Decomposing Coverings and the Planar Sensor Cover Problem

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August 17, 2009

Abstract

We show that a k-fold covering using translates of an arbitrary convex polygon can be decomposed into Omega(k) covers (using an efficient algorithm). We generalize this result to obtain a constant factor approximation to the sensor cover problem where the ranges of the sensors are translates of a given convex polygon. The crucial ingredient in this generalization is a constant factor approximation algorithm for a one-dimensional version of the sensor cover problem, called the Restricted Strip Cover (RSC) problem, where sensors are intervals of possibly different lengths. Our algorithm for RSC improves on the previous O(log log log n) approximation.

1 Introduction

Let us call an object (set) P in the plane *cover-decomposable* if there there exists a constant c > 0 (which may depend on P) such that any collection of translates of P, with the property that every point in the plane has c or more translates covering it, can be partitioned into two covers. Pach conjectured in the 1980s that every convex object is cover decomposable [8, 9], and this remains open. Let us focus on a finite version of this definition and say that P is cover-decomposable if there exists a constant c > 0 such that any finite collection of translates of P can be partitioned into two sub-collections, so that each sub-collection covers every point in the plane covered by c or more translates in the original collection.

In the 1980's, Mani and Pach [7] showed that a unit disk is cover-decomposable (with the constant c being 33.) Also in the 1980's, Pach [8] showed that any centrally symmetric convex polygon is cover-decomposable. Tardos and Tóth [14] showed somewhat more recently that any triangle is cover-decomposable. Finally, a very recent result due to Pálvölgyi and Tóth [11] shows that any convex polygon is cover-decomposable. The constant c in the results of [8] and [11] depends on the convex polygon, in particular the number of its sides, and that is why these results say nothing about the original conjecture of Pach. Examples of non-convex polygons that are not cover-decomposable are known [10].

Motivated partly by questions in scheduling sensors [3], an extension of the cover-decomposability question has recently attracted a lot of attention: Given a collection of translates of P and any integer k, partition the collection into as many sub-collections as possible so that each sub-collection covers every point covered by k or more of the original translates. That is, we would like to be able to decompose a k-fold cover into as many disjoint covers as possible. While the original results on cover-decomposability do yield non-trivial bounds for this question, these are usually far from optimal. For instance, Tardos and Tóth [14] implies that a k-fold cover with translates of a triangle can be partitioned into $\Omega(\log k)$ covers. In this line of work, Pach and Tóth [9] showed that a k-fold cover with a centrally symmetric convex polygon P can be decomposed into $\Omega(\sqrt{k})$ covers, where the constant as before depends on P. Aloupis et al. [1] improved this result and obtained an optimal bound, showing that one can obtain $\Omega(k)$ covers. Both of these results have corresponding efficient algorithms that compute the desired decompositions. Aloupis et al. [2] consider other related problems.

The problem of decomposing multiple coverings seems to be harder if instead of a convex polygon we have a unit disk. Pandit, Pemmaraju and Varadarajan [12] consider a special case where the universe that needs to be covered is the same as the centers of the covering disks. For this version of the problem, better known as the domatic partition problem for *unit disk graphs* [13], they show that it is possible to compute $\Omega(k)$ disjoint covers in polynomial time.

1.1 Sensor Cover

The work on decomposing multiple coverings is related to a problem motivated by scheduling sensors. Suppose we have a universe, which is simply some collection of points, and a set of sensors such that each sensor covers some subset of the universe. Further suppose that each sensor is powered by a battery and thus can only be turned on for some amount of time. We refer to this amount of time as the sensor's *duration*. We are interested in scheduling a start time to each of the sensors such that the entire universe is covered for as long as possible. This problem was introduced by Buchsbaum et al. [3] as the *sensor cover problem*. We only consider the non-preemptive case in which once a sensor has been turned on, it will remain on until its duration has been depleted.

We now formally define the combinatorial sensor cover problem, followed by the geometric instances that are the subject of this paper. We are given a finite universe U that we wish to cover, and a set **S** of n sensors. For each sensor $s \in \mathbf{S}$, we let $R(s) \subseteq U$ denote the region that s covers. We call this region the *range* of s. For each $x \in R(s)$, we say that s is *live* at x. Each sensor s also has a duration d(s) which is some positive integer.

A schedule of the set **S** of sensors is an assignment of a positive integer, called the start time, to each sensor in some subset $\mathbf{S}' \subseteq \mathbf{S}$. We will denote by t(s) the start time of sensor s. The sensors in $\mathbf{S} \setminus \mathbf{S}'$ are said to be unassigned. A sensor s that is assigned a start time t(s) is said to be *active* at times $\{t(s), t(s) + 1, ..., t(s) + d(s) - 1\}$.

