

Title	Restoring wireless sensor network connectivity in damaged environments
Authors	Truong, Thuy T.;Brown, Kenneth N.;Sreenan, Cormac J.
Publication date	2012-08-09
Original Citation	Truong, T. T., Brown, K. N. and Sreenan, C. J. (2012) 'Restoring Wireless Sensor Network Connectivity in Damaged Environments', International Workshop on Cooperative Robots and Sensor Networks (RoboSense), in Procedia Computer Science, 10(Supplement C), pp. 1134-1139.
Type of publication	Article (peer-reviewed);Conference item
Link to publisher's version	http://www.sciencedirect.com/science/article/pii/S1877050912005182 - 10.1016/j.procs.2012.06.161
Rights	© 2012 Published by Elsevier Ltd. Open access under CC BY-NC-ND license - http://creativecommons.org/licenses/by-nc-nd/3.0/
Download date	2026-08-28 17:23:42
Item downloaded from	https://hdl.handle.net/10468/5094



UCC

University College Cork, Ireland
Coláiste na hOllscoile Corcaigh

International Workshop on Cooperative Robots and Sensor Networks (RoboSense)

Restoring Wireless Sensor Network Connectivity in Damaged Environments

Thuy T. Truong, Kenneth N. Brown, Cormac J. Sreenan

Mobile & Internet Systems Laboratory and Cork Constraint Computation Centre, Dept of Computer Science, University College Cork, Ireland

Abstract

A wireless sensor network can become partitioned due to node failure, requiring the deployment of additional relay nodes in order to restore network connectivity. This introduces an optimisation problem involving a tradeoff between the number of additional nodes that are required and the costs of moving through the sensor field for the purpose of node placement. This tradeoff is application-dependent, influenced for example by the relative urgency of network restoration. We propose four heuristic algorithms which integrate network design with path planning, recognising the impact of obstacles on mobility and communication. We conduct an empirical evaluation of the four algorithms on random connectivity and mobility maps, showing their relative performance in terms of node and path costs, and assessing their execution speeds. Finally, we examine how the relative importance of the two objectives influences the choice of algorithm.

Keywords: Wireless Sensor Network, Network Repair, Path Planning, Exploration

©2011 Published by Elsevier Ltd. Selection and/or peer-review under responsibility of RoboSense 2012

Open access under [CC BY-NC-ND license](#).

1. Introduction

Wireless Sensor Networks are becoming increasingly important for monitoring phenomena in remote or hazardous environments, including pollution monitoring, chemical process sensing, disaster response, and battlefield monitoring. As these environments are uncontrolled and may be volatile, the network may suffer damage, from hazards, direct attack or accidental damage from wildlife and weather. They may also degrade through battery depletion or hardware failure. The failure of an individual sensor node may mean the loss of particular data streams generated by that node; more significantly, node failure may partition the network, meaning that many data streams cannot be transmitted to the sink. This creates the network repair problem, in which we must place new radio nodes in the environment to restore connectivity to the sink for all sub-partitions.

There are four main subtasks in the problem: (i) determining what damage has occurred (i.e. which nodes have failed and what radio links have been blocked); (ii) determining what changes, if any, have happened to the accessibility of the environment (i.e. what positions can be reached, and what routes are possible between those positions); (iii) deciding on the positions for the new radio nodes; and (iv) planning and following a route through the environment to place those nodes. The problem thus involves both exploration and optimisation, and may require the placement of nodes before the changes to connectivity and accessibility have been fully mapped. We assume possible locations for new radio nodes are limited to a finite set of positions where a node can be securely placed and which can be accessed. Radio nodes are expensive, and so solutions which require fewer nodes are preferred. Physically moving around the environment may be expensive in energy use, may take significant time, or may expose the agent placing the nodes to danger, and so solutions which allow cheaper path plans are also preferred. Depending on the application, either one

of the two objectives may be more important: placing expensive nodes in, for example, agricultural pollution monitoring favours solutions with fewer nodes, while restoring connectivity during disaster response favours solutions that can be deployed quickly even if they require more nodes. Thus the network repair problem is multi-objective.

