Minimum Spanning Tree on Spatio-Temporal Networks

Viswanath Gunturi

vgvm@iitk.ac.in Dept. of Computer Science and Engineering, Indian Institute of Technology, Kanpur Kanpur, UP 208016, India. Shashi Shekhar shekhar@cs.umn.edu Dept. of Computer Science and Engineering, University of Minnesota, Twin Cities

Minneapolis, MN 55454, USA.

Arnab Bhattacharya arnabb@iitk.ac.in

Dept. of Computer Science and Engineering, Indian Institute of Technology, Kanpur Kanpur, UP 208016, India.

Abstract

Given a spatio-temporal network (ST network) where edge properties vary with time, a time-sub-interval minimum spanning tree (TSMST) is a collection of minimum spanning trees of the ST network, where each tree is associated with a time interval. During this time interval, the total cost of tree is least among all the spanning trees. The TSMST problem aims to identify a collection of distinct minimum spanning trees and their respective time-subintervals under the constraint that the edge weight functions are piecewise linear. This is an important problem in ST network application domains such as wireless sensor networks (e.g., energy efficient routing). Computing TSMST is challenging because the ranking of candidate spanning trees is non-stationary over a given time interval. Existing methods such as dynamic graph algorithms and kinetic data structures assume separable edge weight functions. In contrast, we propose novel algorithms to find TSMST for large ST networks by accounting for both separable and non-separable piecewise linear edge weight functions. The algorithms are based on the ordering of edges in edge-order-intervals and intersection points of edge weight functions.

1 Introduction

A spatio-temporal network is a network consisting of nodes with location information and edges connecting these nodes. The topology and network parameters (such as edge cost) of a spatio-temporal network change with time. These kind of networks appear in numerous applications such as energy-efficient routing in a wireless sensor network [16, 18].

In a typical wireless sensor network, large number of sensor networks are scattered in the observation field. Once deployed, physical access to these nodes may prove

to be difficult. Thus, energy conservation becomes a important constraint in designing algorithms for these kind of sensor networks. In many wireless sensor network applications the nodes are not stationary, i.e., they change their physical position with time, for example, sensor network among robots on a reconnaissance mission [23]. Usually in such scenarios, the sensor nodes physically move on a predetermined trajectory to collect data in observation field [22]. One of the important problems pertaining to these kind of sensor networks is to maintain network connectivity among the individual nodes such that the total cost of transmission among the nodes is minimum. This can be modeled as a spatio-temporal network with nodes representing sensor nodes and transmission link among any two sensor nodes represented as an edge. The weight of an edge in the network represents energy required to transmit along that particular transmission link. Now the problem is to maintain an energy-efficient communication network among the sensor nodes such that there is a path between any two nodes and the total sum of the energy required for transmission for all edges involved is minimum. Traditionally minimum spanning trees have been used to solve these kind of problems [16, 18] in a static environment; but these no longer hold in a non-static environment.

Figure 1(a) shows a wireless sensor network maintained among a group of sensors moving on predetermined trajectories as depicted in Figure 1(b). In Figure 1(a), we assume that there is no direct connectivity between the sensor nodes 1 and 4, and that sensor node 5 is connected only to sensor node 3. This network of sensors is represented as a ST network in Figure 2(a) where the sensors are represented as nodes and the communication link between any two sensors is represented as an edge. Time dependent edge weights represent cost of packet transmission between sensors. Since the sensor nodes are moving, the distance between any two nodes changes with time. The energy required to transmit data



(a) Sensor Network (b) Positions of sensor nodes at various times

Figure 1: Sample wireless sensor network.

from one node to another is directly proportional to the square of distance between them [16]. Thus, even a small change in distance would affect the cost of transmission significantly. The solution to the time-sub-interval minimum spanning tree (TSMST) problem effectively determines the energy-efficient communication paths among these sensor nodes.

1.1 Motivation

The limited energy of the sensor nodes requires efficient transmission of information so that the network lifetime is increased. A lot of work done in this area [13, 16, 18, 20, 21] assume that the sensors nodes are stationary.

Computing TSMST is expensive because of the non-stationary ranking of candidate spanning trees in a ST network. This is illustrated in Figure 2. Figure 2(b) shows the minimum spanning trees (MSTs) at different time instants for the ST network shown in Figure 2(a). The total costs of these minimum spanning trees are given in Table 1. Figure 2(b) shows that both spanning tree and total cost of spanning tree change with time.

1.2 Contributions

We present the problem of time-sub-interval minimum spanning tree (TSMST) in a spatio-temporal network. We propose two algorithms to find the TSMST on a spatiotemporal network and provide analytical evaluations of the proposed algorithms. The algorithms allow the ST network to have both separable as well as non-separable edge weight functions. We also present the experimental analysis of the algorithms proposed.

The rest of the thesis is organized as follows. Chapter 2 defines the concepts used in the paper, followed by the problem definition of TSMST on a spatio-temporal network. Related work is described in Chapter 3. In Chapter 4, two algorithms for solving the TSMST problem are presented. We present correctness and

Time	Total cost						
	MST-a	MST-b	MST-c	MST-d			
1	8	11	13	10			
2	10	7	9	10			
3	13	11	10	12			
4	5	6	6	5			

Table 1: Total cost of MSTs at various times.

time complexity analysis of our algorithms in Chapter 5. Chapter 6 presents the experimental design and performance analysis. We conclude in Chapter 7.

2 Basic Concepts and Problem Definition

We model a spatio-temporal network as a timeaggregated-graph (TAG) [10, 11]. A time aggregated graph is a graph in which each edge is associated with a edge weight function. These functions are defined over a time horizon and are represented as a time series. For instance edge (3,5) of the graph shown in Figure 2(a) has been assigned a time series [4 3 5 2], i.e., the weight of the edge (3,5) at time instants t=1, 2, 3, and 4 are 4, 3, 5, and 2 respectively. The edge weight is assumed to vary linearly between any two time instants. We also assume that no two edge weight functions have same values for two or more consecutive time instants of their time series. If such a case occurs then the values of any one of the edges are increased (or decreased) by small quantity ϵ to make them distinct. For example, in Figure 2(a) weight functions of the edges (1,2) and (2,3) have same values for time t=3 and t=4. The edge weight functions of graph in Figure 2(a) are shown in Figure 3.

Definition 1 (Time-sub-interval). A time-sub-interval, denoted as $i = (i_s, i_e)$, is a maximal sub interval of time horizon [1, K] which has a unique MST. This unique MST is denoted as TMST(i). In other words, the ranking of candidate spanning trees (based on the total cost of tree) is stationary during a time-sub-interval.

For example, Figure 4 shows the 4 time-sub-intervals and the MSTs during those time periods.

Definition 2 (Edge-order-interval). An edge-orderinterval, denoted as $\omega = (\omega_s, \omega_e)$, is a sub interval of time horizon [1, K] during which there is a clear ordering



Figure 2: Spatio-temporal network and its corresponding MSTs at various times.



Figure 3: Edge weight function plot

of edge weight functions, i.e., none of them intersect with each other.

