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A Substrate for In-Network Sensor Data Integration

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Abstract
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Keywords
Sensor networks, Routing, Joins
A Substrate for In-Network Sensor Data Integration

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ABSTRACT
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Categories and Subject Descriptors
C.2.2 [Computer-Communication Networks]: Network Protocols—Routing protocols

General Terms
Sensor networks, Routing, Joins

1. INTRODUCTION
As technology continues to advance, we are nearing a point where sensor networks will combine with intranets and the Internet to form integrated systems: intelligent buildings with visitor guides, surveillance and intrusion detection systems, building control systems, robot teams, etc. As this occurs, designers will need to think not simply about building sensor network systems, but about building sophisticated applications that perform data acquisition and integration across highly distributed networks of heterogeneous device types: streams of data may come from distributed sensors, network monitors and other “soft” sensors, server-based applications, mobile applications, and so on. This leads to a challenge in providing uniform query access to highly dynamic data from remote devices. The Aspen project focuses on this problem: extending the data integration paradigm and query processing capabilities to ad hoc wireless networks, sensors, and stream systems, in order to foster a new generation of data-intensive applications.

The primary goal of sensor network query processing is to minimize the number of messages transmitted (thus reducing battery consumption and congestion). Recent work [7, 11, 12] has shown how certain types of computation can be efficiently pushed into a sensor network built using a tree topology. These approaches exploit the fact that selection, projection, and aggregation can be translated to a tree topology in a natural fashion. However, in contrast to standard acquisition systems, data integration queries require distributed join computation over streams from different groups of sensors, perhaps using time- or space-based windows. For example, an integration query might combine smoke detector and temperature information within the same room; or combine information from distributed weather stations in a valley, detecting cold fronts by correlating temperatures at the perimeter.

A thorough understanding of how to set up join computation, so as to leverage the multi-hop nature of the networks, as well as to allow future cost-based optimization, remains an open question. Most proposals suggest a single strategy for all queries: join at the base [15], in a region near the base [6], or by routing through the base [14]. At the other end of the spectrum lies geographic hash table (GHT)-style routing [13], which can be used to support join at randomly placed nodes. A key point is that the right strategy for join (i) establishes short, low congestion paths that are likely to be used over a long period of time, and (ii) sends the minimum number of tuples in each cycle along these paths.

The establishment of join paths to minimize communication has not been addressed by the existing work. In the routing tree model, most data gets routed through nodes near the root of the tree, causing congestion and forcing certain nodes to expend power disproportionately. Ultimately, the maximally loaded node fails earliest (drops packets, dies, loses connectivity), fragmenting the network. The GHT model uses hashes of key values to disperse routes over the network, reducing hot spots but resulting in longer paths that increase join traffic (unless the hashed keys correlate to geography, in which case we have the same congestion issues). Establishing effective join paths, although similar to routing, is significantly different in objectives — and is the foundation of any future query optimization. The goal of this paper is to devise a substrate that allows the establishment of join paths while considering congestion (delay), power and battery life (packets forwarded). This is a key component in the Aspen project, aiming to develop an optimized query processing architecture supporting long-running data integration queries over heterogeneous multihop wireless networks.

To illustrate the issues, suppose that we have a join of source expressions, possibly with selection conditions, \( \sigma_{\theta_R}(R) \bowtie_{\theta_{RS}} \sigma_{\theta_S}(S) \), in a sensor network: this is a windowed join [3], where we take a snapshot of the tuples emitted by every \( R \) sensor satisfying \( \theta_R \) in each time step, and similarly for each \( S \) sensor; then we combine the tuples of the \( R \) sensors taken within some time- (or space-) based window with the tuples of the \( S \) sensors taken within a (similarly defined) window, if they mutually satisfy predicate \( \theta_{RS} \). Each \( R \) and \( S \) tuple originates at a different place in the network, so each sensor node may have a different transmis-
sion distance. Each \( R \) and \( S \) tuple may not produce a tuple in every cycle, if \( \theta_R \) or \( \theta_S \), respectively, are not satisfied. Finally, each \( R \) tuple may join with between 0 and \( |S| \) tuples from \( S \), in every sampling time step. Given these properties, it is evident (by our optimization criteria above) that the optimal join strategy is not always simply to flood large regions of the network, forward tuples to the root node, or even route through the root node to other destinations [14]. Instead, there are a number of different strategies that are dependent on the query and data. While we provide a formal description in the next section, we list some “rules of thumb”:

- \( R \) and \( S \) tuples that do not join should be dropped early, reducing congestion and battery usage.
- When \( R \) and \( S \) tuples are unlikely to join, they should be joined inside the network: there are fewer join tuples than source tuples to route to the base.
- When the join condition is not very selective relative to \( R \) and \( S \) tuples, the join computation should be done at the base, as this results in fewer messages to the base.

