1$ 's neighbor list. Logs $n_1$ , $n_2$ , and current and previous link qualities	$n_1$ 's neighbor list
Link quality change	Node $n_2$ 's link quality to $n_1$ drops below a statically defined threshold. Logs $n_1$ , $n_2$ , and current and previous link qualities	$n_1$ 's neighbor list

Table 2. Events that are detected based on the gathered metrics, and the metrics needed to discern them

Sympathy consists of two types of nodes: a *Sympathy-sink* and a *Sympathy-node*, shown in Figure 2. In general, the *Sympathy-sink* performs most of the event processing, and receives updated metrics from *Sympathy-node* processes using the IPC framework provided by Emstar. The *Sympathy-sink* contains components to record metric data

from any node, identify events by analyzing metrics, and record event context.

Once an event has been detected, the *Sympathy-sink* updates its data structures and notifies clients interested in the specific event. These clients are passed event-specific data structures. A current client application exists that uses this information

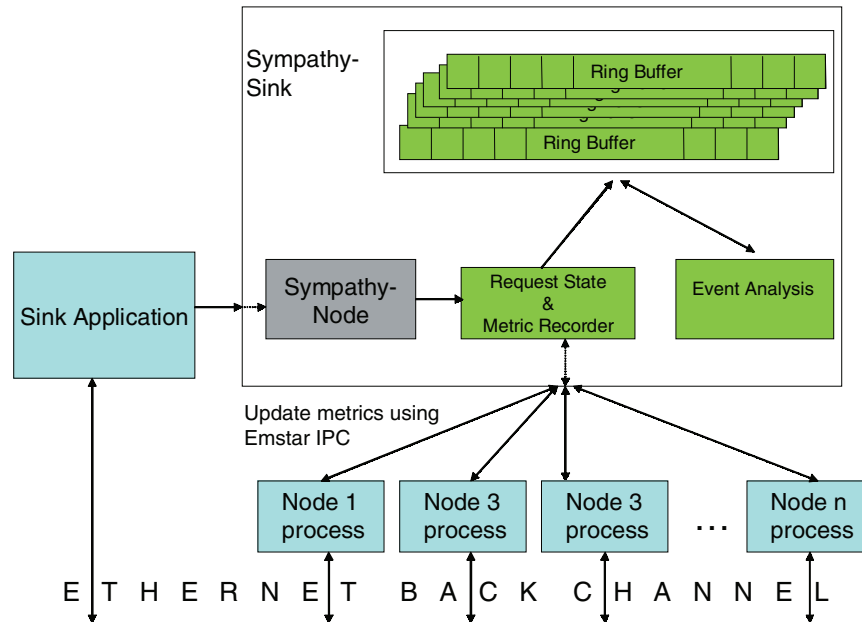


Figure 2. General architecture of a simulated system running with Sympathy. The Sympathy-sink receives updated metrics from Sympathy-node processes using the IPC framework provided by Emstar. The Sympathy-sink contains components to record metric data from any node, process metrics to identify events, and record event context

to determine the frequency of next-hop changes for each node.

### —Implementation—

During application development the pre-deployment Sympathy implementation runs in *emulation mode* on the *ceiling array* as shown in Figure 2.

The ceiling array is a test-bed of mica2 motes connected over an Ethernet back channel to a Linux server running Emstar.<sup>3,4</sup> Emstar is an event-based application framework that facilitates heterogeneous networks of TinyOS-based motes and Linux-based micro-servers. Each node is run as a separate process, communicating using the IPC mechanisms provided by Emstar. Simulation is used in the traditional sense; nesC code is simulated using the EmTos<sup>14</sup> component of Emstar.

The ceiling array is employed for emulation mode which uses real mote radios for communication, but handles all processing on a centralized server running Emstar. The server communicates with each mote over the back channel in order to

get and receive packets from the network. However, because all node processing occurs on the same server, state and debugging information between nodes is communicated using Emstar's IPC.