An edge-order-interval is guaranteed to have a unique MST (see Proposition 1). Two or more consecutive edge-order-intervals may have the same MST. A time-sub-interval is usually composed of one or more edge-order-intervals. For example, in Figure 3, the interval (2.66 3.0) is an edge-order-interval whereas the interval (2.66 3.66] is a time-sub-interval which is a union of three consecutive edge-order-intervals (2.66 3.0), (3.0 3.5) and (3.5 3.66).

Lemma 1. If all the edge weights of a graph are distinct, then there is a unique minimum spanning tree.

Proof. (By contradiction) Let T_1 and T_2 be two different minimum spanning trees of a graph. Let $OT_1 = e_1 e_2 e_3 e_4 \dots e_i e_{i+1} \dots e_{n-1}$ be the increasing order of the edge weights of T_1 and OT_2 = $e'_1 e'_2 e'_3 e'_4 \dots e'_i e'_{i+1} \dots e'_{n-1}$ be the increasing order of the edge weights of T_2 . Here n is the number of vertices in the graph. Without loss of generality assume that e_i is same as e'_i , $\forall j \leq i$. Further assume that $e_{i+1} < e'_{i+1}$. Now consider the cycle generated by adding the edge e_{i+1} to T_2 . Only one such cycle can be created as T_2 is a spanning tree of the graph. Now if this cycle contains only the edges e'_i where $j \leq i$, then it implies that there is a cycle in T_1 as e_j is same as e'_i , $\forall j \leq i$ (a contradiction). Now, if the cycle contains some edges e_j' where $j \leq i$ and e'_{i+1} , then we can replace the edge e'_{i+1} with e_{i+1} and make a minimum spanning tree of lower cost contradicting the fact that T_2 is a MST. Consider the case when the cycle contains the edges e'_i where $j \ge i + 1$. Let e'_i where $j \neq i + 1$ be any edge of the cycle, then we have $e_{i+1} < e'_{i+1} < e'_{i}$. Again, we can replace edge e'_{i+1} with e_{i+1} and make a MST of lower cost contradicting the fact that T_2 is a MST. Therefore, we can conclude that T_1 and T_2 are same.

Proposition 1. An edge-order-interval has a unique MST.

Proof. Using Lemma 1, if all the edge weights are distinct, then there is a unique MST. In an edge-order-interval there is a clear ordering among the edges for all time instants (no two edge weight functions intersect); therefore, there will be an unique MST. \Box



Figure 4: Time sub-interval minimum spanning trees.

2.1 **Problem Definition**

Given an undirected ST network G = (V, E) where V is the set of vertices of graph, E is the set of edges, and each edge $e \in E$ has a weight function associated with it. The weight function is defined over the time horizon [1, K]. The problem of TSMST is to determine the set of distinct minimum spanning trees, TMST(i), and their respective time-sub-intervals, $i = (i_s, i_e)$.

The total cost of TMST(i) is least among all other spanning trees over its respective time-sub-interval $i = [i_s, i_e]$ where $0 \le i_s \le i_e \le K$.

We assume that for all edges $e \in E$, the edge weight function is defined for the entire time interval [1, K]. The weight of an edge is assumed to vary linearly between any two time instants of time series.

In our example of an energy efficient communication network maintained by a group of sensors, the communication network is represented as a ST network shown in Figure 2(a). The collection of distinct minimum spanning trees and their corresponding time-sub-intervals is shown in Figure 4.

3 Related Work

The related work is classified based on candidate spanning tree ranking. The traditional greedy algorithms for determining MST assume stationary ranking. Related work done in the area of non-stationary ranking assume separable edge cost. In contrast our work proposes algorithms for non-stationary ranking case by accounting for both separable and non-separable edge weights.

3.1 Classical Greedy Algorithms

Classical methods for computing minimum spanning trees [4, 5, 17] were developed for static networks and assume stationary ranking of candidate trees (see Figure 5), i.e., they assume that mutual ranking (on basis of total cost) among the spanning trees does not change with time. Therefore, the classical greedy algorithms such



Figure 5: Related work classification

as Kruskal's [17] and Prim's [17] cannot be applied to TSMST problem on spatio-temporal networks.

3.2 Dynamic Graph Algorithms

Dynamic graph algorithms and kinetic algorithms incorporate non-stationary candidate ranking by making use of dynamic data structures such as topology trees [8, 9] and dynamic trees [19]. However, dynamic data structures can model only discrete changes such as single edge insertion, deletion or weight modification [6, 8, 14, 15]. Hence, they cannot handle piecewise linear edge weight functions.

Kinetic algorithms [1, 3, 12] combine parametric optimization along with dynamic data structures. In a parametric optimization problem [7], each edge e is associated with a linear weight function. Kinetic algorithms transform the edge weight functions to a dual plane, i.e., any edge weight function $w_e = a\lambda + b$ where λ represents time, is transformed to a point (-a, b) in the dual plane. Thus any intersection between the edge functions of a tree edge and a non-tree edge in a (λ, w) plane is represented as a common tangent to the convex hulls of the tree and non tree edges in the dual plane.

This method is very efficient when there is a clear separation among the convex hulls of tree and non-tree edges. Otherwise, the convex hulls may overlap. For example, Figure 6 shows the corresponding points in the dual plane for the edge weight functions between time t = 1 and t = 2 for the ST network shown in Figure 2(a). Figure 6 shows the overlapping of the convex hulls formed by the tree and non-tree edges. However, this kind of separation can be seen inside a single cycle and thus would require to creating and maintaining O(m - n + 1) convex hulls (one for each fundamental cycle), where m is the number of edges and n is the number of node.

Moreover, work done in field of non-stationary candidate ranking assume separable edge weights, i.e, they assume that there is no correlation between the different weights of an edge at different time instants. Due to this assumption the kinetic algorithms do not address



Figure 6: Intersecting convex hulls of tree and non-tree edges.

the situation when change points and intersection points overlap. Change points are those time instants where an edge weight function changes its slope and intersection points are those time instants where two or more edge functions intersect, i.e., they have same edge weight. For example, in Figure 3 edge (3,5) has change points at t = 3 and t = 2 and edge weight functions of (1,3) and (2,4) intersect at t = 1.5, whereas the weight functions of edges (1,3) and (2,3) both change and intersect at the same point. At such points the convex hulls may not have a unique common tangent. This implies that the MST cannot be changed even if it is required.

4 TSMST Computation Algorithms

In this chapter, we present two algorithms for computing the TSMST of a spatio-temporal network. Consider again the sample network shown in Figure 2(a) and its edgeweight function plot in Figure 3. The following observations can be inferred from edge weight function plot.

Observation 1. Consider any two consecutive (with respect to time coordinate) intersection points of the edge weight functions. These time coordinates form an edge-order-interval. Within this time interval, all the edge weight functions have a well defined order.

Observation 2. Using the ordering of edge weights within an edge-order-interval, an MST for this interval can be built using a standard greedy algorithm such as Kruskal's [17] or Prim's [17].