We introduce the problem of simultaneous network repair and autonomous exploration and route planning in the presence of unknown obstacles. We assume a set of locations from which sensor data is required by the network, and we assume the agent has knowledge of the network and accessibility prior to the damage occurring. The objective is to connect as many as possible of these locations, placing extra sensors if required, while minimising the number of radio nodes and the mobility costs. We consider two different priorities for the multi-objective problem: minimising mobility costs, and minimising the number of radio nodes. For each one, we develop a greedy approach and a global approach. In each case, the agent computes a plan (or partial plan), and then starts to execute it. When the agent discovers new information about accessibility or connectivity, it recomputes the plan from its current location, and then continues. We evaluate the approaches on randomly generated problems, and analyse their effectiveness under different assumptions.

2. The Network Exploration and Restoration Problem

We assume a rectilinear grid of locations G , in which a subset $G_b \subseteq G$ of grid squares are candidate locations for wireless nodes. The centre of each square is a potential position for a wireless node. We assume an agent can move from a square to one of its 4 rectilinear neighbours, unless that neighbour is blocked. The set of blocked squares before damage is B_b , while the set of blocked squares after damage is B_a , such that $B_b \subseteq B_a \subseteq G$. We assume a node can sense its own square plus neighbouring squares at a distance of R_s , and has a maximum communication range of R_t (e.g. if $R_t = 1$, then the node can communicate with at most its 8 immediate neighbours). We assume a set of C_b of potential radio links, where each potential link can connect two endpoints $\{g_i \in G_b, g_j \in G_b\}$. After damage, the set of candidate locations is $G_a \subseteq G_b$ and the set of potential links is $C_a \subseteq C_b$ and a set of live nodes is $G_A \subseteq G_a$. The set τ represents *terminals*, the squares from which we need sensed data. A set $I \subset G_A$ of active nodes where it still has connection to wider network. We assume the starting location of the agent is at $L \in I$. Figure 1 shows example of pre-damage, current and actual maps of the network. At the start of the problem, we assume the agent knows τ , I , L , B_b , G_b , and C_b . As the agent explores the environment, it will maintain: G_k , the locations where it knows nodes are active; G_e , locations where knows no node exists; C_k , the radio links it knows are possible; C_e , the radio links it knows are broken; B_k , the squares it knows to be blocked; S_e , squares it knows to be free; and L_k , its own current location.

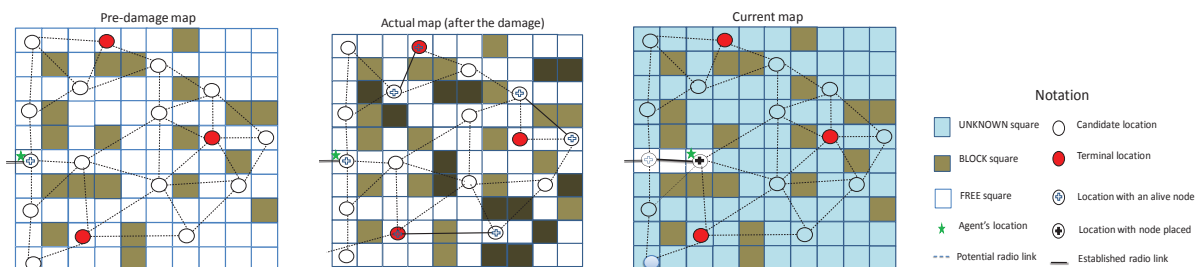


Figure 1: Example network conditions before and after damage.

We assume the agent is able to probe neighbouring squares up to a distance of k , to determine whether or not they are blocked (but cannot probe a distant neighbour if there is a blocked square inbetween). A probe costs α units per square. The agent is able to test a radio link by listening for transmission from an active node. When the agent discovers a new live radio node, it will also be told all of that node's live multi-hop neighbours. There is no cost for listening for transmissions. The agent can detect whether or not there is a sensor node on its current location, and may drop a new node at the centre of that square. The cost of moving one square is m , while the cost of placing a node is w . The objective is to connect as many as possible of the squares in τ to I , placing nodes in those squares if necessary, minimising the sum of the mobility costs and the probe costs, and minimising the number of nodes placed.