Let S be some schedule of **S**. A point $x \in U$ is said to be covered at time t > 0 if there is a sensor s such that $x \in R(s)$ and s is active at time t. For each $x \in U$, define the duration of x in the schedule to be $M(S,x) = max\{j : \forall j' \leq j, \exists s \in S, s \text{ covers } x \text{ at time } j'\}$. (If no sensor covers x at time 1, then define M(S,x) = 0.) The duration of the schedule S is defined to be $M(S) = \min_x M(S,x)$. The goal of the problem is to compute a schedule of maximum duration.

The load at a point $x \in U$ is $L(x) = \sum_{s \in \mathbf{S}: x \in R(s)} d(s)$. The load of the problem instance is $L = \min_x L(x)$. Let *OPT* denote the duration of an optimal schedule. Clearly, $OPT \leq L$, and thus any approximation ratio that is with respect to L is also with respect to *OPT*.

A closely related problem to the sensor cover problem is the *domatic partition problem*. In this problem, we are given a graph with the goal of finding the maximum number of disjoint dominating sets. A *dominating set* is a subset of the vertices such that for each vertex in the graph, either it is in the set or it has a neighbor in the set. Domatic partition can be viewed as a special case of the sensor cover problem where the universe is the vertex set, each vertex of the graph is a sensor, the range of each sensor is its corresponding vertex's closed neighborhood, and each sensor has unit duration. Feige et al. [5] show that it is NP-hard to approximate this problem to within

a log *n*-factor and give a simple randomized algorithm that achieves an $O(\log n)$ -approximation, where *n* is the number of vertices in the graph.

As pointed by Buchsbaum et al. [3], the lower bound above given by Feige et al. implies that general sensor cover cannot be approximated to better than a $\log n$ factor. On the positive side, Buchsbaum et al. [3] present a poly-time algorithm for the sensor cover problem that returns an $O(\log U)$ approximation. This algorithm extends an algorithm for the set cover packing problem [5], which is the special case of the sensor cover problem with the duration of all sensors being 1. In many applications, the sensors do not cover arbitrary subsets of the universe, but rather the points in the universe lie in some geometric space and the sensors cover some geometric subset of the universe. In such cases, we will see that it is possible to do better than the $\log n$ lower bound for general sensor cover.

Restricted Strip Cover (RSC) Here, the universe U is a set of points on the real line, and the range R(s) of each sensor s is an interval on the real line. The RSC was introduced and studied by Buchsbaum et al. [3], who showed that it is NP-hard and give a polynomial-time $O(\log \log \log n)$ -approximation algorithm, where n is the number of sensors. They show that their algorithm does better for special cases of RSC. In particular, they show that their algorithm is a $(2 + \epsilon)$ -approximation for any $\epsilon > 0$ when the sensors are non-nested; this includes the case where the ranges of all the sensors have the same size. They also give an example instance whose load is 4 but the duration of the optimal schedule is 3.

The RSC bears some resemblance to the well studied dynamic storage allocation [6, 4]. The RSC problem can be viewed in the following way. We are given a set of rectangles, and we are allowed to slide each rectangle vertically; the goal is to find a placement of the rectangles so that we cover a horizontal strip that is as tall as possible. In the dynamic storage allocation problem, we are also given a set of rectangles, each of which we are allowed to slide vertically; the goal is to find a placement of the rectangles such that no two of them overlap and the rectangles are contained in a horizontal strip that is as short as possible. The dynamic storage allocation problem admits constant factor approximation algorithms [6, 4], and these are with respect to the load, where now the load is the maximum of the pointwise loads. We refer the reader to [3] for a review of the similarities of the RSC to other problems studied in the literature.

Planar Sensor Cover for Polygon Translates Here, the universe U is a set of points in \Re^2 , and the range R(s) of each sensor is a translate of a fixed convex polygon. In the remainder of this paper, we will refer to this problem as simply the planar sensor cover problem. The results on decomposing multiple coverings have a clear implication for the special case of the planar sensor cover problem where all sensors have unit durations. For instance, the result of Aloupis [1] gives a constant factor approximation for centrally symmetric polygons, since it decomposes an *L*-fold cover into $\Omega(L)$ covers, thus yielding a schedule of duration $\Omega(L)$.

For the planar sensor cover problem with the durations of the sensors not being the same, the best known result is the logarithmic approximation inherited from the combinatorial sensor cover problem.

1.2 Our Contributions

Decomposing Multiple Coverings We obtain an optimal result for translates of an arbitrary convex polygon:

Theorem 1. For any convex polygon P in the plane, there exists a constant $\alpha \geq 1$ so that for any $k \geq 1$ and any finite collection of translates of P, we can partition the collection into k/α sub-collections, each of which covers any point in the plane that is covered by k or more translates in the original collection. Such a partition can be computed by an efficient algorithm.