Observation 3. *There will be a single MST for the entire edge-order-interval.*

4.1 Time Sub-Interval Order (TSO) Algorithm

The time sub-interval order (TSO) algorithm is designed (Algorithm 1) using Observation 1, Observation 2 and Observation 3. The TSO algorithm starts by determining all edge-order-intervals. First, it computes all the intersection points of the edge weight functions. The intersection points are then sorted with respect to time coordinate. This sorted list of all intersection points is termed as *edge-order series*. Then the set δ of all edge-order-intervals is built from the edge-order series. Each item in δ is a pair obtained by picking consecutive elements from the edge-order series.

The algorithm then computes MST for the first edgeorder-interval of δ . Next, MST for the next interval in δ is computed and compared with the previous MST. If the current MST is same as the previous MST, then this interval is combined with the time-sub-interval of the previous MST. Otherwise, the previous MST is output along with its time-sub-interval. The previous MST forms the TSMT for that particular time-sub-interval (which was output). This process continues until there are no more intervals left in δ . Since the algorithm outputs the previous TMST every time, the last TMST has to be output separately.

Observation 4. The time-sub-interval order (TSO) algorithm can be improved by sorting only the edges involved in an intersection instead of sorting all the edges in each edge-order-interval (see Figure 7). This is true because only the edges involved in intersections can change their relative ordering.

The TSO algorithm computes a MST for each intersection point. This would incur an unnecessary overhead if Algorithm 1 Time Sub-interval Order Algorithm for finding TSMST

- 1: Determine the intersection points of edge weight functions for all $e \in E$
- 2: Sort the intersection points with respect to time coordinate to form an edge-order series
- 3: Pick the consecutive elements of the edge-order series to build the set δ
- 4: Compute MST for the fist edge-order-interval of δ and denote as previous MST
- 5: Initialize the time-sub-interval of the previous MST to the first edge-order-interval
- 6: for all remaining edge-order-intervals ω in δ do
- 7: Pick the next interval from δ
- 8: Build Minimum Spanning Tree using any greedy algorithm like Prim's or Kruskal's
- 9: if current MST differs from previous MST then
- 10: Output the previous MST (which is now TMST) along with the time-sub-interval and make current MST as the previous MST
- 11: Set the time-sub-interval of previous MST to ω
- 12: **else**
- 13: Combine ω with the time-sub-interval of previous MST
- 14: **end if**
- 15: **end for**
- 16: Output the previous MST (TMST) along with its time-sub-interval

the MST does not change at a intersection point (e.g., see Figure 9).

Moreover, if the edges involved in intersection are from different bi-connected components, the MST will not change (Proposition 4). A bi-connected component of a graph is a maximal set of edges such that any two edges in the set lie on a common cycle [5]. For example, edges (3,5) and (1,2) of the network shown in Figure 2(a) belong to different bi-connected components, therefore intersection of their weight functions can never produce a change in MST. On the other hand, intersection of weight functions of edges in the same bi-connected component (e.g., edges (1,2), (2,4), (3,4), (1,3), (2,3) in Figure 2(a)) may change the MST.

Similarly, intersection of edge weight functions of two or more tree edges or non-tree edges do not change the MST (Proposition 2 and Proposition 3). For example, in Figure 3 intersection of weight functions of edges (1,3)and (2,3) at time t = 2 does not change the MST because both are non-tree edges. Likewise, intersection of weight functions of edges (1,2) and (2,4) at time t = 2 (see



Figure 8: Edge exchange inside a cycle.

Figure 3) does not change the MST because both are treeedges.

Furthermore, if only one tree edge and one non tree edge (belonging to only one common cycle) are involved in intersection, we can exchange those edges in tree. For example see Figure 8. Here, the weight function of edges (1,2) (a non-tree edge) and (5,6) (a tree edge) intersect at time t = 1.5. Thus instead of building a new MST at t = 1.5 (as done by TSO), exchanging the edges involved in intersection in current MST would give the new MST (see Figure 8). These ideas are presented formally in the following propositions. These are used in designing an incremental algorithm for computing the TSMST.

Proposition 2. The intersection of the edge weight function of two non-tree edges at any time instant will not affect the minimum spanning tree, i.e., the tree will not change.

Proof. Consider the intersection of the edge weight function of two non-tree edges e_x and e_y at a time instant $t = \alpha$. Let $O_1 = e_1 e_2 \dots e_i e_x e_y e_{i+3} \dots e_m$ be the ascending order of weights of the edges before time $t = \alpha$ and $O_2 = e_1 e_2 \dots e_i e_y e_x e_{i+3} \dots e_m$ after time $t = \alpha$. Here, m is number of edges in the graph. Since all the edges have distinct weights, therefore, MST of the graph induced by the edges e_j , where $j \leq i$, will be same for both the series O_1 and O_2 (using Lemma 1). Now due to the intersection, edges e_x and e_y have changed their relative ordering. Previously, i.e., before time $t = \alpha$, edge e_x was not present in the MST. But now its weight has further increased so it will again not be in the MST. Now, the weight of the edge e_y has decreased but it is still more than the next lighter edge (since weight functions of only e_x and e_y have intersected). Therefore, e_y will again not be in the MST. Thus the intersection of the edge weight functions of two non-tree edges does not affect the MST. **Proposition 3.** The intersection of the edge weight function of two tree edges at any time instant will not affect the minimum spanning tree, i.e., the MST will be the same.

Proof. Consider the intersection of the edge weight function of two tree edges e_x and e_y at a time instant $t = \alpha$. Let $O_1 = e_1 e_2 \dots e_i e_x e_y e_{i+3} \dots e_m$ be the ascending order of weights of the edges before time $t = \alpha$ and $O_2 =$ $e_1e_2\ldots e_ie_ye_xe_{i+3}\ldots e_m$ after time $t = \alpha$. Here, m is number of edges in the graph. Since all the edges have distinct weights, therefore, MST of the graph induced by the edges e_j , where $j \leq i$, will be same for both the series O_1 and O_2 (using Lemma 1). Now due to the intersection edges e_x and e_y have changed their relative ordering. Previously i.e., before time $t = \alpha$, edge e_u was present in the MST. But now its weight has decreased so it will again be in the MST. Now, the weight of the edge e_x has increased but it is still less than the next heavier edge (since weight functions of only e_x and e_y have intersected). Therefore, e_x will again be in the MST. Thus the intersection of the edge weight functions of two tree edges does not affect the MST.

Proposition 4. The intersection of the edge weight functions of two edges belonging to different bi-connected components can never change the MST.

Proof. Consider a graph G with two bi-connected components G_1 and G_2 such that $G = G_1 \cup G_2$. The bi-connected components G_1 and G_2 can at most share one vertex (by the maximality of bi-connected components [5]). Consider a spanning tree of G, $T_G = T_{G_1} \cup T_{G_2}$. Now in order to determine the minimum spanning tree of G we have to minimize the total cost of T_G . The minimum value is attained when both T_{G_1} and T_{G_2} have their minimum values. But the minimum value of the total cost of T_{G_1} (T_{G_2}) is attained when T_{G_1} (T_{G_2}) is the MST of G_1 (G_2). This implies that MST of G is the union of the MSTs of its individual bi-connected components.