The Sympathy-sink is virtual and omniscient, using Emstar's IPC to continuously and reliably receive metrics from all Sympathy-nodes without impacting timing or performance, as shown in Figure 2. Interestingly, for identification of most events collected by Sympathy, nodes only need transmit their metrics to a local one-hop neighbor; a centralized node with global knowledge is only needed in order to identify the *missing-node* event. While the Sympathy-sink leverages the Emstar infrastructure to collect metrics from each node, Sympathy has no implicit dependence on Emstar and can be implemented independently.

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***Sympathy has no implicit dependence on Emstar and can be implemented independently.***

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1 The Sympathy-sink analyzes the metrics trans-  
 2 mitted from all Sympathy-nodes, and triggers on  
 3 events. Upon triggering, the Sympathy-sink:

- 4 • provides *temporal context* by storing all  
 5 metrics it has collected from the past 200 time  
 6 units for the node causing the trigger;
- 7 • provides spatial context by storing all metrics  
 8 it has collected from the past 200 time units  
 9 for the nodes neighboring the node where the  
 10 event was detected;
- 11 • aids in correlating seemingly unrelated  
 12 events by printing event and context infor-  
 13 mation to a log file; and calls applications  
 14 interested in the event.

16 For example, route-flapping (frequent changes  
 17 in the routing table, used to detect badly config-  
 18 ured routers or system instability) can be identi-  
 19 fied by examining the next-hop metric collected at  
 20 each node. Currently a route-flapping event is  
 21 defined as a change in next hop. Once this event  
 22 is identified, Sympathy logs the event and its spa-  
 23 tiotemporal context. This information is logged to  
 24 the same file so that temporally and spatially cor-  
 25 related events are easily discernible.

## 27 Post-Deployment Architecture

30 The post-deployment implementation of Sym-  
 31 pathy would differ from the pre-deployment  
 32 architecture in that nodes must consume valuable  
 33 network bandwidth and power in order to  
 34 transmit information to a Sympathy-sink. In  
 35 post-deployment, no IPC is available to convey  
 36 debugging information between nodes, and code  
 37 is run directly on the motes, so the implementation  
 38 must also curtail memory usage in order to  
 39 conform to the mote platform. Since the metric col-  
 40 lection and initial processing occur directly on a  
 41 Sympathy-node, and metrics cannot be continu-  
 42 ally transmitted to the Sympathy-sink, only  
 43 limited events and recent metric values would be  
 44 stored at each Sympathy-node.

45 Owing to the sparser resources available during  
 46 post-deployment, the Sympathy-sink will have  
 47 incomplete knowledge about the state of each  
 48 node due to flaky links and heavy transmission  
 49 costs. As a result, post-deployment debugging  
 50 relies more on inferences of system state based on  
 51 externally observable metrics, and will not be as

precise as the pre-deployment techniques dis-  
 52 cussed here.

53 Because of the power limitations that necessitate  
 54 minimal communication, nodes must decide  
 55 which events are most important to transmit to the  
 56 Sympathy-sink. In addition, precisely defining  
 57 which events and metrics are important, and when  
 58 they should be transmitted, becomes even more  
 59 critical.

60 The Sympathy-sink would have to run on a non-  
 61 resource-constrained node—such as a Linux-  
 62 based stargate—which can accommodate the  
 63 additional storage and processing requirements  
 64 required at the sink. Periodically, the Sympathy-  
 65 sink could flood a request for nodes to send their  
 66 event data and current metric state in order to  
 67 ensure the health of the system.

## 70 Evaluation

71 To demonstrate Sympathy's potential as a debug-  
 72 ging tool, we ran it with a nesC implementation of  
 73 *Tiny Diffusion*,<sup>4</sup> a routing algorithm based on  
 74 directed diffusion.<sup>15</sup> In *Tiny Diffusion* nodes peri-  
 75 odically flood neighbor beacons (to calculate link  
 76 quality), neighbor lists and associated link quali-  
 77 ties (to identify asymmetric links), and *gradients*  
 78 which carry a node's next hop and projected path  
 79 loss (to determine a node's next hop). We ran Sym-  
 80 pathy with *Tiny Diffusion* in simulation, using a  
 81 14-node network. Each simulation ran for 2h at a  
 82 time. Our goal was to determine why *Tiny Diffu-*  
 83 *sion* had been experiencing loss rates an order of  
 84 magnitude higher than expected in data delivery  
 85 to the sink.

