Adaptive Data Fusion for Energy Efficient Routing in Wireless Sensor Networks

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Abstract—While in-network data fusion can reduce data redundancy and, hence, curtail network load, the fusion process itself may introduce significant energy consumption for emerging wireless sensor networks with vectorial data and/or security requirements. Therefore, fusion-driven routing protocols for sensor networks cannot optimize over communication cost only—fusion cost must also be accounted for. In our prior work [2], while a randomized algorithm termed MFST is devised toward this end, it assumes that *fusion shall be performed at any intersection node whenever data streams encounter*. In this paper, we design a novel routing algorithm, called *Adaptive Fusion Steiner Tree (AFST)*, for energy efficient data gathering. Not only does AFST jointly optimize over the costs for both data transmission and fusion, but also AFST evaluates the benefit and cost of data fusion along information routes and *adaptively adjusts whether fusion shall be performed at a particular node*. Analytically and experimentally, we show that AFST achieves better performance than existing algorithms, including SLT, SPT, and MFST.

Index Terms—Sensor networks, data gathering, data fusion, routing.

1 Introduction

Wireless sensor networks have attracted a plethora of research efforts due to their vast potential applications [3], [4]. In particular, extensive research work has been devoted to providing energy efficient routing algorithms for data gathering [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19]. While some of these approaches assume statistically independent information and have developed shortest path tree-based routing strategies [5], [6], others have considered the more realistic case of correlated data gathering [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18]. By exploring data correlation and employing in-network processing, redundancy among sensed data can be curtailed and, hence, the network load can be reduced [8]. The objective of sensor routing algorithms is then to jointly explore the data structure and network topology to provide the optimal strategy for data gathering with as minimum energy as possible.

Regardless of the techniques employed, existing strategies miss one key dimension in the optimization space for routing correlated data, namely, the *data aggregation cost*. Indeed, the cost for data aggregation may not be negligible for certain applications. For example, sensor networks monitoring field temperature may use simple average, max, or min functions which essentially are of insignificant cost. However, other networks may require complex operations for data fusion.[1] Energy consumption of beamforming algorithm for acoustic signal fusion has been shown to be on the same order of that for data transmission [20]. Moreover, encryption and decryption at intermediate nodes will significantly increase fusion cost in the hop-by-hop secure network since the computational cost is on the scale of nJ per bit [21]. In our own experimental study, described in the Appendix, we show that aggregation processes such as image fusion cost tens of nJ per bit, which is on the same order as the communication cost reported in the literature [7], [20].

Differently from transmission cost that depends on the output of the fusion function, the fusion cost is mainly determined by the inputs of the fusion function. Therefore, in addition to transmission cost, the fusion cost can significantly affect routing decisions when involving data aggregation. In our prior work [2], we presented a randomized algorithm termed *Minimum Fusion Steiner Tree (MFST)* that jointly optimizes over both the fusion and transmission costs to minimize overall energy consumption. MFST is proven to achieve a routing tree that exhibits $\frac{5}{4} log(n+1)$ approximation ratio to the optimal solution, where n denotes the number of source nodes.

While MFST has been shown to outperform other routing algorithms, including *Shortest Path Tree* (SPT), *Minimum Spanning Tree* (MST), and *Shallow Light Tree* (SLT) in various system settings, it assumes that aggregation is performed at the intersection nodes *whenever* data streams encounter. However, as we shall show below, such a strategy may introduce unnecessary energy consumption. Specifically, performing fusion at certain nodes may be less efficient than simply relaying the data directly. This observation motivates us to design an adaptive fusion

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1. In this paper, we will consider "aggregation" and "fusion" interchangeable, denoting the data reduction process on intermediate sensor nodes.

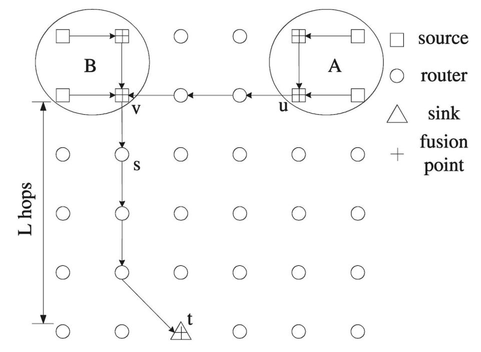


Fig. 1. Illustration of fusion benefit, or disadvantage, in sensor networks.

strategy that not only optimizes information routes, but also embeds the decisions as to when and where fusion shall be performed in order to minimize the total network energy consumption.

1.1 Motivation

Fig. 1 depicts a sensor network where sensor nodes are deployed on grid and sensed information of the source nodes is to be routed to sink t. Arrow lines form the aggregation tree in which nodes u and v initially aggregate data of areas A and B, respectively. As the sink is far away, u and v further aggregate their data at v and then send one fused data to the sink. Assuming each hop has identical unit transmission cost c_0, the fusion cost is linear to the total amount of incoming data, and the unit fusion cost is q_0. Let $w(u)$ and $w(v)$, respectively, denote the amount of data at u and v before the aggregation between them. The amount of resultant aggregated data at v can be expressed as $(w(u)+w(v))(1-\sigma_{uv})$, where σ_{uv} represents the data reduction ratio owing to aggregation. In this scenario, if v performs data fusion, the total energy consumption of the route from v to t, assuming there are L hops in between, is $Lc_0(w(u)+w(v))(1-\sigma_{uv})+q_0(w(u)+w(v))$. On the contrary, if v does not perform data fusion, the total energy consumption of the same route is simply the total relaying cost, $Lc_0(w(u)+w(v))$. To minimize the *total energy consumption of the network*, v should not perform data fusion as long as $\sigma_{uv} < \frac{q_0}{Lc_0}$.

This simple example reveals that, to minimize total network energy consumption, the decision at an individual node has to be based on the data reduction ratio due to aggregation, its related cost, and its effect on the communication costs at the succeeding nodes. Although the criteria can be easily obtained for this simple example, a sensor network confronting various aggregation/communication costs and data/topology structures undoubtedly will dramatically augment the difficulty of the fusion decisions.

1.2 Our Contribution

In this paper, we propose the *Adaptive Fusion Steiner Tree* (AFST), a routing scheme that not only optimizes over both transmission and fusion costs, but also adaptively adjusts its fusion decisions for sensor nodes. By evaluating whether fusion is beneficial to the network based on fusion/transmission costs and network/data structures, AFST dynamically assigns fusion decisions to routing nodes during the route construction process. Analytically, we prove that AFST outperforms MFST. Through an extensive set of simulations, we demonstrate that AFST provides significant energy savings over MFST (up to 70 percent) and other routing algorithms under a wide range of system setups. By adapting both the routing tree and fusion decisions to various network conditions, including fusion cost, transmission cost, and data structure, AFST provides a routing algorithm suitable for a broad range of applications.

In particular, we prove that the routing tree resulting from AFST consists of two parts: a lower part, where aggregation is always performed, and an upper part, where no aggregation occurs. The result can be readily applied in designing clustering algorithms in sensor networks: Based on where fusion stops, the network can be partitioned into clusters where data aggregation is confined to be within the clusters only.

The remainder of this paper is organized as follows: In Section 2, we describe the system model and formulate the routing problem. Section 3 first gives an overview of the randomized approximation algorithm MFST and then presents in detail the design and analysis of the proposed algorithm AFST. In Section 4, we experimentally study the performance of AFST. Section 5 gives the related work and Section 6 concludes the paper.

2 System Model and Problem Formulation

2.1 Network Model

We model a sensor network as a graph $G=(V,E)$, where V denotes the node set and E the edge set representing the communication links between node-pairs. We assume a set $S \subset V$ of n nodes are data sources of interest and the sensed data needs to be sent to a special sink node $t \in V$ periodically. We refer to the period of data gathering as a *round* in this paper.

For a node $v \in S$, we define node weight $w(v)$ to denote the amount of information outgoing from v in every round. An edge $e \in E$ is denoted by $e=(u,v)$, where u is the start node and v is the end node. The weight of edge e is equivalent to the weight of its start node, i.e., $w(e)=w(u)$. Two metrics, $t(e)$ and $f(e)$, are associated with each edge, describing the transmission cost and fusion cost on the edge, respectively.