Our techniques build upon the recent work of Aloupis et al. [1] for centrally symmetric convex polygons. (A polygon is centrally symmetric with respect to the origin if whenever it contains point p it also contains -p.) A key idea of theirs is to focus on the level curves corresponding to the wedges at the vertices of P. The interaction of these level curves can be complex, but they show that is sufficient to work within a region where the interaction is much more controlled. It is only for centrally symmetric convex polygons that they establish such nice properties of the interaction. The notion of level curves is also central to our work, but the main point of departure is the simplicity of the new way in which we handle the level curve interactions.

Restricted Strip Cover We improve upon the $O(\log \log \log n)$ approximation of [3] and give the first constant factor approximation (a ratio of 5) for RSC. The work of [3] starts off with the observation that if all the sensors have unit duration then it is possible to compute a schedule whose duration is equal to the load of the instance. The case of non-uniform duration is handled by reduction to several instances of the uniform duration case. The tool used for this is a technique called *grouping* where several sensors of small duration are combined to form one sensor of large duration. The question of how the groups are to be formed is addressed in a clever way, but the reduction entails a non-constant loss in the load and hence the $O(\log \log \log n)$ approximation factor.

We take a different and conceptually simpler approach here. Our algorithm is greedy and schedules sensors one by one. The scheduling rule manages to ensure that we do not have more than 5 sensors overlapping any particular point at one time. Hence we obtain a schedule whose duration is at least a fifth of the load. One idea that the scheduling rule uses is that if there are two sensors s and s' such that R(s) is strictly contained in R(s'), we schedule s' before we schedule s. Another idea is to consider the duration of the sensors in an indirect way – for the next sensor to be scheduled, the durations of the unscheduled sensors is irrelevant but only their ranges; however the durations of the already scheduled sensors does play a crucial rule. Since our algorithm is greedy it has a simple implementation with a reasonable running time. We have not attempted to optimize the factor of 5 that our analysis guarantees.

Planar Sensor Cover We give a constant factor approximation for the planar sensor cover problem, where the range of each sensor is a translate of a convex polygon, improving upon the previous best logarithmic factor. Essentially, we show that we can obtain a constant factor approximation by invoking several instances of the RSC, one for each vertex of the convex polygon, which we solve using our 5-approximation. Our greedy algorithm for RSC turns out to be exactly what is needed to generalize the result of Theorem 1 to the case of non-uniform durations.

Organization of the Paper In Section 2, we recall crucial tools from previous work on the problem of decomposing multiple coverings. In Section 3, we prove Theorem 1. In Section 4, we present our constant factor approximation for RSC and obtain as a consequence the results on planar sensor cover.

2 Decomposing Coverings: Preliminaries

It is convenient to prove Theorem 1 in its dual form as done in [14, 1]. Suppose we are given a polygon P. Fix O, the centroid of P, as the origin in the plane. For a planar set T and a point x in the plane, let T(x) denote the translate of T with centroid x. Let \overline{P} be the reflection through O of the polygon P. For points p and x in the plane, $p \in P(x)$ if and only if $x \in \overline{P}(p)$.

Because of this transformation, it is sufficient for us to show that there exists a constant $\alpha \geq 1$ so that for any $k \geq 1$ and any collection Q of points in the plane, it is possible to assign each point in Q a color from $\{1, 2, \ldots, \frac{k}{\alpha}\}$, so that any translate of \overline{P} with $|\overline{P} \cap Q| \geq k$ contains a point colored i, for each $1 \leq i \leq \frac{k}{\alpha}$.

Polygons to Wedges Denote the vertices of \overline{P} to be $p_0, p_1, p_2, \ldots, p_{\mu-1}$ in counterclockwise order. Addition and subtraction of indices of these vertices will be taken modulo μ throughout the paper. The set of indices between index i and index j in counterclockwise order are denoted [i, j]. We now transform the problem further, so that instead of dealing with translates of \overline{P} , we can deal with translates of the μ wedges corresponding to the vertices of \overline{P} [9, 14, 1].

Let c be equal to half the minimum distance between two points on non-consecutive edges of \overline{P} . We lay a square grid of side c on the plane; any translate of \overline{P} intersects $\beta \in O(1)$ grid cells, and each grid cell intersects at most two sides of a translate; moreover, if a grid cell does intersect two sides of a translate, then these sides must be adjacent in \overline{P} .

For a subset (region) R of the plane and for a subset X of points, denote $\text{load}_X(R)$ to be the number of points in X that lie in R. We call this value the load of region R with respect to X. Since each translate $\bar{P}(u)$ intersects at most β grid cells, $\bar{P}(u)$ must contain load at least k/β within some grid cell if its load with respect to Q is at least k. We can therefore make the points of Qwithin such a grid cell "responsible" for $\bar{P}(u)$.