Consider the intersection of the weight function of an edge e_x belonging to G_1 with an edge e'_y belonging to G_2 . Let $O_1 = e_1e_2 \dots e_ie_x \dots e_{m_1}$ be the ascending order of the edge weights of edges in G_1 and $O_2 = e'_1e'_2 \dots e'_ie'_j \dots e'_{m_2}$ be the ascending order of the edge weights of edges in G_2 . Here m_1 is the number of edges in the bi-connected component G_1 and m_2 is the number of edges in the bi-connected component G_2 . Now due to this intersection there is no change in O_1 or O_2 . Therefore the MST of G_1 (or G_2) will not change.

Proposition 5. Intersection of weight functions of two or more tree-edges (or non-tree edges) from one biconnected component with two or more non-tree edges (or



Even though heaviest edge is not changing but the TSO algorithm will still recompute MST for each intersection point

Figure 9: Worst case behavior of TSO algorithm.

tree edges) from another bi-connected component cannot change the MST.

Proof. Consider the intersection of weight functions of two tree edges e_1 and e_2 of bi-connected component B with two non-tree edges e'_1 and e'_2 of bi-connected component B'. Using Proposition 4, we conclude that intersection of weight functions of edges belonging to different bi-connected components do not change the MST. Now, inside each of the bi-connected components B and B' either only tree edges are involved or only non-tree edges are involved. Using Proposition 2 and Proposition 3 we conclude that these intersections cannot change the MSTs within the bi-connected components. Now, since MSTs of individual bi-components did not change therefore the MST of the entire graph will also not change. This is because the MST of graph is the union of the MSTs of its individual bi-connected components (Proposition 4).

4.2 Edge Intersection Order (EIO) Algorithm

Here we present an incremental algorithm for computing TSMST. The edge intersection order (EIO) algorithm starts by computing the MST of the network at time t = 1 and then continues to update the tree, only if necessary, at each intersection point. The intersection points are processed in increasing order of their time coordinates. Through preprocessing, some additional information about the edges is stored while computing the MST at time t = 1. This information is used to prune the intersection points which are guaranteed not to cause any change in the MST.

The modified reverse-delete (Algorithm 2) is used to compute the MST at time t = 1. Figure 10 shows the execution trace of the algorithm. The algorithm first computes the depth first search (DFS) tree [5] of the given ST network. A non-tree edge $ne = (f_s, f_e)$, where f_e is the ancestor of f_s , is chosen. Now, edge ne and edges seen while following the parent pointers from node f_s to f_e and ne form a cycle. This cycle is termed as *fcycle*. The heaviest edge of this fcycle is deleted. For example, in Figure 10, edge (2,4) is a non-tree edge where node 2 is an ancestor of node 4 (considering the DFS tree to be rooted at node 2). Now on following the parent pointers from node 4 to node 2, edges (4,3), (3,2) and (2,4) form a fcycle with edge (2,4) being the heaviest. This edge is deleted and an entry in a table called fcycle table is made for FC1 with edges (4,3), (3,2) and (2,4). A DFS tree of the remaining edges is computed. A non-tree edge is picked up and the heaviest edge in its fcycle is deleted and a corresponding entry in the fcycle table is made. This process continues until only n-1 edges are left in the network. At this point there will no non-tree edges after constructing the DFS tree, i.e., all edges are tree edges. These edges form the MST of the network. They are marked as tree edges and all other remaining edges of the original network are marked as non-tree edges.

Data structures used by EIO algorithm The following data structures are used by the EIO algorithm and the modified reverse-delete algorithm. This information is pre-computed before the EIO algorithm starts processing each intersection point:

- Edge-Table: A look up table storing the details of each edge. This table contains, for each edge, a unique edge-id, the two nodes it connects, the biconnected component it belongs to, and a bit vector storing the fcycles of which the edge is a member.
- Fcycle-Table: A look up table storing the details of each fcycle observed while constructing the minimum spanning tree at time t = 1. Each entry of this table contains a unique fcycle-id and a list of its member edges (edges column).

The MST of the network is stored as a bit vector of length equal to the number of edges in the network. The bit vector would contain a bit corresponding to each edge of the network and the edges belonging to MST would be Algorithm 2 Modified Reverse-Delete Algorithm for MST

- 1: Find depth first search tree of the given network
- 2: while non-tree edge is present do
- 3: Pick a non-tree edge and determine all the edges in the fcycle
- 4: Delete the edge which has maximum weight. Record the fcycle in fcycle - table
- 5: Find the DFS tree of the remaining network
- 6: end while
- 7: The remaining edges form the minimum spanning tree

set to one. The edge-table and fcycle-table are indexed using hashing. The information stored in fcycle-table can also be computed at runtime by adding the non-tree edge to the MST and determining the fcycle. This would incur an additional O(n) cost each time. This is avoided by storing the information while constructing MST for time t = 1. The fcycles column of the edge-table is filled by traversing through the fcycle-table. Each fcycle-id from the fcycle-table is chosen and the bit corresponding to this fcycle-id is set for all the edges in the edges column of this entry of fcycle-table. The bi-connected component column of the edge-Table is filled in linear time using the algorithm given in [2].

While considering an intersection point, two levels of filters are applied to prune the intersection points that cannot cause any change in MST. If all the edges involved in an intersection are either non-tree edges or tree edges, then it can be pruned using Proposition 2 and Proposition 3 respectively. Similarly, if all the edges involved in an intersection belong to different bi-connected components, then it can be pruned using Proposition 4.

After applying these filters, the edges are grouped by their bi-connected component number. Now, within each group we again check if the edges are only tree edges or non-tree edges. This is important in cases when the weight functions of two or more tree (or non-tree) edges of one component and one or more non-tree (or tree) edges of another component intersect at a point. These kinds of intersection points cannot cause any change in a tree (Proposition 5). Hence, the filters are applied again after the edges are grouped by their bi-component number. After applying these filters if the intersection point is not pruned, we check if the relative order of edges weights before and after the intersection point are same. The intersection point can be pruned safely if the relative order is same. This can happen when weight functions of two or more edges touch each other at change points (see Figure 3) without changing their relative order.

If an intersection point is not pruned after applying all the filters, then a new MST is made by making changes to the previous MST. If only two edges (per bi-connected component) are involved in the intersection and they are part of only one common cycle, i.e., they are not part of any cycle except the one which is common, then we can directly exchange the edges in the tree, i.e., make the heavier edge between them as non-tree edge and the lighter edge as tree edge. In all other cases we add each of the non-tree edges involved in the intersection to the MST and delete the heaviest edge from their respective fundamental cycles. We can check whether two edges are part of only the common cycle by performing an AND operation on the fcycles column of the two edges and check the number of bits set to 1 in the result. Note that in the twoedges intersection case discussed above, adding the nontree edge to the tree and deleting the heaviest edge from its fundamental cycle would still give the correct MST. The information gathered during initial construction was used to save this unnecessary re computation. The start time of the time-sub-interval of the new MST and end time of the time-sub-interval of previous MST are set to the time coordinate of intersection point at which the MST changed. The previous MST is output along with its timesub-interval. The previous MST forms the TMST for that particular time-sub-interval.