Transmission cost, $t(e)$, denotes the cost for transmitting $w(e)$ amount of data from u to v. We abstract the unit cost of the link for transmitting data from u to v as $c(e)$ and, thus, the transmission cost $t(e)$ is

$$t(e)=w(e)c(e). \tag{1}$$

Notice that $c(e)$ is edge-dependent and, hence, can accommodate various conditions per link, for example, different distances between nodes and local congestion situations.

Fusion cost, $f(e)$ denotes energy consumption for the fusion process at the *end* node v. $f(e)$ depends on the amount of data to be fused as well as the algorithms utilized. In this paper, we use $q(e)$ to abstract the unit fusion cost on edge e. Since data fusion is performed by intermediate nodes to aggregate their own data with their children's, in order to avoid confusion, we use $\widetilde{w}(\cdot)$ to denote the temporary weight of a node *before current data fusion*. Then, the cost for fusing the data of nodes u and v at node v is given by

$$f(e) = q(e) \cdot \Big(w(u) + \widetilde{w}(v)\Big). \tag{2}$$

Key to a sensor data routing protocol with data fusion is the data aggregation ratio. Unfortunately, this ratio is heavily dependent on application scenarios. Here, we use an abstract parameter σ to denote the data reduction ratio due to aggregation. To be more specific, if node v is responsible for fusing node u's data (denoted by $w(u)$) with its own, we have $w(v) = (w(u) + \widetilde{w}(v))(1 - \sigma_{uv})$, where $\widetilde{w}(v)$ and $w(v)$ denote the data amount of node v before and after fusion. Notice that $\sigma_{u,v}$ may be different before and after the fusion process between node u and another node as the weight, $w(u)$, will change by the fusion and the data correlation between node u and v will be different as well.

Due to aggregation cost, node v may choose not to perform data aggregation in order to realize maximum energy saving. Instead, it will simply relay the incoming data of node u. In this case, the new weight of node v is simply $w(v) = (w(u) + \widetilde{w}(v))$. Jointly considering both cases described above, we can summarize the aggregation function at node v as

$$w(v) = (w(u) + \widetilde{w}(v))(1 - \sigma_{uv} x_{uv}), \tag{3}$$

where $x_{uv} \in \{0, 1\}$ denotes whether fusion occurs on edge $e = (u, v)$.

2.2 Problem Formulation

Given the source node set S and sink t, our objective is to design a routing algorithm that minimizes the energy consumption when delivering data from all source nodes in S to the sink t. Not only do we need to design routing paths backhauling sensed information driven by information aggregation, but we also have to optimize over the decisions as to whether aggregation shall occur or not on a particular node.

Mathematically, a feasible routing scheme is a connected subgraph $G' = (V', E')$, where $G' \subset G$ contains all sources ($S \subset V'$) and the sink ($t \in V'$). Depending on whether fusion is performed or not, the edge set E' can be divided into two disjoint subsets, E'_f and E'_n, where $E'_f = \{e | e \in E', x_e = 1\}$ and $E'_n = \{e | e \in E', x_e = 0\}$. Our goal is to find a feasible subgraph G^* such that

$$G^* = \arg\min_{G'} \sum_{e \in E'_f} \Big(f(e) + t(e)\Big) + \sum_{e \in E'_n} t(e). \tag{4}$$

3 Design and Analysis of AFST

While MFST [2] has provided an approximation routing algorithm that jointly optimizes over both the transmission and fusion costs with proven performance bound, it lacks fusion decisions in routing construction. This motivates us to design the *Adaptive Fusion Steiner Tree (AFST)*, which achieves significantly better performance than MFST due to the incorporation of fusion decision.

In designing AFST to solve the optimization problem as presented in (4), our approach is as follows: By exploiting certain network properties, we first propose a heuristic solution termed the *Binary Fusion Steiner Tree* (BFST), which is analytically shown to have better performance than MFST. However, BFST is still constrained to the tree structure obtained from MFST. By employing SPT rather than the structure obtained via MFST, where appropriate, we further improve BFST to AFST. As a result, we are able to analytically show that AFST is capable of achieving better performance than BFST.

As AFST is based on MFST, we first give a brief overview of MFST. Then, we introduce fusion decisions into the routing structure generated by the MFST scheme. Following that, we detail our new solution.

3.1 Brief Overview of MFST

The minimum fusion steiner tree (MFST) is based on the techniques presented in [14], [22]. It first pairs up source nodes (or source with the sink) based on defined metrics and then randomly selects a center node from the node-pair. The weight of the noncenter node will be transferred to the center node, paying appropriate transmission and fusion costs on that edge. Subsequently, the noncenter node will be eliminated and the center node with aggregated weight will be grouped as a new set of sources. This process will then be repeated on the new set until the sink is the only remaining node. The algorithm is detailed below for the sake of completeness.

MFST ALGORITHM

1. Initialize the loop index $i = 0$. Define $S_0 = S \cup \{t\}$, and $E^* = \emptyset$. Let $w_0(v)$ for any $v \in S$ denote its original weight, and let $w_0(t) = 0$.
2. For every pair of nodes $(u, v) \in S_i$:
   - Find the minimum cost path (u, v) in G according to the metric
   $$M(e) = q(e)(w_i(u) + w_i(v)) + \alpha(w_i(u), w_i(v))c(e), \tag{5}$$
   where $\alpha(w_i(u), w_i(v)) = \frac{w_i(u)w_i(v)(w_i(u)+w_i(v))}{w_i^2(u)+w_i^2(v)}$ if (u, v) is a no-sink pair and $\alpha(w_i(u), w_i(v)) = w_i(u)$ if v is just the sink t.
   - Define $K_i(u, v)$ to be the distance under metric $M(e)$ of this path.
3. Find the minimum-cost perfect matching[2] between nodes in S_i. Let $(u_{i,j}, v_{i,j})$ denote the jth matched pair in S_i, where $1 \le j \le |S_i|/2$. If there is only one nonsink node left after matching, match it to itself without any cost and consider it as the last "single-node pair" in S_i.
4. For each matched pair (u, v), add those edges that are on the path defining $K_i(u, v)$ to set E^*.
5. For each pair of nonsink matched nodes (u, v), choose u to be the center with probability $P(u = center) = \frac{w_i^2(u)}{w_i^2(u)+w_i^2(v)}$. Otherwise, node v will

2. Minimum-cost perfect matching is a matching of edges in a graph that guarantees the total cost (distance) for all pairs under $M(e)$ is minimized. For polynomial-time algorithms for this problem, see [23].

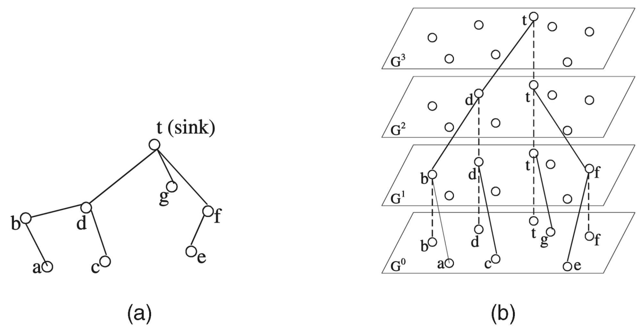


Fig. 2. Expression of data aggregation tree in a 3D binary tree structure. Solid lines in (b) correspond to edges in (a) and dotted lines represent virtual edges. (a) Original aggregation tree. (b) Equivalent 3D aggregation tree.

be the center. For pair (u, t), choose sink t to be the center.

6. Transport the weight of the noncenter node to its corresponding center node. The weight of the center satisfies $w_{i+1}(center) = (w_i(u) + w_i(v))(1 - \sigma_{uv})$.
7. Remove all noncenter nodes from S_i, then the remaining center nodes induce S_{i+1}.
8. If S_{i+1} contains only the sink, we return $G^* = (V^*, E^*)$, where E^* is the set of edges we constructed and V^* includes the source nodes and the sink. Otherwise, increment i and return to Step 2.

In MFST, the size of the set S_i is reduced by half after one iteration of the algorithm. Therefore, the process terminates after $\log(n+1)$ iterations. In the remainder of this paper, we call each iteration a "stage" of the algorithm.

MFST jointly considers both fusion and transmission costs. It has been shown that it yields $\frac{5}{4}log(n+1)$ approximation ratio to the optimal solution. Although extensive experiments [2] have shown that MFST can outperform other routing algorithms, including SLT, SPT, and MST, one optimizing dimension is still missing, namely, the aforementioned fusion decisions at sensor nodes. As MFST requires fusion to be performed along a routing path whenever possible, unnecessary energy may be wasted due to the inefficiency of fusion, for example, little information reduction due to weak correlation and high fusion cost.