Since each grid cell intersects at most two edges of $\overline{P}(u)$, it must be that the intersection of a grid cell with $\overline{P}(u)$ is the same as the intersection of the grid cell with a wedge whose boundaries are parallel to two adjacent edges of $\overline{P}(u)$. If one boundary of the wedge is parallel to the edge $p_{i-1}p_i$ of \overline{P} and the other is parallel with p_ip_{i+1} of \overline{P} , then we call the wedge an *i*-wedge. For a point q in the plane, we denote $W_i(q)$ to be the *i*-wedge with apex q. See Figure 1 for an illustration.



Figure 1: (a) Suppose this triangle is our polygon with vertices indexed accordingly. (b) A 0-wedge, 1-wedge, and 2-wedge with respect to the polygon.

Because of these observations, Theorem 1 is established by applying the following theorem to the points Y within each grid cell G.



Figure 2: An example of a level curve $C_i(r)$ for r = 2. Note that any *i*-wedge with apex on $C_i(2)$ (e.g. the dotted wedge) contains load at least 2.

Theorem 2. There exists a constant $\alpha' \ge 1$ so that for any $k \ge 1$ and any collection Y of points in the plane, it is possible to assign each point in Y a color from $\{1, 2, \ldots, \frac{k}{\alpha'}\}$, so that any i-wedge that contains k or more points from Y contains a point colored j, for each $1 \le j \le \frac{k}{\alpha}$.

We prove Theorem 2 in Section 3. We assume that the point set Y is in general position – a line parallel to a side of \overline{P} contains at most one point in Y. It is straightforward to perturb the input to the original problem so that this assumption holds for Y.

Level Curves We will now define a boundary for an $i \in \{0, 1, \ldots, \mu - 1\}$ and positive integer r. This boundary has the property that any *i*-wedge placed on or "inside" the boundary has load at least r, and any *i*-wedge placed "outside" the boundary has load less than r. That is, the number of points in $W_i(x) \cap Y$ for any x inside the boundary or on the boundary is at least r and is less than r for any x outside the boundary. This boundary is called a *level curve* [1] and extends the definition of *boundary points* [8, 9]. Let \mathcal{W}_i^j be the set of apices of all *i*-wedges W such that $\operatorname{load}_Y(W) = j$. For each $i = 0, 1, \ldots, \mu - 1$, let the level curve $C_i(r)$ be the boundary of the region $\mathcal{W}_i^{\geq r} = \bigcup_{j\geq r} \mathcal{W}_i^j$ for each $i = 0, 1, \ldots, \mu - 1$.

Note that $C_i(r)$ is a monotone staircase polygonal path with edges that are parallel to the edges of an *i*-wedge. See Figure 2. We have the following observations:

Observation 3. For any $x \in C_i(r)$, $r \leq load_Y(W_i(x)) \leq r+1$.

Observation 4. Any *i*-wedge W such that $load_Y(W) \ge r$ contains an *i*-wedge whose apex belongs to $C_i(r)$.

Observe that one of the two extreme edges of the level curve $C_i(r)$ is a semi-infinite ray parallel to edge $p_{i-1}p_i$. Let h_i denote the first point along this ray such that for all points y on the ray that lie after h_i , $W_i(y) \cap Y = W_i(h_i) \cap Y$. We call h_i the *head* of $C_i(r)$. (Because of non-degeneracy, the head is simply the origin of the ray.) The other extreme edge of $C_i(r)$ is parallel to edge $p_i p_{i+1}$. Let τ_i denote the first point along this ray such that for all points y on the ray that lie after τ_i , $W_i(y) \cap Y = W_i(\tau_i) \cap Y$. We call τ_i the *tail* of $C_i(r)$. See Figure 3.

2.1 Simple Algorithm for One Level Curve

Observation 4 implies that is sufficient to prove Theorem 2 for the *i*-wedges with apex on $C_i(k)$, for each $0 \le i \le \mu - 1$. In order to do this, we will need a procedure that takes as input one level curve $C_i(k)$, a positive integer *t*, and a subset $Q \subseteq Y$. The input to the procedure has the guarantee



Figure 3: Level curve $C_i(r)$ with h_i and τ_i denoted.



Figure 4: An example of an interval I(y) (in bold). Note that the *i*-wedges with apex on $C_i(k)$ that contain y are the dotted wedges and all wedges with apex "in between" the apices of the dotted wedges.

that for any *i*-wedge W with apex on $C_i(k)$, we have $|W \cap Q| \ge 2t$. The goal is to output a partial coloring of the points of Q with colors $\{1, 2, \ldots, t\}$ so that any *i*-wedge W with apex on $C_i(k)$ (a) contains a point colored j, for $1 \le j \le t$, and (b) contains at most 2t colored points.