3. Approach

We propose two strategies for solving the problem. The first prioritises mobility cost, and prefers cheap paths that would allow the agent to restore connectivity. The second prioritises node cost, and first prefers plans that require few nodes and then finds cheap paths for visiting those locations. For each strategy we consider two approaches: a greedy method, which first picks a terminal to connect, generates a plan, executes it, and then selects the next terminal, and a global method, which generates a plan for reconnecting all terminals before it begins to execute the plan. In all cases, the process is iterative. The first plan is generated based on the pre-damage map. As the agent starts to move through the environment, it discovers information about mobility and connectivity, and updates its knowledge. When the current plan is considered too expensive, a new plan is generated, and the process repeats.

3.1. Strategy 1: Prioritising Mobility Cost

Greedy Mobility (GM): The agent builds a weighted connectivity graph, augmenting each link in C_b with the cost of the cheapest mobility path between the two candidate locations in G_b . The agent first finds the closest terminal using A* search in the grid, i.e. A* uses a best-first search and finds a least-cost path from a start node to a goal node. It then searches the weighted connectivity graph for the cheapest path which connects the terminal to the network, again using A*, and then determines the cheapest route from its current location to either end of this path. The agent then begins to execute the plan, until it discovers a blocked square or blocked radio links, or it discovers live nodes. At that point it updates its knowledge of the environment, and recomputes, possibly finding a new terminal and a new path.

Global Cheapest Path (GCP): using the same weighted connectivity graph as GM, the agent searches for a low-cost Steiner tree using the Steiner-MST heuristic [1] to find a set of nodes which connects all unconnected terminals to the network. Then, at each stage, the agent finds the shortest path to the closest one of these nodes using A*. As before, when the agent discovers new information that would change the cost, it recomputes, and continues from its current location.

Algorithm 1: Greedy Mobility Algorithm

```

1 while there are unconnected terminals do
2   find  $t$ , the closest unconnected terminal;
3   find  $P$ , the shortest plan that connects  $t$ ;
4   change = false;
5   while  $t$  is unconnected and change == false do
6     listen and probe;
7     if change in knowledge then
8       update knowledge;
9       change = true;
10  else
11    execute next step in  $P$ ;
```

Algorithm 2: Global Cheapest Path Algorithm

```

1 while there are unconnected terminals do
2   find  $N$ , the Steiner nodes in weighted connectivity graph;
3   change = false;
4   while there are unvisited nodes in  $N$  and change == false do
5     find  $P$ , the cheapest path to the next nearest node in  $N$ ;
6     while change == false do
7       listen and probe;
8       if change in knowledge then
9         update knowledge;
10        change = true;
11    else
12      execute next step in  $P$ ;
```

3.2. Strategy 2: Prioritising Node Cost

Greedy Node (GN): The agent first builds a directed weighted connectivity graph. Each candidate location will be a vertex, with connected components merged into supernodes. Each potential link will be represented by two directed edges. An edge connecting a live node to a candidate location will have cost 1, while an edge in the other direction has cost 0. The agent then runs Dijkstra's algorithm to find the cheapest path from the current network to each terminal, where the cheapest path will be the one with fewest additional nodes. The agent then selects the terminal which requires the fewest nodes. Then, at each stage, the agent finds a path to the closest one of these nodes using A*. As above, if the agent discovers information that changes the node costs (live nodes found, broken links in the current node plan), it recomputes.

Global Fewest Node (GFN): Using the same directed weighted graph as GN, the agent finds a Steiner node set connecting all terminals using Steiner-MST. Then, at each stage, the agent finds a path to a closest one of these nodes using A*. As before, when the agent discovers new knowledge that would change the node costs, it recomputes.

Algorithm 3: Greedy Node Algorithm

```

1 while there are unconnected terminals do
2   find  $< t, N >$ , the unconnected terminal requires fewest
3   nodes  $N$  in directed weighted connectivity graph;
4   change = false;
5   while there are unvisited nodes in  $N$  and change == false do
6     find  $P$ , the cheapest path to the next nearest node in  $N$ ;
7     while  $t$  is unconnected and change == false do
8       listen and probe;
9       if change in knowledge then
10        update knowledge;
11        if change in node costs then
12          change = true;
13      else
14        execute next step in  $P$ ;

```

Algorithm 4: Global Fewest Node Algorithm

```

1 while there are unconnected terminals do
2   find  $N$ , the Steiner nodes in directed weighted connectivity graph;
3   change = false;
4   while there are unvisited nodes in  $N$  and change == false do
5     find  $P$ , the cheapest path to the next nearest node in  $N$ ;
6     while change == false do
7       listen and probe;
8       if change in knowledge then
9         update knowledge;
10        if change in node costs then
11          change = true;
12    else
13      execute next step in  $P$ ;