This phenomena can be magnified in the proximity of the sink itself. As aggregated information streams are approaching the sink, their correlation decreases, which will introduce small data reduction owing to fusion. At the same time, directly relaying the data will not incur high communication cost as fewer hops are needed for relaying. Naturally, in this scenario, there is a high probability for direct relaying to outperform aggregation.

To solve this problem, we design AFST, where adaptive fusion decisions will be incorporated into the routing construction process.

3.2 3D Binary Tree Structure

In order to make our analysis more clear, we use a 3D binary tree structure to describe the process of the hierarchical matching technique used in MFST. Fig. 2 illustrates a mapping example of the original aggregation tree and its transformation. From bottom to top, the edges between two layers represent the result of node matching and center selection in each iteration of MFST.

Assuming there are n sources in the aggregation tree G^* obtained via MFST, to perform the transformation, we first clone $N = \lceil \log(n+1) \rceil$ copies of G^*, denoted by $G^1, G^2, \ldots, G^N$. For convenience, we label the original G^* as G^0 and arrange them into vertical layers, as shown in Fig. 2b. For simplification, we will refer to node v's clone in layer k as v_k. Subsequently, we map the original aggregation tree G^*, as shown in Fig. 2a, to a new graph $\hat{G}^*$ embedded into these clones. $\hat{G}^*$ is the targeted 3D binary tree. The process is to map the result of each matching stage k in MFST to the edges between G^k and G^{k+1}. If we match u and v in stage k and v is selected as the center node in MFST, we first add an edge e linking v's clones in G^k and G^{k+1} with zero unit transmission cost $c(e) = 0$. This edge is termed a virtual edge (dotted line). Then, we connect u_k to v_{k+1} with the same unit communication cost $c(e)$ as in G^*.

The result of this transformation is a binary tree which is rooted at the sink in G^N and has all leaves in S residing in G^0. For each source $v \in S$, there is a path going through all clones of G^*, from v in G^0 to the sink t in G^N, via exactly N hops.

In order to guarantee that the resulting 3D tree is binary, the number of source nodes is assumed a power of 2 minus 1. If this is not the case, dummy nodes with weight 0 can be created as needed to complement the binary tree, corresponding to the single node pair matching cases. These dummy nodes have aggregation ratio 0 with any other nodes and incur zero fusion cost. As virtual edges and dummy nodes/edges incur zero cost for communication and fusion, the 3D binary tree is equivalent to the original aggregation tree.

For each node $v_k \in \hat{G}^*$ (the 3D binary tree) in layer k, let w_{v_k} denote the temporary weight of node v after combining the incoming data from lower layers (with or without data fusion). Each edge $e_k = (u_k, v_{k+1}) \in \hat{G}^*$ between the kth layer and the $(k+1)$th layer is characterized by four parameters: edge weight $w_{e_k} = w_{u_k}$, unit transmission cost c_{e_k}, data aggregation ratio σ_{e_k}, and unit fusion cost q_{e_k}. Note that virtual edges have $c_{e_k} = 0$ and $\sigma_{e_k} = 1$ (full aggregation) and dummy edges have $w_{e_k} = 0$ and $\sigma_{e_k} = 0$ (no aggregation).

To incorporate the fusion decision, we use $x_{e_k} \in \{0, 1\}$ to represent whether or not information on edge e_k is fused at the end node of this edge. Therefore, the optimal routing structure is an optimization problem over x_{e_k} as well as the tree structure. Toward this end, we present the *Binary Fusion Steiner Tree* (BFST), an approximate solution to this routing problem.

3.3 Binary Fusion Steiner Tree (BFST)

In BFST, we first obtain a routing tree using the MFST algorithm, where fusion is performed by any intermediate node. Subsequently, we evaluate whether fusion on individual nodes will reduce the energy consumption of the network. If not, the fusion process on the node will be canceled and, instead, data will be directly relayed.

BFST ALGORITHM

1. Run the MFST algorithm to obtain a routing tree with fusion at every node possible. Convert the

resulting aggregation tree to the 3D binary tree as described above. For all edges in the tree, set $x_{e_k} = 1$.

2. From bottom to top, calculate the fusion benefit for each edge in the aggregation tree (excluding virtual edges), which can represent the energy saving by data fusion on that edge. Let $\Delta_{u_k,v_{k+1}}$ denote the fusion benefit of edge $e_k = (u_k, v_{k+1})$. It is defined as

$$\begin{aligned}\Delta_{u_k,v_{k+1}} = (w_{u_k} + w_{v_k})C(v_{k+1}, t_N) \\ - ((w_{u_k} + w_{v_k})(1 - \sigma_{e_k})C(v_{k+1}, t_N) \\ + q_{e_k}(w_{u_k} + w_{v_k})),\end{aligned} \quad (6)$$

where $C(v_{k+1}, t_N)$ denotes the summation of unit transmission costs from v_{k+1} to t_N in MFST. Set $x_{e_k} = 1$ if $\Delta_{u_k,v_{k+1}} > 0$; otherwise, set $x_{e_k} = 0$.

3. For all edges with $x_{u_k,v_{k+1}} = 0$, set $x_{v_k,v_{k+1}} = 0$ to their corresponding virtual edges.

In our analysis, we will employ the 3D binary tree described in the previous subsection. To simplify the analysis, we assume that, in BFST, the data reduction ratio σ is nonincreasing on each path from the source to the sink, while the unit fusion cost q is nondecreasing, excluding virtual edges. This assumption can be naturally justified. First, strong correlation and, thus, high aggregation ratio usually are due to spatial correlation resulting from short distances between nodes. In turn, these short distances will lead to small unit transmission cost. Based on the metric $M(e)$ defined in MFST (which is a combination of fusion cost and transmission cost), it will match strongly correlated nodes before matching weakly correlated nodes. Therefore, for edges on a source-sink path, the aggregation ratio for edges near the sink will not be larger than those further away. Reflected on the 3D binary tree, this will lead to nonincreasing σ on a particular source-sink path. The reason for skipping virtual edges is that their data aggregation ratio is set to 1 and does not affect the actual energy consumption of the network. Second, the unit fusion cost q is determined mainly by the complexity of the fusion algorithm and the input data set. As the information is being routed toward the sink, the data size and complexity will naturally increase due to aggregation on the route. Therefore, performing fusion thereon will incur more computation and, hence, more energy consumption per unit data.

Based on this assumption, we first introduce Lemma 1.

Lemma 1. *x_e is nonincreasing on each path from a source to the sink in BFST.*

Proof. Let Fig. 3 represent a branch of the binary fusion tree produced by BFST in which solid lines represent actual edges in the aggregation tree, dotted lines denote virtual edges added for analysis, and dash-dotted lines are paths to the sink. On any path from a source node to the sink, assume e_k is the first edge with $x_{e_k} = 0$. We will enumerate different cases.

Case 1. If e_k, the first edge not performing fusion, is not a virtual edge, there are two subcases, depending on its succeeding edge, e_{k+1}, as discussed below.

If both e_k and its succeeding edge e_{k+1} are not virtual edges, as exemplified by $e_k = (u_k, v_{k+1})$ and $e_{k+1} = (v_{k+1}, s_{k+2})$ shown in Fig. 3, we have $\Delta_{u_k,v_{k+1}} \leq 0$.

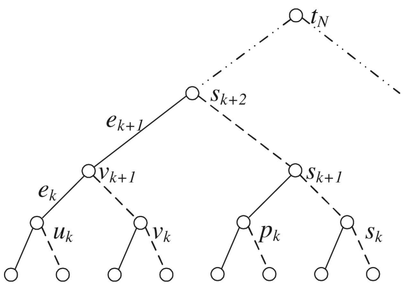


Fig. 3. A fraction of the binary fusion tree for BFST.