86 After the first run, using the events triggered in  
 87 Sympathy, we saw nodes change their next-hop  
 88 selection approximately every 170s. Sympathy  
 89 aided us over traditional debugging techniques by  
 90 highlighting the frequent changes in next-hop  
 91 selection and providing spatial correlation, which  
 92 revealed that during each period on average 39%  
 93 of nodes changed their next hop. While we would  
 94 expect some churn in next-hop selection, the con-  
 95 tinuous flux appeared suspicious.

96 We then investigated the temporal context pro-  
 97 vided for each event by Sympathy: that is, the  
 98 metrics and events that occurred close in time to  
 99 the unusual changes in next hop. Surprisingly, we  
 100 found that most nodes that changed their next hop  
 101  
 102

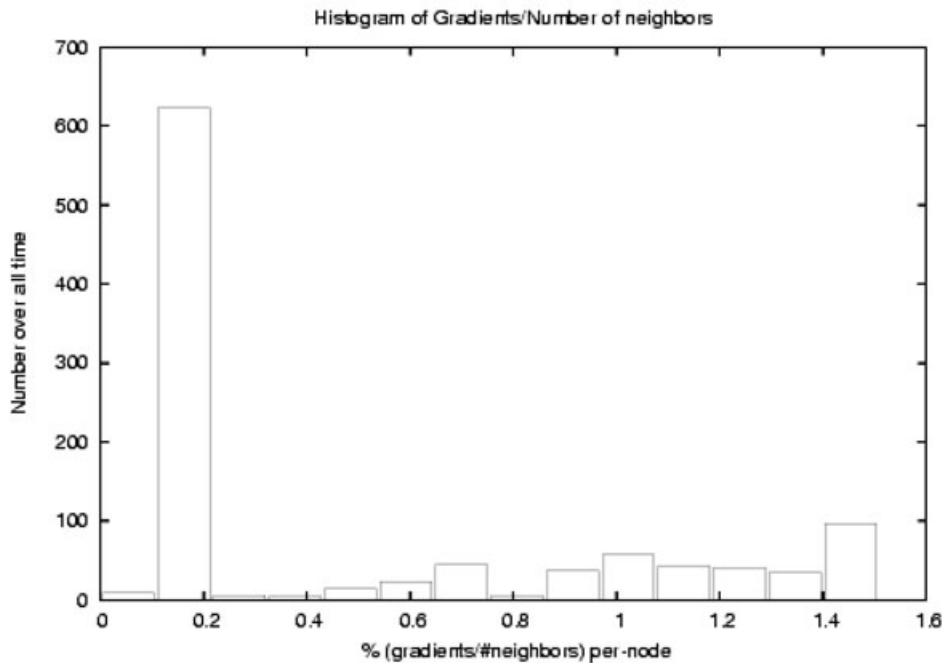


Figure 3. Histogram of number of gradients received by a node that changed its next hop, as a percentage of the number of neighbors in that node's neighbor list. Each node should receive roughly as many gradients as it has neighbors, but the graph shows that most nodes received gradients from only 10% of their neighbors (a minority of nodes may send multiple gradients, resulting in greater than 100%). The final bar represents nodes who heard at least one gradient, but had 0 neighbors recorded

did so because *they had received only one gradient message* and thus had only one choice for a next hop. Clearly, this was the cause for the frequent changes in next-hop selection. Furthermore, there was a high probability that nodes frequently selected high-loss paths, as they were given only one choice for next hop: had they received more than one gradient message, nodes could have chosen a better next hop with lower path loss. This in turn was a probable cause for the high loss rates observed at the sink.