```

4. Experiments

The algorithms presented above are heuristic, and take different approaches to a multi-objective problem. Therefore, we evaluate them empirically on randomly generated maps, to compare their runtimes and the quality of their solutions for both objectives. We assume a pre-damage grid map consisting of $n \times m$ squares each of size 10 units. We randomly select c grid squares to be candidate locations, and g squares to be blocked. For each pair of candidate locations separated by less than 25 units we allow a potential radio link with probability 0.85. For the map after damage, we randomly select a of the candidate locations to be live nodes, and select t candidate locations to be terminals 9 (locations for which we require sensor data). We randomly pick b additional squares to be blocked, and remove $r\%$ of the radio links. For this paper, we ensure that the problems are feasible - i.e. it is possible for the agent to visit a set of locations where placing nodes would reconnect all the terminals. In each case, the algorithms only probe a square that the agent intends to move into. In all experiments, the results are the average of 50 runs at each data point.

First, we consider the effect of varying c , the number of candidates from 40 to 80, while we fix the number of terminals, t , to 6 and the damage level to $< b = 10, r = 10\% >$. The results are shown in the top row of Fig.2. The number of candidates has little impact on the number of nodes required. However, the mobility costs rise to peak at $c = 60$: as we increase locations, there are more options to explore, requiring more backtracking on discovering damage, until there are enough locations to offer easy alternatives. The runtimes of all heuristics increase with the number of candidate locations. GM has the highest runtime, because it is repeatedly forced to recompute on failure. We note that the greedy mobility heuristic has lower mobility cost than the global heuristic, and that the greedy node heuristic requires fewer nodes than the global node heuristic. We believe this is the effect of exploration, as the greedy heuristics are better able to adapt their plans once damage is found.

Secondly, we vary the number of terminals, t , from 4 to 12, while fixing c to 60 and the damage to $< 10, 10 >$. The results are shown in the second row of Fig.2. The number of required nodes increases with the number of terminals to a peak, but then declines. We believe this decline is because as more terminals are required, more of the area must be explored, which reveals more existing live nodes and ultimately simplified the connectivity problem. As expected, the mobility costs continue to rise. Again, GM requires the longest runtime.

Thirdly, we vary the damage level from $< 10, 10 >$ to $< 40, 40 >$, fixing the candidate locations at 60 and the number of terminals at 6. Varying the damage has little impact on the number of new nodes required, but the mobility costs rise to a peak and then fall, as there are fewer deep dead ends for the agent to explore.

Finally, we note that the mobility costs are associated only with the distance travelled. For real scenarios, there is a tradeoff between the speed at which connectivity is restored and the cost of the extra nodes. We assume that it takes the agent 30s to position a new node. We then consider two scenarios, one representing a small robot which moves at 0.1ms^{-1} , and the second representing a larger vehicle moving over rough terrain at 4ms^{-1} . We fix the size of the grid square to be $10\text{m} \times 10\text{m}$. The total time to restore the network is thus time to place the new nodes plus the time to move along the path plus the computation time. The results are shown in Fig.3. We can see that for the slow agent, prioritising mobility cost is most important, with the gain in reduced movement from GM more than compensating for the increased runtime; alternatively, for the faster agent, prioritising the number of nodes gives a faster repair, since the time to place the new nodes outweighs the mobility costs. Thus the WSN restoration problem is subtle, with the