We have sketched a problem of join optimization. This is quite different from query optimization in distributed databases: here we are considering settings where a single join involves pairs of relations that are horizontally partitioned, with each tuple at a different location, with a different number of hops to every other point in the network. Moreover, selectivities may differ for different source tuple values, and the connectivity of the network may gradually change as nodes or links fail, sensors move, batteries deplete, etc. Our contributions in this paper are an efficient content-addressable routing substrate for supporting distributed join computation and future optimization, which:

- Indexes static and slow-changing attributes (e.g., ID, position), allowing for efficient pruning of non-viable tuples
- Supports efficient point-to-point and multicast communication based on join values with short paths, enabling communication among sets of nodes that join
- Enables handling of link and node failures.

These capabilities enable collective cost-based decisions about where to join: at or near one of the source nodes, or at the base. While we defer a cost-based optimization model to future work, we experimentally validate that different join strategies have significant performance implications, and that in-network joins are often useful, in terms of network messages, network congestion hot spots, and device memory usage.

Section 2 argues why a new network substrate is required and discusses prior techniques. Section 3 presents a novel routing scheme that enables efficient join initiation. Section 4 discusses our implementation and presents an experimental evaluation. We conclude and discuss future work in Section 5.

2. THE CASE FOR A NEW SUBSTRATE

We assume windowed joins [3, 9], in which the join occurs between “relations” representing state at different nodes in the network. Given a join of the form \( \sigma \psi (R) \bowtie_{\theta_{RS}} (\sigma \theta_{RS} (S)) \), our goal is to find a partition of \( R \) and \( S \) nodes that minimizes overall network transmissions, such that all \( R \) and \( S \) nodes in the same partition route to some common join point \( j \), where they may join and the result will be sent to the root. This cost is dependent on the routes taken from the \( R \) and \( S \) sensors to the join points, and from there to the base; as well as by the selectivities of the operations. Our goal is to develop techniques to help decide which strategy to use for a given query. We now survey join strategies.

2.1 Join Strategies and Related Work

When selection and join conditions are based purely on static data (IDs, coordinates of immobile devices, device capabilities, etc.), they can be evaluated once\(^1\) by each node to see if they are satisfiable: if the selection fails or there are no other nodes with which to join, then this sensor cannot participate in the query. Hence we refine the predicates in our query expression: \( (\sigma \psi \land \theta_R (R)) \bowtie_{\theta_{RS} \land \psi_{RS}} (\sigma \theta_{RS} \land \psi_{RS} (S)) \) where each \( \psi \) condition only considers static attributes, and \( \psi \) represents the rest of the condition \( \theta \) including at least one dynamic attribute. We factor the predicates into CNF, then separate based on the presence of dynamic attributes (setting \( \psi \) to true if there are no static clauses). Most queries of interest possess such separation, and using the static selections \( \phi_{RS}, \phi_{R} \) helps any strategy (hence in this paper we assume this is always done). Predicates involving non-static components, \( \psi \), must be evaluated in every cycle. The dynamic join condition, \( \psi_{RS} \), must be evaluated at some common point that receives potentially-joining \( R \) and \( S \) data; finally, \( \phi_{RS} \) may be evaluated simultaneously, or during a pre-pruning step. Specifics depend on the strategy used.

2.1.1 Join paths along the routing tree

The vast majority of sensor network query processing research has focused on computation with a single routing tree. Placing computation and data: The problem of adaptively placing in-network query operators in efficient locations is considered in [4], which assumes a directed diffusion infrastructure and periodically performs local neighbor exploration. Complementary work [8] focuses on placement of stored data in the network, collecting statistics about update frequency and query rates, then performing centralized optimization. In this paper, we focus specifically on a routing substrate that could be used to help support the above work, as well as more join-specific optimizations.

\(^1\)Once per occasional network tree reconstruction.
Specialized joins: Several specialized join operations appear in the literature. REED [1] assumes one of the sources is a static table rather than a stream. The work of [6] assumes disjoint regions for the source nodes to be joined, computes a region “on the way to the base station” for nodes that join, then distributes a table snapshot among those nodes. It does not easily generalize to a setting with intermingled nodes, as we target. [16] returns “top-k” answers combining ranking functions over different attributes.

Naïve join: Here, selection conditions are pushed to every sensor node, so that in each epoch, only tuples satisfying $\psi_R$ or $\psi_S$ (for $R$, $S$, resp.) are forwarded to the base over the routing tree. Both join conditions $\phi_{RS}$ and $\psi_{RS}$ are then evaluated at the base station.