To quantify our findings, we graphed the ratio of gradients received vs. number of neighbors. Figure 3 presents the results in a histogram: the vast majority of next-hop changes took place when the node received gradients from 10% or less of its neighbors. This is particularly strange because neighbor lists are recalculated each period from neighbor beacons that are flooded out immediately before the gradient messages. So, on an ideal, minimally varying, 0-loss link, a node

should receive 100% of the gradient messages sent by the nodes on its neighbor list. Yet an order of magnitude fewer gradient messages than neighbor beacons were received.

We theorize that many nodes received such a small percentage of their intended gradient messages owing to collisions caused by synchronization of nodes' gradient floods. Code examination corroborated this theory, revealing that while jitter was added to the transmission of neighbor beacons, no jitter had been added to the transmission of gradient floods.

Sympathy's strength lies in its support for highlighting events and correlating them with metrics in their spatiotemporal context. This is an improvement over traditional debugging techniques in three ways: it facilitates discovery of correlations by associating context with a specific event; it provides event tracking, which involves maintaining state; and it determines which events are important to track (only a finite number of

1 events can be tracked). In addition to highlighting  
2 correlations, Sympathy avoids several iterations of  
3 debugging and rerunning that would otherwise be  
4 needed to capture and analyze metrics in order to  
5 find events.

6 However, Sympathy cannot be used in a  
7 vacuum, nor can it be used to find bugs automati-  
8 cally. We used our knowledge of Tiny Diffusion to  
9 dismiss extraneous correlations, and to add the  
10 second-best gradient to the final list of metrics  
11 collected. While the metrics currently collected by  
12 Sympathy are *not* application specific, ongoing  
13 work will include a comprehensive analysis of  
14 generic metrics, events, and correlators.

## 15 Future Work

16 Our goal is to identify generic metrics that are  
17 useful to collect for a broad class of applications in  
18 order to make inferences about system health and  
19 highlight other interesting configuration and  
20 performance-related properties. Currently we  
21 have identified several metrics that have proven  
22 useful for debugging Tiny Diffusion. While we  
23 began with a TinyOS and Emstar-based imple-  
24 mentation running with Tiny Diffusion, Sympathy  
25 is by no means limited to this environment. Instead  
26 we are using this as a starting platform with which  
27 to develop our ideas. In the near future, we hope  
28 to generalize our initial metrics, develop better  
29 methods for identifying correlations, and include  
30 combining sensor data with system metrics and  
31 results from self-tests and injected probes in order  
32 to ensure expected behavior.

33 Once we determine metrics that can serve as  
34 accurate indicators of system health for a broad  
35 class of applications, nodes can also send back  
36 periodic maintenance reports in order to increase  
37 users' confidence in the system health. In addition,  
38 these metrics can be used to provide insight  
39 into performance and system characteristics as  
40 well as understanding—in real time—how a  
41 configuration change impacts functionality and  
42 performance.

43 We also plan to task motes and inject probes  
44 based on observed metrics. Ideally this can be  
45 done even at individual nodes; however, we will  
46 begin by implementing a centralized node (e.g. a  
47 Sympathy-sink) which receives metrics and based  
48 on its analysis decides it needs further information  
49 from a certain region. At this point, it could either

inject probes or command nodes to perform  
self-tests.

We could also deploy third-party snoopers  
running on a non-resource-constrained, Linux-  
based micro-server. Strategically placed snoopers  
could shift power-heavy debugging, logging,  
and transmission operations off the low-power  
sensor nodes and lengthen overall network  
lifetime. Snoopers also do not interfere with timing  
and protocol issues, making them attractively  
modular.

## 65 Conclusion

66 Standard debugging methods, applications, and  
67 infrastructure do not directly apply to sensor net-  
68 works, as most sensor nodes have extremely  
69 limited storage and energy capabilities. It is not a  
70 question of simply porting debugging tools like  
71 GDB over to a mote: debugging strategies and best  
72 practices must be reformulated to accommodate  
73 sensor networks' limited visibility and inter-nodal  
74 dynamics. A debugging solution that can seam-  
75 lessly move between development and post-  
76 deployment debugging can also facilitate the  
77 natural sensor network design process.