It is known [1] that such a procedure exists. The reason is that for any $q \in Q$, the set $I(q) = \{u \in C_i(k) | q \in W_i(u)\}$ of apexes of *i*-wedges containing q is an "interval" of $C_i(k)$. See Figure 4 for an illustration. We consider these intervals in an order such that if interval I properly contains interval I', then we consider I before I'. Considering intervals in such an order, we add an interval into our working set if it covers a point of $C_i(k)$ that is not covered by previous intervals in the working set. Notice that after all intervals have been considered, the working set forms a cover of $C_i(k)$. Now, we repeatedly throw out intervals from the working set that are redundant – an interval is redundant if throwing it out of the current working set does not affect coverage of $C_i(k)$.

The final non-redundant working set covers $C_i(k)$, but also has no more than two intervals covering any point of $C_i(k)$. We give the color 1 to the points in Q that give rise to the intervals in our working set. We repeat this process t - 1 more times. It is easy to verify that the overall procedure, which we call computeCover(i, Q, t), successfully achieves properties (a) and (b). We have the following observation whose second claim easily follows from the manner in which we pick our non-redundant working set.

Observation 5. The partial cover computed by compute Cover(i, Q, t) has the property that any *i*-wedge with apex on $C_i(k)$ has at most 2t colored points. Furthermore, if q and q' are points in Q such that $q \in W_i(q')$ (that is, I(q) properly contains I(q')), then q' is colored only if q is colored.



Figure 5: An example of a set A_i . In this example, $A_0 = \{2\}$ since only the side of \overline{P} parallel with p_2p_3 has the qualifying property.

3 Decomposing Covers: Algorithm

To prove Theorem 2, we present an algorithm that produces the desired coloring. This is Algorithm 1, but we need to define a notion before it is fully specified.

Consider the natural linear ordering of the lines parallel to side $p_i p_{i+1}$ of \overline{P} with the line through vertices p_i and p_{i+1} being smaller than the line through any of the other vertices of \overline{P} . For $x, y \in \Re^2$, we define the partial order $\langle i \rangle$ such that $x \langle i \rangle y$ if the $p_i p_{i+1}$ parallel line through x is less than the $p_i p_{i+1}$ parallel line through y.

For a vertex p_i , let A_i denote the set of all indices j such that the intersection of \overline{P} with the line parallel to $p_j p_{j+1}$ and through p_i is only the point p_i . See Figure 5 for an example.

Algorithm 1

1: $Y' \leftarrow Y$ 2: for each $i \in \{0, 1, 2, \dots, \mu - 1\}$ do $L \leftarrow \min\{\operatorname{load}_{Y'}(W_z(x)) : x \in \mathcal{C}_z(k) \text{ and } z = i, i+1, \dots, \mu-1\}$ 3: for each $c \in C_i(k)$ do 4: for each $j \in A_i$ do 5:Let $X^{j}(c)$ be the first $\frac{L}{2\mu}$ points in $W_{i}(c) \cap Y'$ in decreasing order with respect to the 6: ordering $<_j$. $X(c) \leftarrow \{W_i(c) \cap Y'\} \setminus \bigcup_{i \in A_i} X^j(c)$ 7: $X_i \leftarrow \bigcup_{c \in \mathcal{C}_i(k)} X(c)$ 8: Run computeCover $(i, X_i, \frac{L}{64\mu})$. 9:

10: Let Y' denote the unscheduled points.

Algorithm 1 calls computeCover (i, X_i, t_i) for each $0 \le i \le \mu - 1$. The set X_i in the *i*-th iteration is an appropriately chosen subset of the points in Y not colored in iterations $0, 1, \ldots, i - 1$. At the beginning of the *i*-th iteration, let L denote, as in the algorithm, the smallest number of uncolored points in a *j*-wedge with apex on $C_j(k)$, for $i \le j \le \mu - 1$. The parameter t_i is chosen to be $\frac{L}{64\mu}$, and we have $\min_{c \in C_i(k)} |W_i(c) \cap X_i| \ge \frac{L}{2}$ (due to the manner in which X_i is chosen in the algorithm, see Observation 8 below). After the call to computeCover $(i, X_i, \frac{L}{64\mu})$, any *i*-wedge with apex on $C_i(k)$ contains points colored $1, 2, \ldots, L/64\mu$. Thus, the algorithm produces a coloring as required in Theorem 2, provided $L \in \Omega(k)$. This is established by the following key Lemma. It states that L, which equals k before the 0-th iteration, drops by a factor of at most 5μ with each iteration.