Base join: This approach builds upon naïve by also pushing static condition $\phi_{RS}$ into the network, determining apriori which nodes have the possibility of participating in the join. If a node has such a possibility and satisfies its selection conditions, it forwards data have the possibility of participating in the join. If a node has such a possibility and satisfies its selection conditions, it forwards data with intermingled nodes, as we target. $\phi_{RS}$ condition is satisfied over static attributes (while maintaining a source vector back to $r$). Nodes $s$ satisfying $\phi_s(s)$ and $\phi_{RS}(r, s)$ (these are target nodes) can communicate directly with $r$ by retracing the steps of the vector. Together (and possibly with other nodes that mutually join), they make an optimization decision about where to send their data during join computation. In the current presentation we omit further discussion of these optimization steps due to lack of space. For concreteness’ sake, we assume that the join takes place at a mutually agreed point, say either $r$, $s$ or the base station, although our implementation extends significantly beyond this simple strategy. The overall goals of the join initiation phase are (i) to have a fully distributed implementation; (ii) to find short paths in hops; (iii) to avoid hot spots; (iv) to handle node or edge failures (e.g., due to diminishing battery power or hardware failure); and (v) to scale to hundreds of nodes.

We observe that the benefit of using a single routing tree is that its hierarchical nature allows for summary structures [11], and allows “directed flooding” up the tree and down to any children whose summary structure includes the target join value. This requires significantly less traffic than flooding the network. But any spanning tree over a graph results in certain nodes in close proximity being numerous hops apart: consider a cycle, where the pairwise distance of a many pairs of nodes increases once the cycle is broken. The original graph has an advantage in average pairwise path length. To gain the best features of the single tree and the graph, we employ multiple routing trees over the same set of nodes: the initial routing tree forms the backbone of the network and is used for common tasks, whereas additional trees are formed afterward and used for directed routing and path distribution. Given multiple trees with well-chosen roots, the union of the trees together defines a spanner, a representation of the graph that preserves approximate pairwise distances. Multiple overlapping trees have previously been used in distributed multicast [5] in high bandwidth scenarios, but our goal and use of multiple trees is quite different here — sensors are typically constrained in bandwidth and power.

However, as soon as we use a graph which has cycles, cycle detection is essential to terminate searches. This is an advantage of hash-based schemes like GHT. We prevent cycles in our approach by restricting our algorithm to use the trees wisely (and not naïvely flood on all sets of edges) to balance the complexity of distributed cycle detection and the quality of the paths. More specifically, we mark packets using a single bit to indicate if the packet is traveling up a tree or down a tree, and do not allow repeated interleaving of these steps. Additionally, in order to minimize redundant transmissions, we develop a number of novel aspects in our algorithm. But we first discuss how the multiple trees are created: clearly, choosing the same edges for each tree has no benefit. The trees significantly impact the distances between nodes, and failure recovery as well, as we show later in our experimental evaluation.

3. A SUBSTRATE FOR JOIN

Join initiation is the phase where the nodes in the relations $R$ and $S$, after passing their respective static selection conditions, learn whether there exists at least one node with which they might join in each sampling interval (depending on dynamic conditions $\psi$). This is achieved by starting at each $r \in \sigma_{RS}(R)$ node (the initiator node), then exploring where the $\phi_{RS}$ condition is satisfied over static attributes (while maintaining a source vector back to $r$). Nodes $s$ satisfying $\phi_s(s)$ and $\phi_{RS}(r, s)$ (these are target nodes) can communicate directly with $r$ by retracing the steps of the vector. Together (and possibly with other nodes that mutually join), they make an optimization decision about where to send their data during join computation. In the current presentation we omit further discussion of these optimization steps due to lack of space. For concreteness’ sake, we assume that the join takes place at a mutually agreed point, say either $r$, $s$ or the base station, although our implementation extends significantly beyond this simple strategy. The overall goals of the join initiation phase are (i) to have a fully distributed implementation; (ii) to find short paths in hops; (iii) to avoid hot spots; (iv) to handle node or edge failures (e.g., due to diminishing battery power or hardware failure); and (v) to scale to hundreds of nodes.