From (6), we have $\sigma_{u_k,v_{k+1}} C(v_{k+1}, t_N) \leq q_{u_k,v_{k+1}}$. As $\sigma_{u_k,v_{k+1}} \geq \sigma_{v_{k+1},s_{k+2}}$ and $q_{u_k,v_{k+1}} \leq q_{v_{k+1},s_{k+2}}$ based on our assumption, and the total unit transmission cost from v_{k+1} to t_N is more than that from s_{k+2} to t_N, i.e., $C(v_{k+1}, t_N) > C(s_{k+2}, t_N)$, we can infer that

$$\sigma_{v_{k+1},s_{k+2}} C(s_{k+2}, t_N) < \sigma_{u_k,v_{k+1}} C(v_{k+1}, t_N) \leq q_{v_{k+1},s_{k+2}}.$$

This will lead to $\Delta_{v_{k+1},s_{k+2}} < 0$. Consequently, we have $x_{v_{k+1},s_{k+2}} = 0$.

If e_k is not a virtual edge, but its succeeding edge, e_{k+1}, is, as exemplified by $e_k = (p_k, s_{k+1})$ and $e_{k+1} = (s_{k+1}, s_{k+2})$, the same conclusion can be obtained similarly.

Case 2. If e_k is a virtual edge, as exemplified by $e_k = (v_k, v_{k+1})$, according to the BFST algorithm, its matching pair edge $e'_k = (u_k, v_{k+1})$ must have $x_{u_k,v_{k+1}} = 0$. From the result of Case 1, we also have $x_{v_{k+1},s_{k+2}} = 0$.

Inductively, we can conclude that all succeeding edges of an edge that does not perform fusion will not perform fusion either. Since the fusion decision $x_{e_k} \in \{0, 1\}$, it is evident that x_e is nonincreasing on the path from source to sink. □

Theorem 1. *The total cost of BFST is no more than MFST.*

Proof. Since BFST retains the same tree structure as MFST, for all edges with $x_{e_k} = 1$, the BFST and MFST schemes will consume the same amount of energy. For any edge with $x_{e_k} = 0$, owing to Lemma 1, any edge e_i on the path from this edge to the sink satisfies $x_{e_i} = 0$. This means that all edges on the path after e_k have a negative effect on energy conservation. In other words, performing fusion will introduce additional cost. Therefore, BFST is a better algorithm than MFST by avoiding fusion when direct relaying is a better choice. □

Intuitively, Lemma 1 depicts that the routing tree generated by BFST can be divided into two parts: the lower part, where data aggregation is always performed, and the upper part, where direct relaying is employed. As no data aggregation is performed in the upper part of the tree, instead of sticking to MFST, we can further improve the routing structure to reduce energy consumption. Inspired thereby, we develop AFST.

3.4 Adaptive Fusion Steiner Tree (AFST)

AFST further improves BFST by introducing SPT into the routing tree. Similarly to BFST, it performs a matching process as in MFST in order to jointly optimize over both transmission and fusion costs. During the matching process, it also dynamically evaluates if fusion shall be performed or not. If it is determined at a particular point that fusion is not beneficial to the network, as shown by the analysis of BFST, we can conclude that any succeeding nodes on the routing path shall not perform fusion either. Consequently, we can employ SPT as the strategy for the remainder of the route as SPT is optimal for routing information without aggregation. Our analysis shows that AFST achieves better performance than BFST and, therefore, MFST.

AFST ALGORITHM

1. Initialize the loop index $i = 0$. Define $S_0 = S \cup \{t\}$, and $E^* = \emptyset$. Let w_{v_0} for any $v \in S$ equal to its original weight and let $w_{t_0} = 0$.
2. For every pair of nonsink nodes $(u, v) \in S_i$: Find the minimum cost path (u, v) in G according to the metric
$$M(e) = q_{u_i,v_{i+1}}(w_{u_i} + w_{v_i}) + \alpha(w_{u_i}, w_{v_i})c(e). \quad (7)$$
Define $K_i(u, v)$ to be the distance under metric $M(e)$ of this path.
3. Find minimum-cost perfect matching between nodes in S_i. If there is only one nonsink node left after matching, match it to itself without any cost, and consider it as the last "single-node pair" in S_i.
4. For each matched pair (u, v), calculate the fusion benefit for node u and v, respectively, according to this new definition:
$$\Delta_{u_i,v_{i+1}} = (w_{u_i} + w_{v_i})SP(v_i, t) - \Big(q_{e_i}(w_{u_i} + w_{v_i}) + (w_{u_i} + w_{v_i})(1 - \sigma_{e_i})SP(v_i, t)\Big), \quad (8)$$
where $SP(v_i, t)$ denotes the summation of unit transmission cost from v_i to the sink t using shortest path.
We call (u, v) a nonfusion pair if there is no fusion benefit regardless of which node is selected as the center. It means that the two following inequations are satisfied:
$$\Delta_{u_i,v_{i+1}} < 0 \text{ and } \Delta_{v_i,u_{i+1}} < 0. \quad (9)$$
Otherwise, we call them a fusion pair.
5. For each nonfusion pair (u, v),
   - Add those edges that are on the shortest paths of (u, t) and (v, t) to set E_n^*.
   - Remove both nodes u and v from S_i.
6. For each fusion pair (u, v),
   - Add those edges that are on the path defining $K_i(u, v)$ to set E_f^*.
   - Choose u to be the center with probability
   $$P(u = center) = \frac{w_{u_i}^2}{w_{u_i}^2 + w_{v_i}^2}.$$
   Otherwise, v will be the center. For pair (u, t), choose sink t to be the center.
   - Transport the weight of noncenter node to its corresponding center node. According to (3), the weight of the center satisfies $w_{i+1}(center) = (w_{u_i} + w_{v_i})(1 - \sigma_{u_i,v_{i+1}})$.
   - Remove all noncenter nodes from S_i, then the remaining center nodes induce S_{i+1}.
7. If S_{i+1} is empty or contains only the sink, we return $G^* = (V^*, E^*)$ $(E^* = E_f^* + E_n^*)$, where E_f^* and E_n^* are the set of fusion edges and nonfusion edges, respectively, and V^* includes source nodes and the sink. Otherwise, increment i and return to Step 2.

The size of set S_i is reduced at least half after one run of the algorithm. However, the process may terminate sooner than MFST and BFST if fusion is deemed unworthy in the early iterations.

Theorem 2. *The total cost of AFST is no more than BFST.*

Proof. The tree resulting from AFST also contains a lower part, where aggregation is always performed, and an upper part, where no aggregation occurs. The lower part of AFST is the same as that of BFST due to their MFST-based matching procedure and thus incurs the same cost as well. The task left is then to show that, for any nonfusion pair (u, v) satisfying (9), their transmission costs based on SPT in AFST are no more than the corresponding routing costs, including fusion and transmission costs, incurred in BFST. The proof is given below.

From (9), we have $\sigma_{u_k,v_{k+1}}SP(v_k, t) < q_{u_k,v_{k+1}}$ and $\sigma_{v_k,u_{k+1}}SP(u_k, t) < q_{v_k,u_{k+1}}$, where $SP(v_k, t)$ denotes the summation of unit transmission cost from v_k to the sink t using the shortest path. Without loss of generality, assume that v is selected as the center in BFST, and our goal is to prove

$$w_{v_k}SP(v_k, t) + w_{u_k}SP(u_k, t) < w_{u_k}c(u_k, v_{k+1}) + q_{u_k,v_{k+1}}(w_{u_k} + w_{v_k}) + (w_{u_k} + w_{v_k})(1 - \sigma_{u_k,v_{k+1}})SP(v_{k+1}, t). \quad (10)$$

For that, we have

$$\begin{aligned} &w_{v_k}SP(v_k, t) + w_{u_k}SP(u_k, t) \\ &\le w_{v_k}SP(v_{k+1}, t) + w_{u_k}(c(u_k, v_{k+1}) + SP(v_{k+1}, t)) \\ &= (w_{u_k} + w_{v_k})SP(v_{k+1}, t) + w_{u_k}c(u_k, v_{k+1}) \\ &\le (w_{u_k} + w_{v_k})(1 - \sigma_{u_k,v_{k+1}})SP(v_{k+1}, t) \\ &\qquad + q_{u_k,v_{k+1}}(w_{u_k} + w_{v_k}) + w_{u_k}c(u_k, v_{k+1}). \end{aligned}$$

□

When it is determined that the fusion benefit is positive for every node, the tree structure obtained from AFST degenerates to the tree from MFST. However, when fusion is not always beneficial for all nodes, AFST will stop doing nonsensical data fusion and directly deliver data to the sink for more energy saving; as a result, it can significantly outperform MFST. From the process of route construction, we can see that AFST can dynamically assign fusion decisions to routing nodes during the route construction process by evaluating whether fusion is beneficial to the network based on fusion/transmission costs and network/data structures.