Lemma 6. Suppose at the beginning of iteration *i*, all *j*-wedges with apex on $C_j(k)$ have load at least *L* from points in *Y'* for $j \ge i$, where *L* is larger than some absolute constant. (Note that *Y'* always denotes the uncolored points in the algorithm.) After the *i*-th iteration of the algorithm, any *j*-wedge $W_j(x)$, for j > i, and with apex *x* on $C_j(k)$ has load at least $\frac{L}{5\mu}$ from points in *Y'*.

Proof. There are two main cases to consider:

- p_i and p_j are antipodal vertices of \overline{P} that is, there are parallel lines through p_i and p_j with the convex polygon sandwiched between them.
- p_i and p_j are not antipodal vertices of P.

We use the following terminology for iteration i: for two distinct points q and q', if $W_i(q) \subseteq W_i(q')$, we say that q dominates q'. Notice that if q and q' are both unscheduled before iteration i, then q' is scheduled in iteration i only if q is already scheduled. (This is Observation 5.) For the rest of this proof, let Y' denote the points that are not scheduled just before iteration i, let X_i denote set of candidate points that are eligible to be scheduled in iteration i (as constructed in the algorithm), and let Y_i denote the points that are actually scheduled in iteration i.

The analysis will rely heavily upon the following two observations.

Observation 7. For any $z \in C_i(k)$, we have that $load_{Y_i}(W_i(z)) \leq \frac{L}{32\mu}$.

Observation 8. For any $z \in C_i(k)$, $load_{X_i}(W_i(z)) \geq \frac{L}{2}$.

Observation 7 is a consequence of Observation 5. To see Observation 8, note that for each $c \in C_i(k)$, $\operatorname{load}_{X_i}(W_i(c)) \ge \operatorname{load}_{X(c)}(W_i(c)) \ge L - \mu \cdot \frac{L}{2\mu} = \frac{L}{2}$. **Case 1:** p_i and p_j are not antipodal vertices of P.

Let $W_j(x)$ be as in the statement of the Lemma. The argument is trivial if $W_j(x) \cap C_i(k) = \emptyset$. So let us assume that $W_j(x) \cap C_i(k) \neq \emptyset$. There are two cases – in the first, we encounter p_j after p_i and before the vertices antipodal to p_i when walking counter-clockwise around \overline{P} , and in the second, we encounter p_j after the vertices antipodal to p_i and before p_i . We will focus on the first case, since the other is symmetric. Let z be the intersection point of the boundary of $W_j(x)$ and $C_i(k)$. If $W_j(x)$ does not contain in its interior the tail τ_i of the level curve $C_i(k)$, then $W_j(x) \cap Y_i \subseteq W_i(z) \cap Y_i$, and so $\operatorname{load}_{Y_i}(W_j(x)) \leq \operatorname{load}_{Y_i}(W_i(z)) \leq \frac{L}{32\mu}$. It follows that the load of unscheduled points in $W_j(x)$ after iteration i is at least

$$L - \frac{L}{32\mu} > \frac{L}{5\mu}.$$

Let us therefore assume that $W_j(x)$ does contain in its interior the tail τ_i of $C_i(k)$. See Figure 6. Let *a* denote the point where the boundaries of the wedges $W_i(z)$ and $W_i(\tau_i)$ intersect. If $\log d_{X_i}(W_i(a)) \geq \frac{L}{16\mu}$, then since $\log d_{Y_i}(W_i(a)) \leq \log d_{Y_i}(W_i(\tau_i)) \leq \frac{L}{32\mu}$, there are unscheduled points in $W_i(a)$ after iteration *i*. Since any point in $W_i(a)$ dominates points in $W_j(x) \cap Y_i$ that are not contained in $W_i(z) \cup W_i(\tau_i)$, we conclude that $W_j(x) \cap Y_i \subseteq (W_i(z) \cup W_i(\tau_i)) \cap Y_i$. Thus,

$$\operatorname{load}_{Y_i}(W_j(x)) \le \operatorname{load}_{Y_i}(W_i(z)) + \operatorname{load}_{Y_i}(W_i(\tau_i)) \le \frac{L}{16\mu}$$

Therefore there must be at least $L - \frac{L}{16\mu} > \frac{L}{5\mu}$ unscheduled points left in $W_j(x)$.