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3.1 Constructing Multiple Trees

We build over the existing TinyDB [11] routing tree construction algorithm, which we briefly summarize. Nodes begin in a listening/broadcast mode, where they announce their presence and their distance from the root (initially infinity, except for the root, at distance 0). Each node determines the neighbor nearest the root that it can reliably hear from. It chooses that node to be its current parent
and broadcasts its new depth; the process repeats until the network stabilizes. We collect additional information: Bloom filters on the IDs and other static attributes of all of the nodes in a subtree to facilitate equijoin; other summary structures — histograms or intervals for range joins on 1D data, R-Trees and quadrants for 2D data — as well as the depth of the subtree. The summary structures act like a generalized index structure [2] and support directed forwarding of messages in the tree. Depth is used in the construction of additional routing trees and in routing.

To create an additional routing tree, we query over the last-built tree for each node’s score: at leaf nodes this score is initialized to be the sum of the node’s depth from the root on every existing tree; at intermediate nodes it is recursively updated to be the maximum score of the subtree. The node with the highest final score is chosen as the root of the new tree. The new root node builds its own tree using the algorithm described above, with one variation. When two candidate parents have equal distance from the new root, we favor the one that is not a parent in a previous tree, and in the absence of such, we choose the parent with the fewest children (to minimize the number of siblings for the current node). The purpose of this step is to ensure path diversity and avoid hot spots.

### 3.2 Routing: Finding Paths Satisfying $\phi_{RS}$

As discussed previously, join initiator nodes (say $r$) perform a multicast based on $\phi_{RS}$, looking for nodes satisfying the condition with $r$. The request is forwarded in the network in a directed fashion based on summary structures. Ultimately the request may reach a target node. We encode the routing path taken by a message as a vector of node IDs: destination nodes receive packet vectors to $r$, which can be used to send replies to $r$, ensuring both parties can now communicate without subsequent exploration. Since physical packets are small (under 30 bytes in TinyOS), we fragment logical messages (which may contain join keys, source routes, and data) into smaller physical packets. We implement a retry mechanism to ensure packet delivery in the absence of node failure.

Rather than naively flooding, our BestRoute algorithm (Algorithm 1) takes a number of steps to reduce redundant transmissions and avoid cycles. The initial part of the algorithm, Lines 1 – 5, determines when the message has a recipient known to the receiver (the current node or, if the join is on ID, a known neighbor) satisfying $\phi_{RS}$. We postpone a discussion of the middle portion of the algorithm to the next paragraph. The packet forwarding portion of the algorithm, Lines 25 – 40, is based on the following observation: we prefer to route from a node down one or more subtrees if their summaries are positive, because this allows for directed flooding. However, there is no guarantee that every node is reachable in this fashion. Hence, for correctness, every request must make its way up one tree to its root (also searching downwards from each node on the way). Yet there is no need to traverse up all of the trees in the same flood; in fact, avoiding this reduces exploration traffic and prevents a number of types of cycles. Following this logic, we start from the initiating node and begin exploring downward (the descending stage), forwarding to any child node in any tree whose node matches the join condition (Lines 25 – 27). We also spawn an exploration request up the parent node on each tree: this is the ascending stage of Lines 28 – 30. Exploration requests are typically relayed by broadcast (Line 35) to all neighboring nodes.

Hence, a node that hears an exploration request must ensure that it is actually an intended recipient: the sender must be a child or parent node (Lines 9 – 13). Additionally (Lines 14 – 22), the node determines whether the traversal is in ascending mode (if so, we need to continue exploring up the same tree, UpTree) or descending mode (if so, we can only search downwards, and only if some summary is positive for the join condition).