3.5 Application in Clustering

Clustering in sensor networks is often used to closely group correlated sensors together in order to perform local decision making, detection, or classification. To facilitate these operations, fusion and transmission cost shall be considered due to severe resource constraints. While the concept of clustering has been widely applied, clustering itself is often based on static techniques mainly based on geographic proximity, fixed cluster number, or certain cluster sizes.

The two-layer structure of AFST naturally provides a new clustering technique for sensor networks. Separated by the routing nodes not performing fusion, the lower part of AFST routing tree is composed of discrete branches within which data of every member will be fused together. These branches can be considered as clusters decided by energy consumption due to fusion and communication. Therefore, AFST provides a clustering algorithm as a byproduct that is energy efficient for gathering correlated data. Sensors in the same cluster will employ MFST-based routing structure, while cluster heads (roots of the branches) will directly send the aggregated data to the sink via shortest path without fusion. Since AFST is a randomized algorithm, we can rerun the process to generate a different structure and, therefore, reassign the role of cluster heads to different nodes. Load balancing in terms of fusion is thus naturally implemented.

4 Experimental Study

In this section, we compare the performance of AFST with other routing algorithms. In particular, we select MFST, SPT, MST, and SLT to represent the class of routing schemes where fusion occurs on all routing nodes if possible. For routing schemes that do not perform aggregation, we employ SPT as it is the optimal routing strategy in this class. To distinguish it from the SPT scheme where data aggregation opportunistically occurs where information streams intersect, we denote the SPT without performing aggregation by SPT-nf, a short name for SPT-no-fusion.

We study the impact of network connectivity, correlation coefficient, and unit fusion cost on different algorithms. Concurring with our design goal and analysis of the AFST algorithm, our key finding of the experiments is that AFST can adapt itself to a wide range of data correlations and fusion cost. Therefore, AFST can achieve better performance in all kinds of system setups.

4.1 Simulation Environment

In our setup, 100 sensor nodes are uniformly distributed in a region of a $50m \times 50m$ square. We assume that each node produces one 400-byte packet as original sensed data in each round and sends the data to the sink located at the bottom-right corner. All sensors act as both sources and routers. We also did sets of experiments with a different number of sensors and different sizes of field; the results are similar and omitted here.

We assume the maximal communication radius of a sensor is r_c, i.e., if and only if two sensor nodes are within r_c, there exists a communication link between them or an edge in graph G. By varying r_c, we can control the network connectivity and, hence, equivalently the network density. We instantiate the unit transmission cost on each edge, $c(e)$, using the first order radio model presented in [7]. According to this model, the transmission cost for sending one bit from one node to another that is d distance away is given by $\beta d^\gamma + \varepsilon$ when $d < r_c$, where γ and β are tunable parameters based on the radio propagation. We set $\gamma = 2$ and $\beta = 100pJ/bit/m^2$ to calculate the energy consumption on the transmit amplifier. ε denotes energy consumption per bit on the transmitter circuit and receiver circuit. Typical values of ε range from 20 to $200nJ/bit$ according to [20]. We set it to be $100nJ/bit$ in our simulation.

We model data reduction due to aggregation based on correlation among sensed data. The correlation model employed here is an approximated spatial model where the correlation coefficient (denoted by ρ) decreases with the distance between two nodes provided that they are within the correlation range, r_s. If two nodes are more than r_s distance apart, the correlation coefficient is simply $\rho = 0$. Otherwise, it is given by $\rho = 1 - d/r_s$, where d denotes the distance between the nodes. If node v is responsible for fusing node u's data (denoted by $w(u)$) with its own, we assume that the weight of node v after fusion is given by

$$w(v) = \max(w(u), \widetilde{w}(v)) + \min(w(u), \widetilde{w}(v))(1 - \rho_{uv}),$$

where $\widetilde{w}(v)$ and $w(v)$, respectively, denote the data amount of node v *before* and *after* fusion.

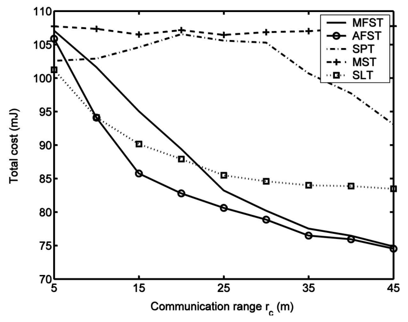
Recall that we use σ to denote the data reduction ratio due to aggregation. From (3), $w(v) = (w(u) + \widetilde{w}(v))(1 - \sigma_{uv})$ if fusion is performed at node v, we can get that the data reduction ratio σ_{uv} is proportional to the correlation coefficient ρ. By varying the correlation range r_s, we can control the average correlation coefficient of the network and further control the average data reduction after data fusion. For example, a very small r_s essentially eliminates the correlation among sensors ($\rho \rightarrow 0$) so that the amount of output data is equal to the summation of all input data. While an extremely large r_s makes the sensed data completely redundant ($\rho \rightarrow 1$), as a result, the fused data size equals the bigger data size between the two input data. In our simulation, we use ρ instead of σ to describe the impact of data structure for ease of understanding. For the fusion cost, we assume that q is constant and use ω to denote the average fusion cost per bit at each node.

In the following sections, we will study the performance of AFST and other algorithms under various system setups, including network connectivity, correlation coefficient, and fusion cost.

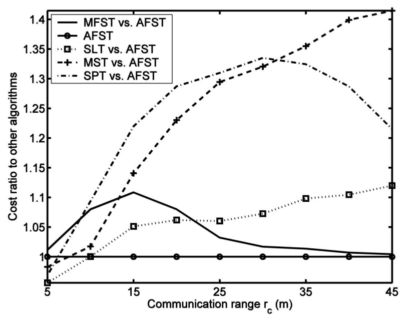
4.2 Impact of Network Connectivity

Since r_c denotes the communication range of a node, by varying r_c, we can control the connectivity of the network. Here, we set ω, the average unit fusion cost, to be $80nJ/bit$, which is a typical value, as demonstrated by our experimental study for fusion cost described in the Appendix. And, we set r_s, the correlation range, to be $50m$ to simulate a network with moderate data reduction.

Fig. 4a summarizes the performance of all algorithms studied. The larger r_c is, the more strongly the network is connected. As we can see, MST wastes precious energy on data fusion at numerous relaying nodes and, hence, incurs

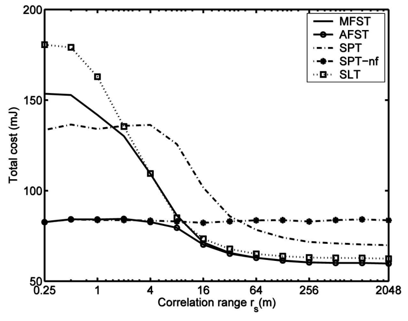


(a)

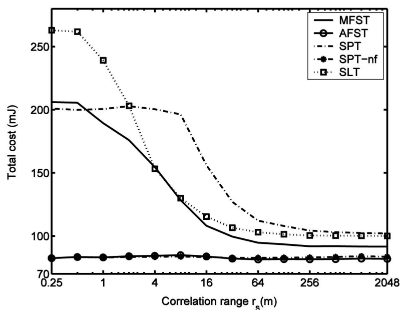


(b)

Fig. 4. Impact of network connectivity to energy consumption ($\omega = 80nJ/bit$, $r_s = 50m$, and $r_c = 5 \sim 45m$). (a) Total cost. (b) Cost ratio to other algorithms.



(a)



(b)

Fig. 5. Impact of average correlation coefficient to energy consumption ($r_c = 30m$ and $r_s = 0.25 \sim 2000m$). (a) Low fusion cost ($\omega = 50nJ/bit$). (b) High fusion cost ($\omega = 120nJ/bit$).

high cost when the data reduction is not high. On the contrary, SPT wastes energy owing to redundant data transmissions and also induces high cost since it tends to use fewer hops to reach the sink. As SLT is a hybrid tree structure balancing MST and SPT, it achieves better performance than both of them. However, inherently constrained by its algorithm construction, energy consumption of SLT is still relatively high.

As MFST explicitly considers fusion cost, it can effectively trade off between multihop relay benefitting from high data reduction ratio and single-hop transmission benefitting from less fusion cost. In a dense network with strong network connectivity, the benefit due to this flexibility to the network energy cost is more apparent. When r_c is larger than 20m, MFST performs better than all other algorithms except AFST.