We now describe the terminology used in the EIO algorithm. While considering an intersection point at time t, S_t is the set of all intersection points whose time coordinate is t. An intersection point in S_t is denoted as p_r , where $r \in [1, 2, \ldots, |S_t|]$. The set of all S_t 's form Γ . $B_{p_r} = [b_1, b_2, \ldots]$ is the set of groups obtained after grouping the edges involved in the intersection by their bi-connected components. s_i and s_j are the decreasing order of edges weights (of a particular bi-connected component group) before and after the time of the intersection point. The edge intersection order algorithm is formally presented as Algorithm 3.

Execution Trace of EIO Algorithm We next present an execution trace of the EIO algorithm for the example in Figure 2(a). The algorithm starts by computing the biconnected components of the given graph and filling the corresponding columns in the edge table. This can be done in linear time [2]. The algorithm then determines the intersection points of the edge weight functions. They are then sorted on the time coordinate to form the edge-order series. Minimum spanning tree at t = 1 is built using Algorithm 2 and the fcycle-table is populated. Step by step execution of Algorithm 2 and the filling of the fcycle-table is shown in Figure 10.



Figure 10: Trace of modified reverse delete algorithm for building MST.



Figure 11: Trace of EIO Algorithm for ST network shown in Figure 2(a).

After building the MST for time t = 1 a bit vector is created by setting the bits corresponding to tree-edges to 1 (MST(I) in Figure 11). The edge-table and MST(I) is shown in Figure 11. After that the remaining intersection points belonging to the remaining intervals of δ are grouped by their time coordinate to build S_t (here, S_t is the set of all intersection points with time coordinate as t). The set of all S_t 's form Γ . The algorithm then updates the MST, if necessary, by exchanging the edges at the intersection points. After t = 1 the next interval in δ starts t = 1.25. There are two pairs of edges intersecting at t = 1.25. Both these pairs involve only tree edges or non-tree edges, and thus, these are pruned by the if conditions at line 10 and line 13.1 Similarly, the intersection of edge (3,5) and (2,3) is pruned since they belong to different bi-connected components.

¹Either the previous MST or the current MST may be used here because any edge can be involved in only one intersection at a time.

Now for the intersection between the edges (2,4) and (1,3) at t=1.5, the condition in line 30 is evaluated by performing an bitwise AND operation of their respective fcycle-id columns. Since the edges (2,4) and (1,3) do not share a cycle (as per fcycles column of edge-table) the non-tree edge (2,4) is added to current MST and heaviest edge in the fundamental cycle is deleted and MST is updated (now it will be MST(II) in Figure 11). This step is essential because even if the edges do not share a cycle as per fcycles column of edge-table they still lie on a common cycle [5]. The next intersection point involving tree and non-tree edge of same component is at t=2.66 between (3,4) and (2,3). Here, the edges (3,4) and (2,3) share a cycle (if condition at line 30 is true) and thus are exchanged to create MST(III). Similarly the next exchange is at t=3.66. Since the EIO algorithm outputs the older MST after every change, the last TMST has to be output separately after the main loop.

4.3 Relaxation of Edge Presence Assumption

In this section, we relax the assumption that an edge is always present. The absence of an edge can be represented by assigning time intervals during which the edge is absent. Such a case arises when some of the sensor nodes move very far from other sensor nodes. Consider a case when an edge e is not present during the time interval [2.5 2.9]. Further assume that its weight at time instants t = 1, 2, 3, and 4 is 2, 3, 6, and 8 respectively. The edge absence information can be combined with the edge weight time series by expanding the series to define weights at smaller time intervals. For example, in the above case, the edge weights would be defined at time instants $t = 1.0, 1.1, 1.2 \dots 2.4, 2.5 - \epsilon$ and then at time instants $t = 2.9 + \epsilon, 3.0, \dots 3.9, 4.0$. The edge weight at these new intermediate time instants can be determined by interpolating original weight function².

The absence of an edge for a certain time period affects the MST and the bi-connected components of the graph. If a non-tree edge does not exist after a certain time instant then there will no change in the MST. On the contrary, if a tree edge ceases to exist then it is replaced by a non-tree edge of lowest weight such that the MST remains connected and optimal. This is done by adding each of the non-tree edges (in increasing order of their weights) to the MST and if the tree edge (which is absent) in found in the cycle created, then it is replaced by that particular non-tree edge. If multiple tree edges are absent during a particular time interval then each of these tree edges is re-

²Since the edge function is linear, interpolation works nicely.

placed by a non-tree edge. In such cases, each of the nontree edges (in increasing order of their weights) is added to the MST and if any of the tree edges is found in the cycle created by the addition of non-tree edge, then it is replaced by that particular non-tree edge. The tree edges are stored in a hash table for this case. Now, when an edge reappears (either tree or non-tree), it is added to the MST and the heaviest edge is deleted from the cycle created. For practical purposes, we assume that the graph is never disconnected due to disappearance of edges. Therefore, at most m - n + 1 edge can be absent during any particular time interval.

When an edge is absent during a certain time interval, the bi-connected component information of the edges change. This information can be recomputed in linear time using the algorithm given in [2]. This updated information may be useful for pruning some of the intersection points which may not be pruned otherwise. The bi-connected component information has to be recomputed again after the edge appears. Re-computation of bi-connected components can be delayed until the next intersection point is encountered. This is useful in cases when there are no intersections during the period of absence. The bi-connected component information is only used by the EIO algorithm.

5 Analytical Evaluation

The correctness proof and the asymptotic analysis of the edge-intersection order algorithm and the time subinterval order algorithm are presented in this chapter.

5.1 Analysis of TSO algorithm

Theorem 1. *The time-sub-interval order (TSO) algorithm is correct.*

Proof. The correctness of the TSO algorithm can be established by using Observation 1. The minimum spanning tree changes whenever there is a change in ordering of the edges. The TSO algorithm addresses this by recomputing the minimum spanning tree for each interval in δ . This means that it recomputes the ordering of edges again after every intersection point. Moreover, from Observation 1, we can say that the ordering or edges do not change inside an edge order interval. This proves that the TSO algorithm is correct.

Asymptotic analysis of TSO algorithm Since the edge weight is assumed to vary linearly between any two time instants in a time series, there can be at most $O(m^2)$ (where *m* is the number of edges) intersections among

the edge weight functions in the worst case. Now if this happens between all time instances in the entire time horizon $[1, \ldots K]$, the total number of intersections will be $O(m^2K)$. The time needed to sort all the intersection points is $O(m^2K \log(m^2K))$. For each intersection point TSO recomputes the MST which takes $O(m \log m)$ per intersection point. Thus, the total time complexity of the TSO algorithm is $O(m^3K \log m + m^2K \log(m^2K))$.