#### Algorithm 1: BESTROUTE

<table>
<thead>
<tr>
<th>Line</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1:</td>
<td>if $\phi_{RS}(SVal,CN,TAttr)$ then return and acknowledge: routing is complete</td>
</tr>
<tr>
<td>2:</td>
<td>if $TAttr$ is ID and some neighbor $N$ of $CN$ has $\phi(SVal,N,TAttr)$ then</td>
</tr>
<tr>
<td>3:</td>
<td>Forward $P$ to $N$</td>
</tr>
<tr>
<td>4:</td>
<td>return and acknowledge: complete</td>
</tr>
<tr>
<td>5:</td>
<td>end if</td>
</tr>
<tr>
<td>6:</td>
<td>if sender initiated the request and is a child of $CN$ in tree $T$ then</td>
</tr>
<tr>
<td>7:</td>
<td>UpTree $\leftarrow T$</td>
</tr>
<tr>
<td>8:</td>
<td>end if</td>
</tr>
<tr>
<td>9:</td>
<td>Set SourceIsChild if sender is a child of $CN$ in UpTree</td>
</tr>
<tr>
<td>10:</td>
<td>Set SourceIsParent if sender is a parent in any tree</td>
</tr>
<tr>
<td>11:</td>
<td>if not SourceIsParent and not SourceIsChild then</td>
</tr>
<tr>
<td>12:</td>
<td>return without acknowledgment: spurious message</td>
</tr>
<tr>
<td>13:</td>
<td>end if</td>
</tr>
<tr>
<td>14:</td>
<td>if not SourceIsParent and TopNode is not PathV.end then</td>
</tr>
<tr>
<td>15:</td>
<td>return without acknowledgment: spurious message</td>
</tr>
<tr>
<td>16:</td>
<td>end if</td>
</tr>
<tr>
<td>17:</td>
<td>if SourceIsChild and TopNode is PathV.end then</td>
</tr>
<tr>
<td>18:</td>
<td>Set IsAscending</td>
</tr>
<tr>
<td>19:</td>
<td>end if</td>
</tr>
<tr>
<td>20:</td>
<td>if not IsDescending and not exists $T$ where $P$ is sent by parent in $T$, and $CN$ has a child $N$ in $T$ with a summary satisfying $\phi_{RS}(SVal,N,TAttr)$ then</td>
</tr>
<tr>
<td>21:</td>
<td>return and acknowledge: redundant search</td>
</tr>
<tr>
<td>22:</td>
<td>end if</td>
</tr>
<tr>
<td>23:</td>
<td>ExploreSet $\leftarrow \emptyset$</td>
</tr>
<tr>
<td>24:</td>
<td>for all trees $T$ do</td>
</tr>
<tr>
<td>25:</td>
<td>if not IsAscending and some child $N$ of $CN$ in tree $T$ has a summary satisfying $\phi_{RS}(SVal,N,TAttr)$ then</td>
</tr>
<tr>
<td>26:</td>
<td>Add $N$ to ExploreSet</td>
</tr>
<tr>
<td>27:</td>
<td>end if</td>
</tr>
<tr>
<td>28:</td>
<td>if IsAscending and $(T = \text{UpTree} \lor CN$ is initiating the request) then</td>
</tr>
<tr>
<td>29:</td>
<td>Add $CN$’s parent $N$ in $T$ to ExploreSet</td>
</tr>
<tr>
<td>30:</td>
<td>end if</td>
</tr>
<tr>
<td>31:</td>
<td>end for</td>
</tr>
<tr>
<td>32:</td>
<td>Append $CN$.ID to PathV</td>
</tr>
<tr>
<td>33:</td>
<td>if IsAscending then TopNode $\leftarrow$ PathV.end</td>
</tr>
<tr>
<td>34:</td>
<td>if</td>
</tr>
<tr>
<td>35:</td>
<td>Broadcast updated $P$ to every node in ExploreSet</td>
</tr>
<tr>
<td>36:</td>
<td>else if</td>
</tr>
<tr>
<td>37:</td>
<td>Unicast updated $P$ to the node in ExploreSet</td>
</tr>
<tr>
<td>38:</td>
<td>end if</td>
</tr>
<tr>
<td>39:</td>
<td>Wait for acknowledgment by all nodes in ExploreSet</td>
</tr>
<tr>
<td>40:</td>
<td>return and acknowledge: complete</td>
</tr>
</tbody>
</table>

As a node is found to satisfy the join condition, it can use vector PathV and use it to establish a path back to the sender. At this stage, we actually do not limit our traversal to the multiple routing trees, but exploit the full graph. We employ an optimization called short-circuiting, which helps “shorten” the routes established by the BestRoute algorithm. Whenever a node can directly communicate (in symmetric fashion, with high stability) with another node whose ID is more than one step “ahead” on the path vector, it immediately short-circuits to that neighbor and removes the intervening node(s) from the path vector in the packet header.

### 4. IMPLEMENTATION AND EVALUATION

We implement and experimentally compare the most promising strategies from above, showing their performance differences. These include the naive strategy, an exact (as opposed to approximate) version of base, a version of GPSR/GHT, and a version of In-net over our multiple-tree routing substrate. We consider equality and range predicates, and both static and dynamic attributes.
We implemented our algorithms in 10,600 lines of nesC and compiled them using the toolkit for TinyOS 2.0. Our current implementation generates 71KB of code (including packet queuing, fragmenting, and reassembly) and uses a minimum of 3.5KB of memory to maintain 3 summary structures for each routing tree, state for up to 20 neighbors (including summary structures for each child subtree), and buffers for 30 simultaneous route requests. This fits easily within the 8KB RAM and 128KB program memory of the IRIS series motes. Experiments on motes are conducted using the TOSSIM [10] simulator, specifically to have results that incorporate errors and retransmissions due to the standard radio model.

TOSSIM is perhaps the most realistic simulator of the Crossbow MICAz and IRIS hardware platforms. Experiments were run on Xeon X3220 workstations with 4GB of RAM and Fedora 7.