As expected, AFST performs well in all communication ranges, almost steadily outperforming all other algorithms. This can be explained as follows: In a network with moderate data correlation, data from nodes that are far apart has little correlation and, hence, leads to small reduction ratio if aggregated. Therefore, performing data fusion over them cannot significantly benefit the network but still incur the fusion cost. AFST can effectively avoid such situations by evaluating fusion benefit. If the data reduction ratio due to correlation together with the fusion cost could not justify the fusion process, it employs the shortest paths toward the sink by using direct relay. Therefore, the cost of AFST continuously decreases along with the increase of communication range. Notably, it has significantly less energy cost for a weakly connected network resulting from a short communication range as well. It can be reasoned in the same way.

Fig. 4b illustrates the cost ratio of other algorithms to AFST. As shown in the figure, the proposed AFST can save over 40 percent energy compared to MST, up to 35 percent more energy than SPT, and about 10 percent more energy than SLT when the connectivity degree is high. Compared with MFST, AFST can save around 10 percent of energy in weakly connected environment while maintaining the same or better performance when the network is strongly connected.

4.3 Impact of Correlation Coefficient

Naturally, performing aggregation is futile in a network with no data redundancy ($\rho = 0$). Even in a network with 100 percent data redundancy ($\rho = 1$), data fusion at all possible nodes may not bring a benefit because of the high fusion cost. In this simulation, we fix the sensor node transmission range and study the impact of correlation coefficient to the performance of AFST. We increase the correlation range, r_s, from 0.2 to $2,000m$ which corresponds to varying ρ from 0 to 1.

Fig. 5a and Fig. 5b depict the total energy costs under light fusion cost and heavy fusion cost, respectively, for AFST and other algorithms like MFST, SPT, SLT, and SPT-nf. Naturally, costs of all algorithms with data fusion decrease as ρ increases. This exemplifies that data aggregation in sensor

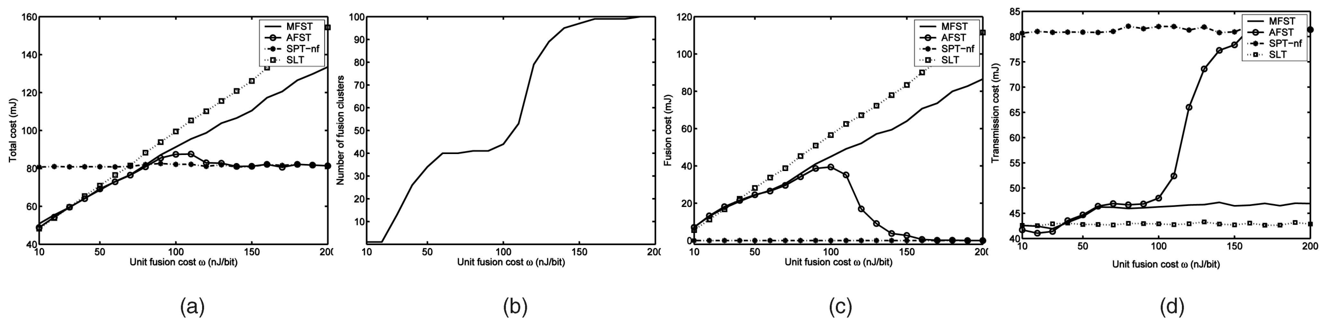


Fig. 6. Impact of unit fusion cost on energy consumption ($r_c = 30m$, $r_s = 20m$, and $\omega = 10 \sim 200nJ/bit$). (a) Total cost. (b) Number of fusion clusters. (c) Fusion cost. (d) Transmission cost.

networks can greatly benefit the routing performance by reducing redundancy among correlated data. As SPT-nf totally ignores data aggregation, its cost remains constant.

When the data correlation in the network is very weak ($\rho \rightarrow 0$), AFST follows SPT-nf, the optimal solution, by avoiding any data aggregation. When the data correlation in the network increases, AFST dynamically adjusts its decisions accordingly.

We also observe that different fusion cost will affect AFST as well by comparing Fig. 5a and Fig. 5b. As shown in Fig. 5a, when fusion cost is low, AFST performs data fusion partially in order to benefit from data aggregation and resultant data reduction, even when the correlation degree in the network is weak (r_s being 4m). When the data in network is highly correlated ($\rho \rightarrow 1$), AFST follows MFST to pursue the most energy savings by performing data fusion at each possible node. On the other hand, Fig. 5b illustrates the performance of AFST when the fusion cost is high. As we can see, even when $\rho \rightarrow 1$, there are only a few nodes (about 15 percent) performing data fusion. This shows that AFST chooses not to perform fusion most of the time as the fusion cost itself is too high, overwhelming the benefit of reduction in data and communication costs. As a result, AFST performs better than any algorithm performing network-wise fusion. At the same time, it also outperforms SPT-nf in the first case as SPT-nf does not perform fusion at all.

Fig. 5a and Fig. 5b demonstrate that the cost of AFST is extremely smooth in the whole range of the correlation coefficient and steadily outperforms others. As correlation among nodes often varies from application to application, from node to node, and even from time to time, only a general algorithm such as AFST optimized for a wide range of ρ can accommodate those versatile scenarios.

4.4 Impact of Unit Fusion Cost

In this set of experiments, we study the impact of varying unit fusion cost on the algorithms. Fig. 6 illustrates the results when ω, the unit fusion cost, increases from $10nJ/bit$ to $200nJ/bit$.

Fig. 6a shows the total cost of AFST as compared with other algorithms as the unit fusion cost increases. As we can see, the total costs of MFST and SLT increase unboundedly along with the increase of ω, even though MFST has a lower slope. On the contrary, AFST follows the performance curve of MFST first and then leans toward SPT-nf, the optimal solution when fusion cost is high. The figure can be best explained when we jointly examine it with Fig. 6b, which depicts the number of clusters, the branches of the routing tree that always perform aggregation on their nodes. All algorithms with network-wise fusion are unable to stop fusion even when fusion cost is extremely high. However, for AFST, as shown in Fig. 6b, when ω is very small, there are only two fusion clusters. This denotes that data fusion is performed on almost all nodes, which takes advantage of the low fusion cost. When ω increases, AFST increases the number of fusion clusters and, hence, reduces the number of fusions due to reduced fusion benefit in order to balance the fusion cost and transmission cost. And, when ω is too large, AFST can achieve the same constant cost as SPT-nf by completely stopping data fusion.

Fig. 6c and Fig. 6d provide us a closer look at the routing behaviors by breaking the total cost into transmission and fusion costs. As both SLT and SPT-nf have fixed tree structure when the network topology is determined, their transmission costs are fixed as well. Naturally, the fusion cost of SLT increases linearly with ω, while there is no fusion cost in SPT-nf.

As MFST jointly explores the transmission and fusion costs to optimize the routes, it can trade off between them. As a strategy, it can explore long one-hop transmission in order to reduce the number of fusions and, hence, fusion cost. As a result, the transmission cost in MFST increases in order to prevent the fast increase of fusion cost. Consequently, the increase of fusion cost and total cost in MFST are significantly slower than SLT. However, when ω increases more and fusion cost is dominant in the total cost, adjustment of routing tree structure will have insignificant impact and, hence, MFST's fusion cost increases almost linearly while its transmission cost remains constant.