Relaxation of edge presence assumption Now, consider the case when the edge presence assumption is relaxed. Even though the number of time instants in the edge weight time series increases, the total number of intersection points do not change because we are not adding any new weight functions. Let L be the number of disjoint time intervals during which any of the edges is absent. During each of these L intervals, if any of the tree edges is absent then it has to replaced by a non-tree edge. The replacement involves observing the cycles created by each of the O(m - n + 1) non-tree edges in increasing order of their weights. Since there can be at most n-1 tree edges, this takes $O(mn + m \log m)$ time. Here, each tree edge is not processed individually. All the tree edges are stored in a hash table and are checked in the cycles created by the addition of each non-tree edge. Then after an edge (either tree or non-tree) reappears, it is again added to MST and the heaviest edge is deleted from the cycle created. Now, there can be at most m - n + 1 edges absent during a time interval (assuming that the graph always remains connected). Therefore, this step takes O(mn) time. Therefore the total complexity is $O(Lmn + Lm \log m)$. Thus, the overall complexity of the TSO algorithm becomes $O(m^3 K \log m + m^2 K \log(m^2 K) + Lmn + Lm \log m).$

5.2 Analysis of Modified Reverse Delete Algorithm

Theorem 2. *The modified reverse delete algorithm produces a MST.*

Proof. (By contradiction) Let T_1 be the spanning tree generated by the algorithm and let T_2 be the MST. Let $OT_1 = e_1e_2 \dots e_ie_{i+1} \dots e_{m-n+1}$ be the increasing order of edge weights of T_1 . Let $OT_2 =$ $e'_1e'_2 \dots e'_ie'_{i+1} \dots e'_{m-n+1}$ be the increasing order of edge weights of T_2 . Without loss of generality, assume that e_j is same as e'_j , $\forall j \leq i$. Further assume that $e_{i+1} > e'_{i+1}$. Now consider the cycle generated by adding the edge e'_{i+1} to T_1 . Only one such cycle can be created as T_1 is a spanning tree of the graph. Now if this cycle contains only the edges e_j where $j \leq i$, then it implies that there is a cycle in T_2 as e_j is same as e'_j , $\forall j \leq i$ (a contradiction). Now, if the cycle contains some edges e_j where $j \leq i$ and e_{i+1} , then the algorithm would have chosen edge e_{i+1} to delete instead of e'_{i+1} because the algorithm deletes the heaviest edge of the cycle. Consider the case when the cycle contains the edges e_j where $j \geq i + 1$. Let e_j , where $j \neq i + 1$, be any edge of the cycle. Then, $e'_{i+1} < e_{i+1} < e_j$. Again, the algorithm would have chosen edge e_{i+1} instead of e'_{i+1} . Therefore, we can conclude that T_1 and T_2 are same.

Asymptotic analysis of Modified Reverse Delete Algorithm The algorithm determines the DFS tree of the graph in each iteration. This takes O(m + n) where m is the number of edges and n is the number of nodes. Finding the heaviest edge in a fcycle takes O(n) time. This happens when the fcycle contains all the nodes of the graph. After each iteration the number of edges decreases by one. Therefore, the total number of iterations required are m - n + 1 (one for each non-tree edge deleted). Therefore, the total time taken is given by the sum of the series $(m + n) + (m - 1 + n) + \ldots + (2n - 1)$. This series has m - n + 1 terms. Thus, the overall complexity of the algorithm is $O(m^2)$.

5.3 Analysis of EIO algorithm

Theorem 3. *The edge intersection order (EIO) algorithm is correct.*

Proof. The EIO algorithm prunes an intersection point if only tree edges or non-tree edges are involved. Proposition 2 and Proposition 3 show the correctness of this filtering step. Similarly, an intersection point is pruned if all the edges involved in it belong to different components. The correctness of this filtering step is evident from Proposition 4. An intersection point is also pruned if two or more tree edges (or non-tree edges) of one bi-connected component intersect with two or more non-tree edges (or tree edges) of another bi-connected component. The correctness of this filter step is shown in Proposition 5. Furthermore, an intersection is pruned if the relative order of edge weights do not change after the intersection. This is because in such cases, as there is no change in the relative order of edges and all the edges have distinct weights (before and after the intersection), there will be no change in the MST (using Lemma 1).

After the filtering steps the algorithm checks if the edges involved can be directly exchanged or not. Otherwise the non edge is added to the MST. This addition can create only one cycle. The cycle property of minimum spanning trees [17] states that given a cycle, the heaviest edge in that cycle does not belong to any minimum spanning tree. Hence, using this we can add the non tree edges

and delete the heaviest edge without creating any cycles or affecting the correctness of the minimum spanning tree. Thus, the EIO algorithm is correct.

Storage costs of the data structures The edge-table has an entry for each edge in the ST network. Thus it would have m entries, where m is number of edges in the ST network. Now the number of fcycles in graph is bounded by O(m - n + 1) (one for each edge deleted during construction of MST at t=1) where m and n are number of the edges and nodes of ST network. Thus, the length of the bit vector for fcycles column of edge-table is m - n + 1 (one bit for each fcycle). Therefore the total storage cost of edge-table is $O(m^2)$. Similarly, the total number of entries in fcycle-table is m - n + 1 and each entry of fcycle-table has a list which can have a worst case length of O(m). Therefore, the total storage cost of fcycle-table is $O(m^2)$.

Asymptotic analysis of EIO algorithm The running time of the EIO algorithm is sensitive to the number of intersection points and number of edges involved per intersection point. Here, we consider two kinds of intersection points: one, in which all the edges are involved and the other, where only two edges (or a constant number) are involved. First consider the case of a two-edge intersection. The number of two edge intersections (or constant number) between a pair of consecutive time instants is $O(m^2)$. Since the edge-table is indexed using hashing, all the filtering steps would take only O(1) time. Similarly, step 21 (determining s_i and s_j) would take only constant time as there are only two (or constant number) edges. Steps 33-36 can take O(n) (n being the number of nodes in graph) time in the worst case (when the fundamental cycle involves all the nodes of the graph). Thus, the two edge intersection case would take $O(m^2n)$ worst case time (for one consecutive pair of time instances in the time series). The maximum number of times this can happen is O(K) (once between every two time instances of the time series).

Now, consider the case when O(m) edges intersect at a single point. In this case step 21 would take $O(m \log m)$ time. This kind of intersection would involve a maximum of O(m - n + 1) non-tree edges. Thus step 33 would take O(n) per non-tree edge making a total of $O(mn + m \log m)$ time in the worst case. This kind of intersection can happen only O(K) times. This is because the edge weight functions vary linearly between two time instances of the time series, and thus they can all meet at only one point between two time instants of the time series. Consider the case when length of the time series is very long. Let the length of time interval when $O(m^2)$ intersections (two edge intersections) occur be K_1 and O(m) edge intersections be K_2 where $K_1 + K_2 = K$. The time required to sort the intersection points in two-edge intersection case is bounded by $O(m^2K_1\log(m^2K_1))$, whereas it would take $O(K_2\log K_2)$ time to sort when O(m)edges are involved in the intersection. Therefore the total time required for sorting all the intersection points is $O((m^2K_1 + K_2)\log(m^2K_1 + K_2))$. Thus the total worst case time required by the EIO algorithm is the sum of time spent on two-edge intersections, O(m)edge intersections and, the time required to sort all the intersection points. Thus the overall time complexity of the EIO algorithm is $O(m^2nK_1 + mnK_2 + K_2m\log m + (m^2K_1 + K_2)\log(m^2K_1 + K_2))$.