**Methodology.** To understand our algorithms under different conditions, we generated 9 runs each of synthetic network configurations with 100 nodes in the following topologies: random with an average of 6 neighbors per node (“sparse random”); random with 7, 8, and 13 average neighbors (“moderate,” “medium,” and “dense random”); and grid with an average of 7 neighbors (“grid”). Unless otherwise specified, experiments were conducted on 3 different sensor layouts for each topology. We also constructed 50- and 200-node networks, both having 8 neighbors on average per node. We also validated our algorithms on real sensor data and a real topology, using the Intel Berkeley Research Lab dataset 7.

**Metrics.** Our algorithms and measurements focus on packet transmissions, rather than actual energy, because in some settings sending packets is the predominant consumer of energy, packets are approximately the same length making the conversion simple, and we aim to generalize to a variety of sensor types with different energy consumption profiles. Given that, we are evaluating the initialization phase to be compatible with arbitrary join queries we are interested in (1) path profiles, for example, length, maximum number of paths per node (2) total and maximum routing traffic per node, when a random pair of nodes is chosen for a join.

### 4.1 Path Profiles and Traffic

The first task of any in-network join algorithm is to discover which pairs of nodes must join. Note that both sources and targets can detect if they are potential participants, but they must discover that there is a matching target or source, respectively.

For BestRoute we study 1, 2 and 3 trees and consider the shortest discovered path. For GPSR, we implemented the strategy outlined in Section 2.1, using a routing destination selected by a hash of the join key. Figures 1a and b show the average join path length and maximum node load, respectively, for routes connecting all pairs of nodes (100 nodes and 9900 pairs) 10 pairs at a time, across different topologies. Further experiments (not plotted due to space constraints) confirmed that the load on roughly the top 15 most traversed nodes followed a similar pattern to Figure 1b, in that we saw benefits in BestRoute from going from 1 to 2 to 3 trees, and that GPSR performed worse than BestRoute with 2 and 3 trees. Overall, our observations are that (a) using 3 trees provides near-optimal paths on average; (b) GPSR does not give near-optimal paths; (c) GPSR has significantly worse load distribution for the top 15 nodes. We conclude that given reasonably long-running joins, join initialization using BestRoute with 3 trees is the best strategy.

**Initiation Traffic.** Another critical factor is how much traffic is created during exploration related to join initiation. Figure 2 confirms that the amount of traffic generated by BestRoute is significantly lower than flooding.

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*Node Scale-up and Number of Trees.* Figure 3 shows that as we scale the number of nodes from 50 to 200, for our algorithm, per-path load on individual nodes (Figure 3b) remains quite consistent, with a slightly more significant benefit to 3 trees when we get to 200 nodes. As expected, average path length (Figure 3a) increases as the network diameter grows; again, with 200 nodes there is a noticeable benefit in using 3 trees. We conclude here that three trees is the optimal choice, because it provides short paths and reduced hot spots while only slightly increasing the state required at each node. Further increasing the number of trees leads to diminishing returns and progressively larger memory requirements.

**Joining Real Data.** Next, we used the Intel Research-Berkeley real-life dataset, focusing on position data (over which we constructed an R-tree summary structure) and humidity. Our query was 

\[ R \land (R.x < S.x \land S.hum - R.hum > 1000) \land S \text{ id} < 10 \text{m} \land S \text{ id} < R \text{ id} \land \text{ abs}(R.hum - S.hum) > 1000 \]

which forms join pairs of nodes at most 5 meters apart, and reports results whenever they encounter a humidity difference greater than 1000. For this experiment, we performed an in-network join at the endpoint closer to the base station (breaking ties arbitrarily). Figure 7 reports the experiment in log scale. Total traffic was over 100MB, but the congestion as well as total traffic was halved by in-network execution. GHT performed worse than Naive/Base, and the Yang+07 algorithm [14] generated the most traffic.

### 4.2 Path Distribution

We next consider the load with respect to spatial distribution of sensors, showing 3D plots where the plane represents the coordinates of each sensor node and the height of each bar represents the number of paths through that node (bars are projected against the axes). We show results for 3 queries over the synthetically generated topologies. We assigned simulated static sensor values for a static attribute \( x \) to every node in the network, sampled from an exponential spatial distribution with range \([7, 60]\), with nodes towards the center of the network biased towards higher values. Static attribute \( y \) is sampled from \([0, 10]\) random uniform distribution.