78 In this paper we presented the preliminary  
79 design of Sympathy, a tool that enables the debug-  
80 ging of sensor networks during the development  
81 phase. It is based on a triggering system that iden-  
82 tifies a priori events, provides spatiotemporal  
83 context to aid in isolating the source, and calls  
84 applications interested in an event. Using this  
85 tool, we demonstrate that it is possible to draw  
86 interesting conclusions based on collecting  
87 metrics, detecting seemingly unrelated events, and  
88 drawing even very simple correlations between  
89 them. Without Sympathy or a similar tool, it  
90 would have been difficult to quickly determine  
91 that Tiny Diffusion nodes were switching their  
92 next hops, and realize the periodicity of this  
93 behavior. Furthermore, it is not necessarily  
94 obvious that this behavior could have been corre-  
95 lated with the number of gradient messages  
96 received by each node. While Sympathy cannot  
97 yet be used for post-deployment debugging, it is  
98 already a useful stepping stone for analysis of  
99 event correlation methods, and for determining  
100 what metrics are most useful for health monitor-  
101 ing and fault detection in deployed systems.  
102

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## References

- 1 Szewczyk R, Polastre J, Mainwaring A. Lessons from a sensor network expedition. In *First European Workshop on Wireless Sensor Networks*, Berlin, Germany, January 2004.
- 2 Cerpa A, Elson J, Estrin D, Girod L, Hamilton M, Zhao J. Habitat monitoring: application driver for wireless communications technology. In *ACM SIGCOMM*, April 2001.
- 3 Girod L, Elson J, Cerpa A, Stathopoulos T, Ramanathan N, Estrin D. EmStar: a software environment for developing and deploying wireless sensor networks. In *Proceedings of the 2004 USENIX Technical Conference*, Boston, MA, 2004 (to appear).
- 4 Heidemann J, Silva F, Estrin D. Matching data dissemination algorithms to application requirements. In *Sensys*, Los Angeles, 2003.
- 5 Goldszmidt G, Yemini Y. Distributed management by delegating mobile agents. In *15th International Conference on Distributed Computing Systems*, June 1995.
- 6 Zhao J, Govindan R, Estrin D. Computing aggregates for monitoring wireless sensor networks. In *Proceedings of the IEEE ICC Workshop on Sensor Network Protocols and Applications*, Anchorage, AK, 2003.
- 7 Zhao J, Govindan R, Estrin D. Residual energy scans for monitoring wireless sensor networks. In *Proceedings of the IEEE Wireless Communications and Networking Conference*, Florida, 2002.
- 8 Tolle G, Culler D. Snms: application-cooperative management for wireless sensor networks. In *Proceedings of the Second ACM Conference on Embedded Networked Sensor Systems*, ACM, 2004.
- 9 Szewczyk R, Polastre J, Mainwaring A, Culler D. Lessons from a sensor network expedition. In *1st European Workshop on Wireless Sensor Networks*, January 2004.
- 10 Feng J, Megerian S, Potkonjak M. Model-based calibration for sensor networks. In *IEEE International Conference on Sensors*, October 2003.
- 11 Kiciman E, Fox A. Detecting application-level failures in component-based internet services. In *IEEE Transactions on Neural Networks* 2005; Spring.
- 12 Fox A, Kiciman E, Patterson D, Jordan M, Katz R. Combining statistical monitoring and predictable recovery for self-management. In *Proceedings of Workshop on Self-Managed Systems*, October 2004.
- 13 Ruan Y, Pai V. Making the 'box' transparent: system call performance as a first-class result. In *Proceedings of the 2004 USENIX Technical Conference*, Boston, MA, 2004 (to appear).
- 14 Girod L, Stathopoulos T, Ramanathan T, Estrin D. Tools for deployment and simulation of heterogeneous sensor networks. *Tech. Rep.*, CENS-TR-37, April 2004.
- 15 Intanagonwiwat C, Govindan R, Estrin D. Directed diffusion: a scalable and robust communication paradigm for sensor networks. In *Proceedings of the Sixth Annual International Conference on Mobile Computing and Networking*, Boston, MA. ACM Press, August 2000; 56–67.

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