Let us therefore consider the case where $\operatorname{load}_{X_i}(W_i(a)) < \frac{L}{16\mu}$. This means that $\operatorname{load}_{X_i}(W_i(\tau_i) \setminus W_i(a)) > \frac{L}{2} - \frac{L}{16\mu} > \frac{L}{3}$. Again, $\operatorname{load}_{Y_i}(W_i(\tau_i) \setminus W_i(a)) \leq \operatorname{load}_{Y_i}(W_i(\tau_i)) \leq \frac{L}{32\mu}$, and this means the load of the points in $W_i(\tau_i) \setminus W_i(a)$ that are unscheduled after iteration *i* is at least $\frac{L}{3} - \frac{L}{32\mu} > \frac{L}{5\mu}$. But $W_i(\tau_i) \setminus W_i(a) \subseteq W_j(x)$, and this means that the load of the unscheduled points in $W_j(x)$ after iteration *i* is at least $\frac{L}{5\mu}$.



Figure 6: Illustration for the nonantipodal case.

Case 2: p_i and p_j are antipodal vertices of P.

Again, the argument is trivial if $W_j(x) \cap C_i(k) = \emptyset$. So let us assume that $W_j(x) \cap C_i(k) \neq \emptyset$. Since $\operatorname{load}_{Y'}(W_j(x)) \geq L$, if $\operatorname{load}_{X_i}(W_j(x)) \leq \frac{L}{2}$ then $W_j(x)$ will clearly have load at least $\frac{L}{5\mu}$ after iteration *i*. So assume that $\operatorname{load}_{X_i}(W_j(x)) > \frac{L}{2}$.

Consider the line parallel with $p_{i-1}p_i$ through x and the line parallel with p_ip_{i+1} through x. Note these lines are parallel with the boundaries of an *i*-wedge. Let $H_t(x)$ denote the halfplane consisting of all points y such that $y \leq_t x$. Let $W_j^1(x) = H_{i-1}(x) \cap H_i(x) \cap W_j(x)$. Let $W_j^2(x) = (H_i(x) \cap W_j(x)) \setminus W_j^1(x)$. Let $W_j^1(x)$. Let $W_j^2(x) = (H_{i-1}(x) \cap W_j(x)) \setminus W_j^1(x)$. See Figure 7 and Figure 8 for an illustration. Note that $W_j^1(x), W_j^2(x)$, and $W_j^3(x)$ form a partition of $W_j(x)$. Also note that $W_j^1(x)$ cannot be empty but $W_j^2(x)$ or $W_j^3(x)$ could be empty. Since these three sets form a partition of $W_j(x)$ and $\operatorname{load}_{X_i}(W_j(x)) > \frac{L}{2}$, it must be that one of the three sets has load at least $\frac{L}{6}$ from X_i . We first handle the case when $\operatorname{load}_{X_i}(W_j^1(x)) \geq \frac{L}{6}$ has a symmetric proof with the $W_j^2(x)$ case.



Figure 7: If we are working with the corresponding *i*-wedge and *j*-wedge (part (a)), then we obtain the corresponding $W_j^1(x)$, $W_j^2(x)$, and $W_j^3(x)$ (part (b)).



Figure 8: If we are working with the corresponding *i*-wedge and *j*-wedge (part (a)), then $W_j^1(x) = W_j(x)$ and $W_j^2(x) = W_j^3(x) = \emptyset$ (part (b)).

Case 2(a): $\operatorname{load}_{X_i}(W_j^1(x)) \ge \frac{L}{6}$.

Consider any point $z \in W_j^1(x) \cap \mathcal{C}_i(k)$. Let a_z denote the "leftmost" point where the boundaries of $W_i^1(x)$ and $W_i(z)$ intersect, and let b_z denote the "rightmost" point where the boundaries of



Figure 9: Illustration for Case 2(a): the region R_z . Note that although this figure is drawn with respect to a scenario as in Figure 7, the analysis still holds for the scenario as in Figure 8 (i.e. when the boundaries of an *i*-wedge are not parallel with the boundaries of $W_i^1(x)$).



Figure 10: Illustration for Case 2(a): the constructed point z'.

 $W_j^1(x)$ and $W_i(z)$ intersect. Let R_z be the quadrilateral with vertices a_z, x, b_z , and z. That is, $R_z = W_j^1(x) \cap W_i(z)$. Suppose that $\operatorname{load}_{X_i}(R_z) \geq \frac{L}{5\mu} + \frac{L}{32\mu}$. Again, since $\operatorname{load}_{Y_i}(W_i(z)) \leq \frac{L}{32\mu}$, and all points in R_z are in $W_i(z)$, R_z contains (unscheduled) load at least $\frac{L}{5\mu}$ after iteration i. Since $R_z \subseteq W_j^1(x), W_j^1(x)$ contains (unscheduled) load at least $\frac{L}{5\mu}$ after iteration i, and we are done. See Figure 9 for an illustration.