**Query 1.** \( \sigma_{40 < R.x < 100} R \land \sigma_{s.x < 125} S \land \sigma_{40 < s.x < 100} S \), imposes heavy communication at the core of the network. Figure 4 shows the results on the grid network topologies; other topologies behave similarly. After adding a second tree, we see a major reduction in the load placed on the interior nodes, with an evenly distributed path load in the middle of the network. Intuitively, by switching trees, our algorithm “short-circuits” across the middle of the network without traversing nodes at or near the root. (We omit the 3-tree case, which provided minor benefits beyond the second tree in this query.)

**Query 2** considers joins at the fringes: \( \sigma_{0 < R.x < 125} R \land \sigma_{R.id < 125} R \land \sigma_{0 < S.x < 125} S \), generated with the random dense topology (but representative of the others), shows that for the 1-tree case, this workload places high load at and near the root. In contrast, 3 trees produces significantly fewer and lower hot spots. We omit the runs using 2 trees, which fell in the middle, due to lack of space.

For Query 3, the endpoints in the join are evenly distributed
Throughout the network: $\sigma_{i,j} \leq 25R_{y,R}M_{x,y}^+ + 5\sigma_{i,j} \leq 5S_y$. Figure 6 shows this for the random medium topology (similar effect is observed on all the other three topologies). Here, two trees provide some benefit but three trees provide the most gain — not only to the maximum load of the top nodes, but also the overall number of heavily loaded nodes is significantly reduced.

4.3 Congestion (Stress)

We apply several techniques to improve the performance of our system under high data rates. First, each node tracks free buffer memory; if it is running low on space, it notifies its neighbors through a congestion bit carried by data messages. Neighbors attempt to route around the node. For traffic sent through a congested node $n$ towards the base station, the sender picks an alternative node $n$ at the same level in the first routing tree (so long as it is not also congested). For traffic sent through $n$ towards some other destination node $n_d$, the node preceding $n$ on the path replaces $n$ with an alternative neighbor that can reach the $n$’s successor on the path. This scheme does not lengthen the paths traversed by any message. Of course, in some cases congestion avoidance might be impossible: in the extreme case the removal of the congested node $n$ might disconnect the network. In this case, $n$ will stop acknowledging received packets and discard them until it manages to send its outgoing messages. Other nodes needing to traverse $n$ will attempt to resend their packets later.

Multipath routing has been proposed to better reduce maximum load on nodes and congestion, before they occur. A similar strategy to the above can be used here: when a packet may be routed through several alternate nodes at any step in the path, the routing algorithm can randomly choose among these nodes.

In order to evaluate our system under congested settings, we took the query used for real life data and varied the sampling frequency from 0.003 values/cycle to 1 value/cycle, while executing for a fixed number of sampling cycles. We measured the freshness (propagation delays of the data values), and the number of packets dropped. In Figure 8a, for Naive (same as Base in this case), GHT, and Yang+07, the delay between the production of data values and their reception at the base station begins to grow for frequencies above 0.05 values/cycle, exceeding 100 cycles. In other words, result freshness for Naive, GHT, and Yang+07 worsens significantly under high sampling frequencies. Moreover, all methods except In-net begin to drop data values in this range, as they cannot keep up with the increased sampling frequency (Figure 8b). At very high frequencies Yang+07 has fewer drops than GHT: sending data on a single tree allows for opportunistic combining of physical packets more efficiently than GHT. To summarize, In-net incurs delays at least 4 times lower than GHT, 7 times lower than Naive, and 12 times lower than Yang+07 — with better overall result quality.

4.4 Failure Handling during Join Initiation

Failed links and nodes are a frequent occurrences in sensor networks, especially due to limited battery life. There are two failure cases in join initiation: (1) during exploration, which we do not focus on since BestRoute explores redundant paths and trees at this stage; and (2) after exploration, when path vectors between join pairs have been established, and the nodes need to coordinate. Suppose node $n_1$ is sending to node $n_2$ along path vector $[n_1, ..., n_f, ..., n_d]$, and $n_f$ is unreachable from its predecessor $n_{f-1}$. We initiate RepairRoute (Algorithm 2) which unlike BestRoute explores paths sequentially rather than in parallel, while tolerating link failures rather than node failures. RepairRoute searches for any node $n_y$ along the vector $[n_{f-1}, ..., n_d]$, and if successful the new path to $n_y$ is merged with the original path vector. During this time $n_{f-1}$ queues up messages in a repair buffer; and on success immediately forwards all of these messages along the new path. A special case is when $n_2$ is the base station. If $n_{f-1}$ can communicate with another node $n_3$ at the same level as $n_2$ in the main tree, then we forward the request to $n_3$. This single tree repair strategy in isolation requires only one routing tree, and we use it as a baseline in our comparison with RepairRoute.
Algorithm 2 \textsc{RepairRoute}(CN, P, PathV, TopNode, DestNode, PathVR, State). Input: Receiving node CN, incoming packet P, path vector from start PathV, top of ascending part of path vector TopNode, DestNode destination of the failed routing, path from the failed node to DestNode PathVR, acknowledgement ACK or NACK in State.