Relaxation of edge presence assumption Now, consider the case when the edge presence assumption is relaxed. Even though the number of time instants in the edge weight time series increases, the total number of intersection points do not change because we are not adding any new weight functions. Let L be the number of disjoint time intervals during which any of the edges is absent. The bi-connected component information has to recomputed at the start of each interval and at the end of each interval. Thus, the bi-connected component information has to be computed 2L times and each of these computations take O(m + n) time [2]. During each of these L intervals, if any of the tree edges is absent then it has to replaced by a non-tree edge. The replacement involves observing the cycles created by each of the O(m - n + 1) non-tree edges in increasing order of their weights. Since there can be at most n-1 tree edges, this takes $O(mn + m \log m)$ time. Here, each tree edge is not processed individually. All the tree edges are stored in a hash table and are checked in the cycles created by the addition of each non-tree edge. Then after an edge (either tree or non-tree) reappears, it is again added to MST and the heaviest edge is deleted from the cycle created. Now, there can be at most m - n + 1 edges absent during a time interval (assuming that the graph always remains connected). Therefore, this step takes O(mn) time. Therefore the total complexity is $O(Lmn + Lm \log m)$. Thus, the overall complexity of the EIO algorithm becomes $O(m^2 n K_1 + m n K_2 + K_2 m \log m + (m^2 K_1 + m n K_2 + K_2 m \log m n + m n K_2 + K_2 m \log m n K_2 + K_2 +$ K_2) log $(m^2 K_1 + K_2) + Lmn + Lm \log m)$.

6 Experimental Evaluation

The purpose of the experimental evaluation was to compare the execution times of the TSO and EIO algorithms. The two algorithms were compared on synthetic datasets. The experimental parameters that were varied in experiments are: (1) length of time series, (2) number of edges, and (3) number of nodes. In our experiments we generated the networks randomly. Given the number of nodes (n) and number of edges (m) of the network, first, a spanning tree containing n - 1 edges is generated for the network. This is to guarantee that the network is connected; otherwise, the TSMST cannot be determined. Edges are then randomly added to this spanning tree till the number of edges becomes m. After that a time series is associated with each edge. The time series is also generated randomly. The experiments were conducted on an Intel Xeon workstation with 2.40GHz CPU, 8GB RAM and Linux operating system.

6.1 Effect of Length of Time Series

Figure 12(a) shows the performance of EIO and TSO algorithm as the length of the time series increases. Execution time of both the algorithms increase with time. The figure shows a superior performance of the EIO algorithm over the TSO algorithm. This is due to the increase of intersection points that occurs with the increase in the length of time series. Since the TSO algorithm recomputes the MST at each intersection point, it takes much more time than the EIO algorithm, which just updates the MST with no recomputing. Experiments reveal that execution time of both TSO and EIO algorithms vary linearly with length of time time series.

6.2 Effect of Number of Edges

Figure 12(b) shows the performance of EIO and TSO algorithm as the number of edges increases. Execution time of EIO algorithm was observed to increase quadratically. Execution time of the TSO algorithm increased much more rapidly than that of the EIO algorithm. Both the previous experiments clearly showed the superior performance of the EIO algorithm over the TSO algorithm. The EIO algorithm was faster than the TSO algorithm by an order of magnitude. Moreover, the difference in the execution times of the two algorithms increased with increase in length of time series and number of edges.

Figure 13 shows the performance of the EIO algorithm for four different network sizes. The execution time increased linearly with length of time series in all cases. The execution time increased at a faster rate as the size of the network increased. For instance, execution time increased much more rapidly for a network with 300 nodes and 1000 edges than for a network with 100 nodes and 650 edges.

6.3 Performance Evaluation of the Filters

Figure 14 shows the total number of the intersection points and the number of intersection points pruned by the EIO algorithm. The figure shows that the number of intersection points increase with increase in size of network. The figure also shows that a large number of intersection points were pruned by the EIO algorithm. This clearly shows the superior performance of the filters used in the EIO algorithm. Table 3 and Table 2 show the percentage of intersection points filtered by individual filters.

7 Conclusions

The time-sub-interval minimum spanning tree (TSMST) problem is a key component of various spatio-temporal applications such as wireless sensor networks. The paper proposes two novel algorithms for TSMST computation. The time sub-interval algorithm (TSO) computes the TSMST by recomputing the MST at all time points where there is a possible change in the ranking of candidate spanning trees (i.e., it recomputes the MST at all the intersection points of edge weight functions) and then outputs the set of distinct MSTs along with their respective time-sub-intervals. The edge intersection order algorithm (EIO) updates the MST, only if necessary, at these time points. Both these algorithms are based on a model for spatio-temporal networks called timeaggregated graphs. The asymptotic complexity of the TSO algorithm was $O(m^3 K \log m + m^2 K \log(m^2 K))$ and the asymptotic complexity of the EIO algorithm was $O(m^2 n K_1 + m n K_2 + K_2 m \log m + (m^2 K_1 + m n K_2 + K_2 m \log m + m n K_2 + m$ K_2) log $(m^2K_1 + K_2)$). Computational complexity analysis shows that the EIO algorithm is faster than the TSO by a factor of almost O(m). Experiments also show that the EIO is faster than the TSO algorithm by an order of magnitude.

In future, we plan to evaluate the performance of the algorithms using real datasets. We also plan to extend the algorithms to give optimal solutions subject to the constraint that the edge weight functions are non-linear in nature.

References

 P. Agarwal, D. Eppstein, L. J. Guibas, and M. R. Henzinger. Parametric and kinetic minimum spanning trees. *Proceedings of 39th Annual IEEE Symposium on Foundations of Computer Science* (FOCS), pages 596–605, 1998.

	Pe				
Network size	Only tree edges	Only non- tree edges	Different bi- connected components	No change in relative order	Total intersec- tion points
Nodes=100 Edges=130	73.42	10.69	0.87	0.07	356885
Nodes=100 Edges=150	58.95	20.06	0.37	0.05	481301
Nodes=100 Edges=650	5.56	87.74	0	0	8185234
Nodes=300 Edges=330	92.51	2.05	0.25	0.01	2388274
Nodes=300 Edges=350	85.77	4.5	0.57	0.01	2676646
Nodes=300 Edges=650	33.7	44.5	0	0.01	9157842

Table 2: Performance of filters for time series length=90.