On the contrary, AFST can better balance the fusion and transmission costs by adjusting the number of fusion clusters. When the unit fusion cost is insignificant, AFST effectively reduces its transmission cost by fully exploiting data fusion. In this case, AFST's cost is similar to that of MFST. When the unit fusion cost continues to increase, AFST can reduce data fusion points and employ more shortest paths for direct relaying. Therefore, while its transmission cost increases rapidly, the fusion cost also simultaneously decreases rapidly. As a result, the total cost can be kept low. When the unit fusion cost is extremely

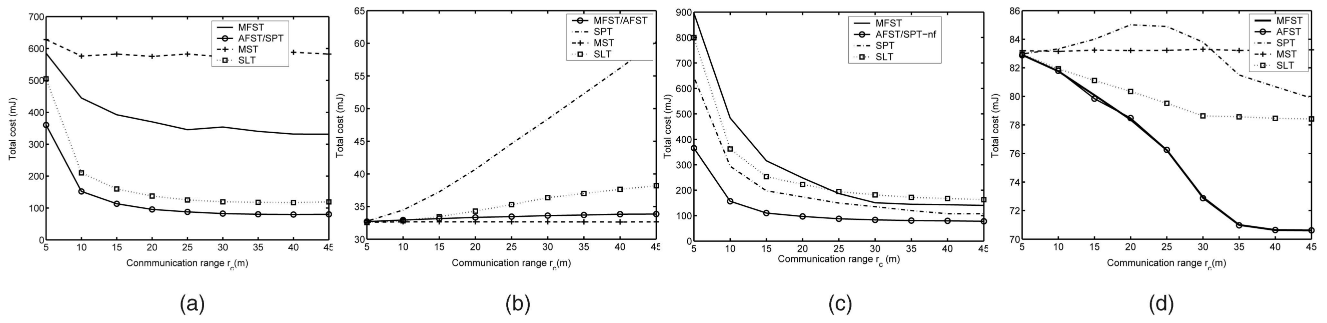


Fig. 7. Total cost at extreme cases of data correlation ($r_c = 30m$ and $\omega = 80nJ/bit$). (a) $\rho \rightarrow 0$ without fusion cost. (b) $\rho \rightarrow 1$ without fusion cost. (c) $\rho \rightarrow 0$ with fusion cost. (d) $\rho \rightarrow 1$ with fusion cost.

large, AFST simply approaches SPT-nf with no node performing fusion and, hence, obtains zero fusion cost. In this case, the total cost equals the transmission cost and remains constant.

As described in Section 2, fusion cost may vary widely from network to network, from application to application. As an example, a temperature surveillance sensor network may have little fusion cost to calculate the max, min, or average temperature. On the other hand, a wireless video sensor network may incur significant fusion cost when performing image fusion. Our experiments show that, among all algorithms, AFST can adapt best to a wide range of fusion costs and, hence, be applicable to a variety of applications.

4.5 Extreme Cases of Correlation Coefficient

In this set of experiments, we study the performance of AFST when the correlation coefficient takes extreme values. We examine the scenario where there is no data redundancy ($\rho \rightarrow 0$) and the scenario of 100 percent data aggregation ($\rho \rightarrow 1$). Fig. 7 summarizes the results. Two cases, with or without fusion cost, are studied for each of the scenarios. In all cases, r_c is varied from 5m to 45m, denoted by the x-axis. We use $r_s = 0.1m$ to simulate the case of $\rho \rightarrow 0$ and $r_s = 2000m$ to simulate the case of $\rho \rightarrow 1$.

4.5.1 Without Fusion Cost

We first disregard fusion cost. The simulation results shown in Fig. 7a and Fig. 7b concur with those described in [15]. In a weakly correlated network, SPT is the optimal solution, while MST is the worst. On the contrary, in a strongly correlated network, MST is the optimal solution and SPT is the worst. Fig. 7a also shows that AFST is the same as the optimal solution, SPT, in a weakly correlated network and has a gain factor of 3 compared with MFST. Fig. 7b shows that both AFST and MFST closely approximate the optimal solution, MST. The approximation ratio is within 5 percent and they can save 10 percent energy compared with SLT.

4.5.2 With Fusion Cost

In this set of simulations, we include fusion cost and study the two extreme scenarios again. We set ω, the unit fusion cost, to be $80nJ/bit$.

Fig. 7c illustrates that AFST can achieve the optimal performance by avoiding data fusion completely compared with all other algorithms with inefficient data fusion on uncorrelated data.

When $\rho \rightarrow 1$, as illustrated in Fig. 7d, since the unit fusion cost is comparable to the average of transmission cost, AFST behaves similarly to MFST by performing network-wise data fusion and performs better than all other algorithms.

4.6 The Number of Fusion Clusters in AFST

Fig. 8 illustrates the number of fusion clusters with varying correlation coefficient and unit fusion cost. When $\rho \rightarrow 0$, the cluster number equals 100, denoting that no data fusion occurs. When the unit fusion cost is small, the number of fusion clusters decreases rapidly with the increase of ρ. When ρ approaches 1, the cluster number becomes 1, meaning that all nodes will perform fusion and the network becomes a full fusion tree. At the same time, when unit fusion cost increases, AFST will trade off the fusion cost with the transmission cost. As a result, the decreasing of the cluster number slows down. For example, for $\omega = 80nJ/bit$, a unit fusion cost comparable to the average unit transmission cost, there are 33 fusion clusters when $\rho \rightarrow 1$. This means, on average, there are only three nodes in a cluster performing data fusion. The fused data are then forwarded to the sink via shortest paths directly with simple relaying. If ω keeps increasing, fewer nodes perform fusion to avoid the high fusion cost.

5 Related Work

If the complete knowledge of all data correlations is available in advance at each source, theoretically the best

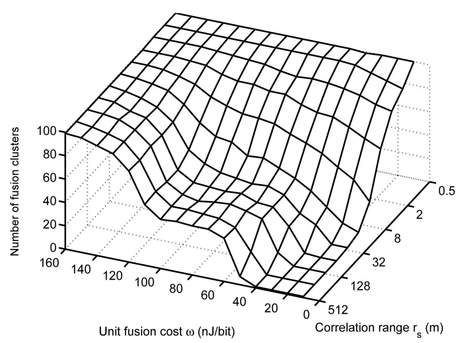


Fig. 8. The number of fusion clusters in AFST.

routing strategy is to use a distributed source coding typified by Slepian-Wolf coding [24]. In this technique, compression is done at the original sources in a distributed manner to achieve the minimum entropy and, hence, avoid the need for data aggregation on the intermediate nodes. An optimal rate allocation algorithm for nodes in the network is proposed in [15] and SPT is employed as the routing scheme. However, implementation of distributed source coding in a practical setting is still an open problem and likely to incur significant additional cost because of the requirement on the knowledge of network-wise correlation.

Routing with data aggregation can be generally classified into two categories: routing-driven and aggregation-driven. Routing-driven algorithms [7], [8], [9], [12], [13] emphasize source compression at each individual node and aggregation occurs opportunistically when routes intersect. On the contrary, routing paths in aggregation-driven algorithms [14], [15], [16] are heavily dependent on data correlation in order to fully benefit from information reduction resulting from data aggregation. In [15], the authors proved that the minimum-energy data gathering problem is NP-complete by applying the reduction set-cover problem and claiming that the optimal result is between SPT and the traveling salesman path. In [14], a hierarchical matching algorithm is proposed, resulting in an aggregation tree with a logarithmic approximation ratio to the optimal for all concave aggregation functions. In this model, each node can theoretically obtain the joint entropy of its subtree to receive the maximal aggregation ratio. However, aggregation only depends on the number of nodes in the subtree rooted at the aggregation node, regardless of the correlation among the data.

Indeed, the idea of embedding fusion decisions in routing has been implicitly explored in the literature. For example, LEACH [7] is a cluster-based protocol in which sensors directly send data to cluster heads where data fusion is performed. Aggregated data is then delivered to the sink through multihop paths. The authors of [16] proposed an optimal algorithm MEGA for foreign-coding and an approximating algorithm LEGA for self-coding. In MEGA, each node sends raw data to its encoding point using directed MST and encoded data is then transmitted to the sink through SPT. LEGA uses SLT [25], [26] as the data gathering topology, and achieves a $2(1+\sqrt{2})$ approximation ratio for self-coding. LEGA and MEGA implicitly assume that fusion stops after the first aggregation as encoded data cannot be recoded again. However, the decisions regarding fusions in these schemes are rather static and cannot adapt to network/data structure changes. As demonstrated earlier, this decision shall be based on various conditions of the networks in order to minimize energy consumption.

6 Conclusion

In this paper, we propose AFST, a routing algorithm for gathering correlated data in sensor networks. AFST not only optimizes over both the transmission and fusion costs, but also adaptively adjusts fusion decisions for sensor nodes as to whether fusion should be performed. Generalized from MFST, an algorithm guarantees an approximation ratio of $\frac{5}{4}\log(n+1)$ of the optimal solution, AFST is analytically shown to be a better algorithm than its ancestor. Extensive experiments show that AFST achieves near optimal solutions under various networking conditions, including broad scopes of fusion/transmisison costs and network/data structures.

Furthermore, our analytical result indicates that AFST partitions the routing tree into two distinct parts based on whether aggregation is performed or not. Naturally, AFST also provides a clustering scheme with near optimal routing performance, where fusion can be confined within the clusters only.