1: if \text{CN} appears on \text{PathVR} then return ACK, routing complete
2: if for some neighbor N of \text{CN}: N appears on \text{PathVR} then
3: Forward P to N
4: return ACK, routing complete
5: end if
6: if CN is the initiator and State=NACK then
7: return NACK: repair is unsuccessful
8: end if
9: if sender is a child of \text{CN} in tree UpTree then Set IsAscending
10: else Set IsDescending
11: end if
12: if \text{IsDescending} and (isAscending or (IsDescending and P was previously seen as descending)) then return NACK
13: if \text{IsDescending} and not exists T where P is sent by parent in T; and \text{CN} has a child N in T with a summary on ID positive for \text{DestNode} then return NACK
14: end if
15: \text{ExploreList} ← [ ]
16: for all trees T do
17: if \text{IsDescending} and some child N of \text{CN} in tree T has a summary on ID positive for \text{DestNode} then
18: Add N to \text{ExploreList}
19: end if
20: if \text{IsAscending} and (T = UpTree or \text{CN} is the initiator) then
21: Add CN’s parent N in T to \text{ExploreList}
22: end if
23: end for
24: Append \text{CN}.ID to PathV
25: if IsAscending then TopNode ← PathV.end
26: if \text{|ExploreList|} > 0 then
27: if \text{State}=ACK then
28: Unicast to first node N in \text{ExploreList}
29: return same result returned by N
30: else if P’s sender exists in \text{ExploreList} at position i and i < |ExploreList| then
31: Unicast P to the node N at position i + 1
32: return same result returned by N
33: end if
34: end if
35: return NACK

Our evaluation consists of failing up to 16 out of 100 nodes while executing \(\sigma_{id < 255 \land h(u, \sigma_p) \neq \varnothing \land u = \text{Root} \land u = \text{Sum}.id \geq 50 / h(u, \sigma_p) \neq \varnothing\), where \(h(u, \sigma_p) = (\text{hash}(u) \% 1 / \sigma_p) = 0\) on the medium random topology. This query expands Query 3 with dynamic predicates: attribute \(u\) is dynamic and it is generated to conform to selectivity estimates \(\sigma_u\) or \(\sigma_x\). As in Query 3, multiple attributes are joined, and we expect the endpoints in the join to be fairly evenly distributed throughout the network, because of the uniform \(y\) predicate, and also because by construction there is no spatial correlation between node IDs. Thus endpoints are separated by long paths, which makes failure recovery non-trivial.

We evaluate RepairRoute and single tree repair for this query. For a given number of nodes set to fail, their times of failure are scattered across the iteration run. We study the increase in the overall traffic and percentage of successfully established source-target join pairs. A given join pair is considered successfully established if both source \(x\) and target \(s\) are aware that they are joining, and both agree on a join node \(j\), which also knows to join them. RepairRoute L1 and L2 differ in the summary structure used for routing. While L1 utilizes a Bloom filter of the IDs of children in a particular subtree, L2’s Bloom filter also holds the children’s immediate neighbors, thus increasing the likelihood of success at the expense of some added exploration. As indicated by Figure 9a, by using RepairRoute we can recover completely from up to 3% node failures. We achieve up to 20% increase in the number of successfully established pairs over single tree repair. In Figure 9b we observe that for node failures up to 12% we maintain comparable traffic per successfully established pair with single tree repair.

5. CONCLUSIONS AND FUTURE WORK

This paper proposes a substrate for supporting \textit{join initiation}: discovery of short paths among sets of nodes that mutually satisfy some join condition, and thus are eligible to join in each cycle. This is the basis of in-network join computation, which we have shown to perform better than alternative strategies in a number of cases. Our methods scale to hundreds of nodes.

We are currently focusing on further mote-specific energy-reducing techniques. Then, the next phase of our research agenda is to build upon this substrate and address the issues of query optimization. The first step is to choose a cost model appropriate for sensor networks, which considers overall message transmissions, but also hot spots. The subtlety here is that the cost model needs to take into account opportunities for shared computation: we could share a single join point across multiple source nodes, or alternatively we could keep them separate — a problem we refer to as \textit{multi-pair} optimization. We hope to choose an initial join strategy and join point based on predicted selectivities, then monitor and react to actual selectivities and move the join point as appropriate.

6. REFERENCES