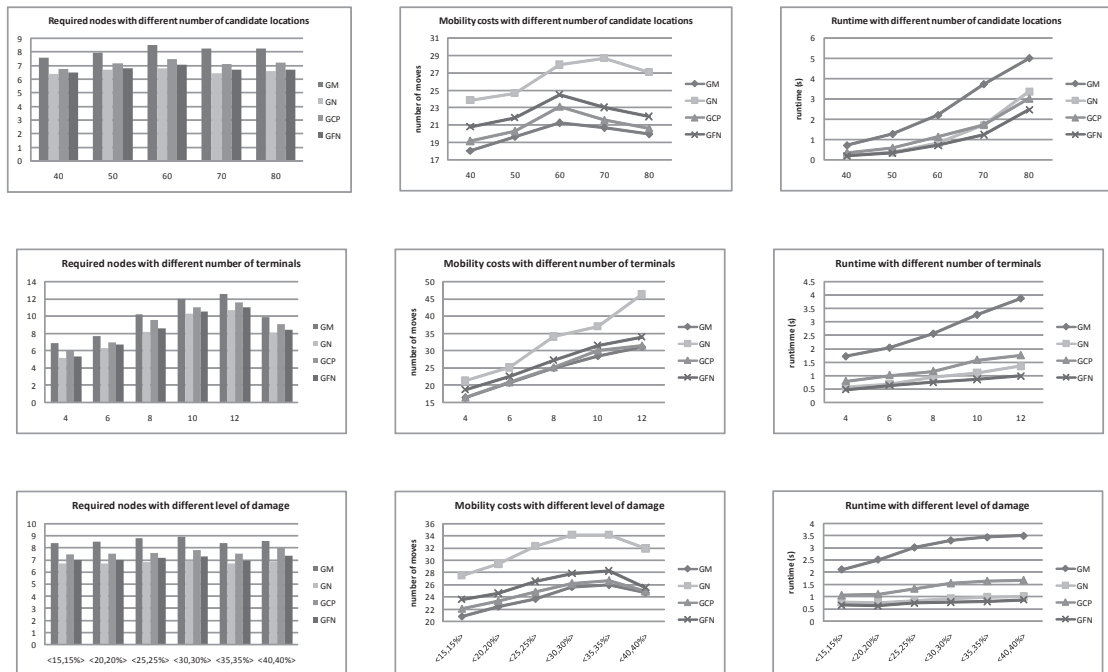


Figure 2: The effect of varying the number of candidate locations, terminals and damage level.

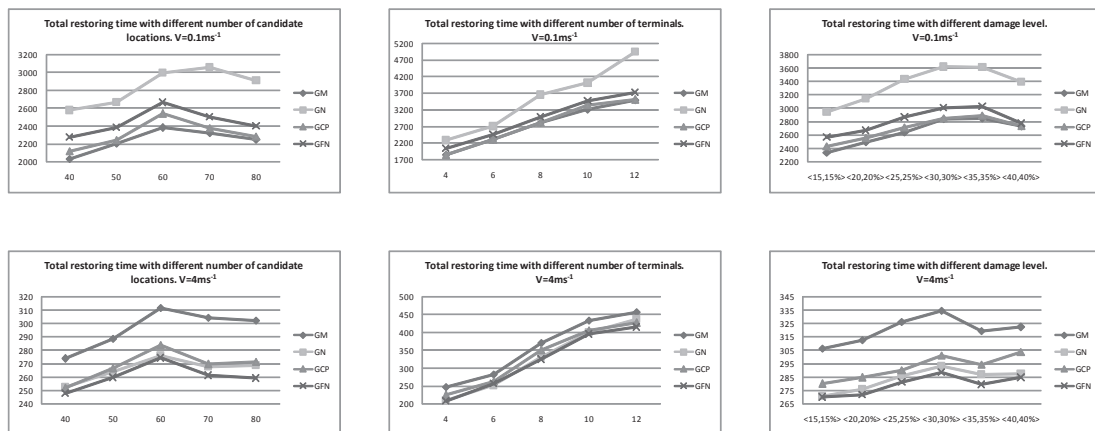


Figure 3: The effect of different agent speeds

choice of approach clearly dependent on the details of the specific problem. Solution methods must take into account the main objectives (minimising infrastructure and minimise time), but also consider the capabilities of the agent that will implement the eventual solution.

5. Related Work

The subject of network restoration for wireless sensor networks has been an active area of research. The different approaches can be classified as (i) deploying redundant nodes so as to be able to cope with a pre-determined number

of failures, (ii) use of mobile (actor) nodes that can be moved into position in order to restore connectivity, (iii) dispatching mobile nodes in a pre-emptive manner to avoid failures in connectivity, and (iv) the deployment of additional nodes to restore connectivity after failures have occurred. The latter work is closest to our research but is different in two respects, firstly in that we optimise both the number of additional nodes as well as the path length needed for their deployment, and secondly in that we explicitly take into account the impact of obstacles that can alter both the available paths and the ability of nodes to communicate directly. We now provide a summary of the related papers.