As an ongoing effort, we are theoretically quantifying the performance improvement of AFST over MFST. In our future work, we plan to develop an online algorithm based on AFST that can be executed in a distributed manner by sensor nodes.

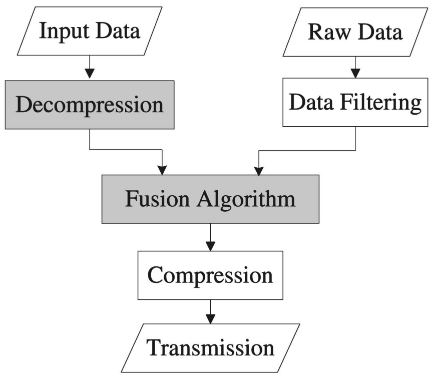


Fig. 9. Measurement model for data aggregation.

Appendix A

Data Fusion Energy Cost Experiment

We have performed a series of experiments to investigate the aggregation cost in sensor networks. Our platform used is Sim-panalyzer [27], an extension of Simple Scalar [28] for power analysis. Simple Scalar is a well-established architectural simulator that provides cycle-level tool sets for detailed processor-architecture study. As its extension, Sim-panalyzer provides analytical power simulation models for ARM CPU and Alpha CPU. In our experiments, we choose StrongARM SA-1110 as our embedded core as it is commonly used for high performance sensor node design in academic research and industrial development.

A.1 Measurement Model for Data Aggregation

We first detail the model of data aggregation process used in our simulation. As illustrated in Fig. 9, we assume that each sensor is capable of data sensing, preprocessing, and data aggregation. A sensor node will compress its local raw data before transmitting it on the route back to the sink. If it receives data from another node, in a compressed form, to perform data aggregation, the node shall decompress the data first and perform the designated aggregation algorithm with its own raw data. The aggregated data will then be compressed and routed to the next hop. In this model, the aggregation cost is composed of two parts, marked in

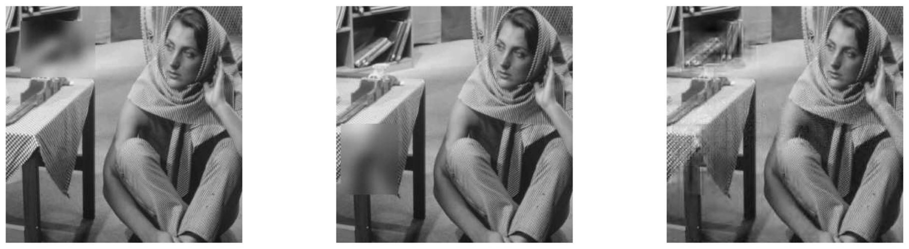


Fig. 10. Image fusion example. (a) Input image. (b) Local image. (c) Fused image.

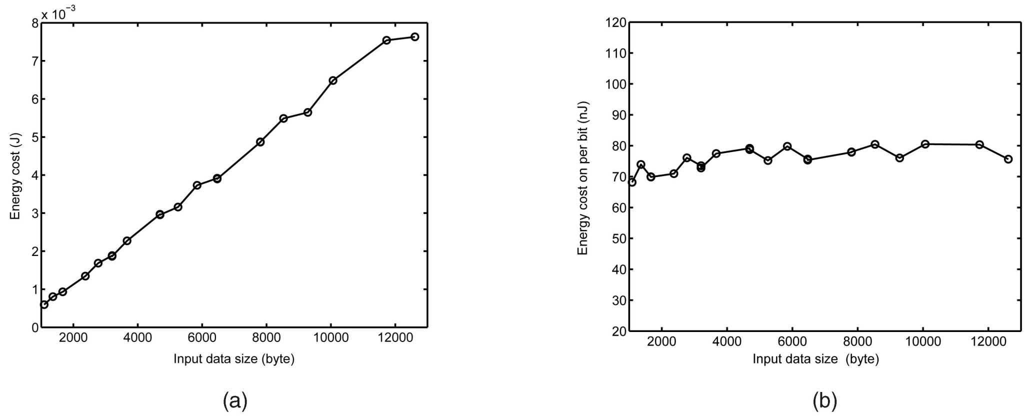


Fig. 11. Wavelet image fusion cost. (a) Energy cost. (b) Per bit energy cost.

gray in Fig. 9, the cost for decompressing the input data and the cost for performing the fusion algorithm itself. In the following, we will only focus on these two parts.

Energy consumption of a system contains static power dissipation and dynamic power dissipation. Dynamic power dissipation denotes the application processing energy with a given instruction set and data set. Evidently, this part is the investigating target of our experiment. Equation (11) is a model for dynamic power dissipation commonly employed in energy measurement [20].

$$E_{total} = C_{total}V_{dd}^2 + V_{dd}\left(I_0 e^{\frac{V_{dd}}{nV_T}}\right)\left(\frac{N}{f}\right). \quad (11)$$

Here, N represents the number of cycles for executing the algorithm with the given data set. It is determined by the algorithm complexity and affected by the compiling method. C_{total} denotes the total switched capacitance during the execution of the algorithm. C_{total} is proportional to N and it is also affected by the switching activity parameter. V_{dd} and f are the core supply voltage and clock frequency of the CPU, respectively. V_T denotes thermal voltage. I_0 and n are core specific, which we assign $1.196mA$ and 21.26, according to [20]. The SA-1110 core can be configured to various combinations of supply voltage and system clock. In our experiment, we use 100MHz clock and 1.5V for core voltage.

A.2 Image Fusion

One of our experiments is wavelet-based image fusion. Wavelet-based image fusion is generally considered to be the most efficient algorithm for image fusion and different approaches have been proposed [29]. In our experiment, we simulate a simple and efficient method described in [29]. According to the measurement model illustrated in Fig. 9, a fusion node will use Discrete Wavelet Transformation (DWT) to generate wavelet coefficients from local image. To perform fusion with another node's data, the node will use Zerotrees expansion to decompress the input data into wavelet coefficients. Given the wavelet coefficients of the two input images, the averages of these coefficients are computed as those for the fusion result. While this algorithm is simple, it provides a lower bound on the computation cost. More complex algorithms for a better fusion result will undoubtedly incur even higher cost. Consequently, the aggregation cost is the cost of the decompression process and the merging process.[3]

The gray-scale images depicted in Fig. 10 are used in the simulation. Fig. 10a is the input image representing data from another node. Notice that it has a blurred area at the top-left corner. Fig. 10b is the local image at the fusion node, with a blurred area at the bottom-left corner. Fig. 10c is the fused image by performing the aforementioned fusion algorithm on Fig. 10a and Fig. 10b. Notice that, in the fused image, the blurred areas are effectively eliminated.

Fig. 11a and Fig. 11b depict our experiment results. During our simulation, we scaled the image content from 64×64 pixels to 220×220 pixels. Reflected on the X axis of the figures, it is the total data size in bytes of the two input images of the fusion algorithm. As we perform two-level

3. The cost of the final Zerotree compression on the merged data shall not be considered as part of the fusion cost as the node would perform Zerotree compression on its local data even if fusion was not performed.

DWT and apply the embedded coding scheme [30], [31] using Zerotrees, the compression ratio is approximately 8:1. Therefore, the X axis ranges from 1 KB (corresponding to 64×64 pixels) to 12 KB (corresponding to 220×220 pixels) as the summation of two image sizes. The total image fusion energy consumption in $Joule$ is shown in Fig. 11a, while the per bit energy cost is shown in Fig. 11b. As we can see, the total image fusion cost monotonically increases with the input data size. Fig. 11b shows that the per bit energy cost remains roughly constant at $75nJ/bit$, comparable to per bit communication cost reported in the literature [7], [20]. The irregular variations of per bit energy cost between consecutive measurements (image sizes) are due to the Zerotrees encoding scheme.

We have also performed a study on other fusion algorithms such as byte-wise Huffman coding. The result is also on the order of tens of nJ/bit. We omit the details here due to space limits. From our experimental study, we can conclude that the fusion cost for certain sensor networks is comparable to the transmission cost. Therefore, the impact of fusion cost to energy efficient data gathering in sensor networks is an important area that needs to be carefully investigated.

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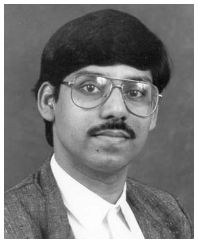

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