- [2] V. A. Alfred, J. D. Ullman, and J. E. Hopcroft. *Data Structures and Algorithms*. Addison Wesley Longman, 1983.
- [3] J. Basch, L. J. Guibas, and J. Hershberger. Data structures for mobile data. In *Proceedings of the eighth annual ACM-SIAM Symposium on Discrete Algorithms (SODA)*, pages 747–756, 1997.
- [4] B. Chazelle. A faster deterministic algorithm for minimum spanning trees. In Proceedings of the 38th Annual Symposium on Foundations of Computer Science (FOCS), page 22, 1997.
- [5] T. H. Cormen, C. E. Leiserson, R. L. Rivest, and C. Stein. *Introduction to Algorithms*. MIT Press, 2001.
- [6] D. Eppstein, Z. Galil, G. F. Italiano, and A. Nissenzweig. Sparsification – a technique for speeding up dynamic graph algorithms. *J. ACM*, 44:669–696, 1997.
- [7] D. Fernández-Baca, G. Slutzki, and D. Eppstein. Using sparsification for parametric minimum spanning tree problems. *Nordic J. of Computing*, 3(4):352– 366, 1996.
- [8] G. Frederickson. Data structures for on-line updating of minimum spanning trees. SIAM J. Computing, 14:781–798, 1985.

- [9] G. Frederickson. Ambivalent data structures for dynamic 2-edge-connectivity and k smallest spanning trees. *SIAM J. Computing*, 26:484–538, 1997.
- [10] B. George, S. Kim, and S. Shekhar. Spatio-temporal network databases and routing algorithms: A summary of results. In *Proceedings of Symposium* on Spatial and Temporal Databases (SSTD), pages 460–477, 2007.
- [11] B. George and S. Shekhar. Time-aggregated graphs for modelling spatio-temporal networks. *Journal on Semantics of Data*, XI:191, 2007.
- [12] L. J. Guibas. Kinetic data structures: a state of the art report. In *Proceedings of the Third Workshop on the Algorithmic Foundations of Robotics (WAFR)*, pages 191–209, 1998.
- [13] W. R. Heinzelman, A. Chandrakasan, and H. Balakrishna. Energy-efficient communication protocol for wireless microsensor networks. *Proceedings of the 33rd Hawaii International Conference on System Sciences - 2000 (HICSS)*, 8:8020, 2000.
- [14] M. R. Henzinger and V. King. Maintaining minimum spanning trees in dynamic graphs. In Proceedings of 24th International Colloquium on Automata, Languages, and Programming, pages 594– 604, 1997.
- [15] J. Holm, K. de Lichtenberg, and M. Thorup. Polylogarithmic deterministic fully-dynamic algorithms

	Pe				
Network size	Only tree edges	Only non- tree edges	Different bi- connected components	No change in relative order	Total intersec- tion points
Nodes=100 Edges=130	72.88	10.33	0.9	0.05	196732
Nodes=100 Edges=150	58.79	19.8	0.49	0.06	264020
Nodes=100 Edges=650	5.72	87.75	0	0	4506094
Nodes=300 Edges=330	92.14	1.91	0.26	0.01	1317133
Nodes=300 Edges=350	85.77	4.27	0.12	0.02	1476097
Nodes=300 Edges=650	34.38	45.19	0	0.01	5031355

Table	3:	Performance	of	filters	for	time	series	length=	:50
								<u> </u>	

for connectivity and minimum spanning tree. In *Proceedings of 30th ACM Symp. Theory of Computing* (STOC), pages 79–89, 1998.

- [16] G. Huang, X. Li, and J. He. Dynamic minimal spanning tree routing protocol for large wireless sensor networks. *Proceedings of the 1st IEEE Conference* on Industrial Electronics and Applications (IEA), pages 1531–1535, 2006.
- [17] J. Kleinberg and E. Tardos. *Algorithm Design*. Pearson Education, 2009.
- [18] S. Muruganathan, D. Ma, R. Bhasin, and A. Fapojuwo. A centralized energy-efficient routing protocol for wireless sensor networks. *IEEE Communications Magazine*, 43:8–13, 2005.
- [19] D. D. Sleator and R. E. Tarjan. A data structure for dynamic trees. In *Proceedings of the thirteenth annual ACM Symposium on Theory of Computing* (STOC), pages 114–122, 1981.
- [20] J.-Z. Sun. Query optimization based on userspecified delay item for wireless sensor networks. *Proceedings of the 2007 international conference on Wireless communications and mobile computing*, pages 493–498, 2007.
- [21] N. Trigoni, Y. Yao, A. Demers, J. Gehrke, and R. Rajaraman. Multi-query optimization for sensor networks. *Lecture Notes in Computer Science*, 3560:307–321, 2005.

- [22] A. Verma, H. Sawant, and J. Tan. Selection and navigation of mobile sensor nodes using a sensor network. *Pervasive and Mobile Computing*, 2(1):65– 84, 2006.
- [23] S. Yoon and C. Qiao. A novel approach to reconnaissance using cooperative mobile sensor nodes. In *Proceedings of Military Communications Conference (MILCOM)*, pages 1–7, 2006.



Figure 12: Comparison of EIO and TSO algorithms.



Figure 13: EIO algorithm: Execution time with respect to length of time series.



Figure 14: Number of intersection points in different datasets.

Algorithm 3 Edge Intersection Order (EIO) algorithm for finding TSMST	
1: Compute the bi-connected components of the given graph and update bi-connected column of edge-table	_
2: Determine the intersection points of the edge weight functions	
3: Sort the intersection points with respect to time coordinate	
4: Find the MST at $t = 1$ (let this be previous MST) using Algorithm 2 and populate the fcycle-table	
5: Set the start time of time sub interval of previous MST to 1	
6: Construct S_t s from the intersection points	
7: for all $S_t \in \Gamma$ do	
8: Set MST-change flag and new-MST-exist flag to FALSE	
9: for all intersection points $p_r \in S_t$ do	
10: if all edges are tree edges or non-tree edges then	
11: continue	
12: end if	
13: if all edges belong to different bi-connected components then	
14: continue	
15: end if	
16: group the edges into bi-connected components (build set B_{p_r})	
17: for all $b_i \in B_{p_r}$ do	
18: if all edges are tree edges or non-tree edges then	
19: continue	
20: end if	
21: Determine s_i and s_j .	
22: if s_i and s_j are same then	
23: continue	
24: end if	
25: Set MST-change flag to TRUE (all subsequent steps will change MST)	
26: if new-MST-exist is FALSE then	
27: Create a new MST (i.e., create a new bit vector and assign the same values as of previous MST), let the current MST	nis
28: Set new-MST-exist flag to TRUE	
29: end if	
30: if only two edges intersect and they are part of only the common cycle then	
31: update the current MST (set the bit corresponding to heavier edge to 0 and lighter edge to 1).	
32: else	
33: for all non tree edges in s_j do	
34: find their fundamental cycle and delete heaviest edge	
35: update the current MST	
36: end for	
37: end if	
38: end for	
39: end for	
40: if MST-change flag is set to TRUE then	
41: Output the previous MST (TMST) with its time-sub-interval and make current MST as previous MST	
42: end if	
43: end for	
44: Output the previous MST (TMST) along with its time-sub-interval	