In [2],[3] the goal is to deploy $k-1$ redundant nodes with the intention of achieving k -connectivity, for example by placing nodes at the intersection between the communication range of each pair of nodes. The number of additional nodes required by these approaches is prohibitive. Several papers consider the use of mobile actor nodes in network restoration, e.g. [4], [5], [6],[7]. The papers propose different strategies to choose the moving actors, for example, based on estimating the shortest moving distance and/or degree of connectivity. The solution space is limited, focused on dealing with a single failure and re-connecting just two networks at a time, and with an assumption that mobility is unimpeded by obstacles. [8] proactively deploys additional helper mobile nodes, controlling their trajectories in response to predicted network disconnection events. The work assumes that the mobile nodes are always fast enough to reach the desired destination in case of a predicted disconnection event, and that a full map of the physical terrain and radio environment is available. Details of how to determine the number of mobile nodes that are needed and the related path planning are not provided. [9] and [10] assume multiple simultaneous failures involving many failed nodes and a network that is partitioned into many segments. The approach is to re-connect those segments in a centralized manner with the main objective of using the smallest number of additional nodes. [9] uses a spider web approach to reconnect the segments while [10] forms a connectivity chain from each segment toward a centre point and then seeks to optimize the number of additional nodes that are needed.

6. Conclusion

We have defined the new problem of simultaneous network repair and autonomous exploration and route planning in the presence of unknown obstacles. We represent the problem as a multi-objective problem of minimising the number of required nodes and mobility costs. We present two strategies, prioritising mobility costs and prioritising the number of nodes, and for each we develop two heuristic approaches, one greedy and one with a global view. In all cases, the agent computes a plan based on some initial knowledge and begins to execute it. As it moves, it discovers more knowledge of the environment, and modifies its plan as required. We evaluate the approaches in simulation, assessing the impact of increasing damage, increasing nodes to be connected, and increasing locations for radio nodes. In addition, we show that different agent speeds have a significant impact on performance, and must be taken into account when selecting the algorithm. In future work we will explore a wider range of environments, consider continually spreading damage, and investigate the use of teams of agents working in parallel.

Acknowledgment

This work is part of the Irish Higher Education Authority PRTLIV funded NEMBES project.

- [1] B. Y. Wu, K.-M. Chao, *Spanning Trees and Optimization Problems*, Chapman & Hall / CRC Press, USA, 2004.
- [2] B. Khelifa, H. Haffaf, M. Merabti, D. Llewellyn-Jones, Monitoring connectivity in wireless sensor networks., in: ISCC, IEEE, 2009.
- [3] H. M. Almasaeid, A. E. Kamal, On the minimum k -connectivity repair in wireless sensor networks., in: ICC, IEEE, 2009, pp. 1–5.
- [4] K. Akkaya, F. Senel, Detecting and connecting disjoint sub-networks in wireless sensor and actor networks, *Ad Hoc Netw.* 7.
- [5] A. Abbasi, M. Younis, U. Baroudi, Restoring connectivity in wireless sensor-actor networks with minimal topology changes, in: *Communications (ICC)*, 2010 IEEE International Conference on, 2010, pp. 1–5.
- [6] K. Akkaya, F. Senel, A. Thimmapuram, S. Uludag, Distributed recovery from network partitioning in movable sensor/actor networks via controlled mobility, *IEEE Trans. Comput.* 59 (2010) 258–271.
- [7] M. Sir, I. Senturk, E. Sisikoglu, K. Akkaya, An optimization-based approach for connecting partitioned mobile sensor/actuator networks, in: *Computer Communications Workshops (INFOCOM WKSHPS)*, 2011 IEEE Conference on, 2011, pp. 525–530.
- [8] L. Dai, V. Chan, Helper node trajectory control for connection assurance in proactive mobile wireless networks, in: *Computer Communications and Networks*, 2007. ICCCN 2007. Proceedings of 16th International Conference on, 2007, pp. 882–887.
- [9] F. Senel, M. Younis, K. Akkaya, A robust relay node placement heuristic for structurally damaged wireless sensor networks, in: *Local Computer Networks*, 2009. LCN 2009. IEEE 34th Conference on, 2009, pp. 633–640.
- [10] S. Lee, M. Younis, Recovery from multiple simultaneous failures in wireless sensor networks using minimum steiner tree, *Journal of Parallel Distributed Computing* 70 (2010) 525–536.