So we now assume that $\operatorname{load}_{X_i}(R_z) \leq \frac{L}{5\mu} + \frac{L}{32\mu}$ for each $z \in W_j^1(x) \cap \mathcal{C}_i(k)$. Since $\operatorname{load}_{X_i}(W_i(z)) \geq \frac{L}{2}$, we must have $\operatorname{load}_{X_i}(W_i(a_z) \cup W_i(b_z)) \geq \frac{L}{2} - (\frac{L}{5\mu} + \frac{L}{32\mu}) > \frac{L}{8}$. Let z_1 be the "leftmost" point on $\mathcal{C}_i(k) \cap W_j^1(x)$, and let z_2 be the "rightmost" point on $\mathcal{C}_i(k) \cap W_j^1(x)$. Notice that a_{z_1} is just z_1 itself, and so $\operatorname{load}_{X_i}(W_i(a_{z_1})) \geq \frac{L}{2}$. Similarly, $\operatorname{load}_{X_i}(W_i(b_{z_2})) \geq \frac{L}{2}$. Let z' be the last point on $\mathcal{C}_i(k)$, while walking from z_1 to z_2 , such that $\operatorname{load}_{X_i}(W_i(a_{z'})) \geq \frac{L}{16}$. Thus

$$\operatorname{load}_{X_i}(W_i(b_{z'})) \ge \operatorname{load}_{X_i}(W_i(a_{z'}) \cup W_i(b_{z'})) - \frac{L}{16} \ge \frac{L}{16}.$$

See Figure 10 for an illustration.

Now consider any point $z'' \in W_j^1(x) \setminus W_i(z')$. It must be that $W_i(z'')$ either contains $W_i(a_{z'})$ or contains $W_i(b_{z'})$ which both have load in X_i of at least $\frac{L}{16}$. Suppose that $W_i(z'')$ contains $W_i(a_{z'})$; the other case is similar. The points in $W_i(a_{z'})$ dominate z'' and we will not schedule z'' in iteration i until we have scheduled all points in $W_i(a_{z'}) \cap X_i$. But since $\operatorname{load}_{Y_i}(W_i(a_{z'})) \leq \frac{L}{32\mu} < \frac{L}{16} \leq \operatorname{load}_{X_i}(W_i(a_{z'}))$, this means we will not schedule z''.

It follows that $W_j^1(x) \cap Y_i \subseteq W_i(z') \cap Y_i$, and thus $\operatorname{load}_{Y_i}(W_j^1(x)) \leq \operatorname{load}_{Y_i}(W_i(z')) \leq \frac{L}{32\mu}$. And so the load of unscheduled points in $W_j^1(x)$ after iteration *i* is at least $L - \frac{L}{32\mu} \geq \frac{L}{5\mu}$. Case 2(b): $\operatorname{load}_{X_i}(W_i^2(x)) \ge \frac{L}{6}$.

If $W_j^2(x) \cap C_i(k) = \emptyset$, then the lemma trivially holds. So for now on, we will assume $W_j^2(x) \cap C_i(k) \neq \emptyset$. Let $z \in C_i(k)$ be a point such that $W_i(z) \cap W_j^2(x) \neq \emptyset$. Note that both $W_j^2(x)$ and $W_i(z)$ have a boundary parallel with the side $p_{i-1}p_i$. There are only two types of intersections between these two wedges:

- 1. $z \in W_j^2(x)$, the boundary of $W_j^2(x)$ parallel with the side $p_{j-1}p_j$ intersects both boundaries of $W_i(z)$, and the boundary of $W_j^2(x)$ parallel with the side $p_{i-1}p_i$ does not intersect with $W_i(z)$.
- 2. $x \in W_i(z)$, the boundary of $W_i(z)$ parallel with the side $p_i p_{i+1}$ intersects both boundaries of $W_j^2(x)$, and the boundary of $W_i(z)$ parallel with the side $p_{i-1}p_i$ does not intersect with $W_i^2(x)$.

See Figure 11 for an illustration.



Figure 11: Illustration for case 2(b): (a) A type 1 intersection. (b) A type 2 intersection.

Let $\{v_1, v_2, v_3, \ldots\}$ denote the points in $X_i \cap W_j^2(x)$ in decreasing order according to the partial order $\langle i$. Let $\ell = \max\{t | v_t \in Y_i\}$. If $\ell \leq \frac{L}{10}$ then $\operatorname{load}_{Y'}(W_j(x)) \geq \frac{L}{6} - \frac{L}{10} > \frac{L}{5\mu}$ after iteration *i*, so assume that $\ell > \frac{L}{10}$.

Since $v_{\ell} \in X_i$ there is a $u \in C_i(k)$ so that $v_{\ell} \in X(u)$ in iteration *i* of the algorithm. Suppose that the intersection between $W_i(u)$ and $W_j^2(x)$ is a type 1 intersection. Let $T_{v_{\ell}} = W_i(u) \setminus H_{j-1}(v_{\ell})$. Note that since $W_j^2(x) \neq \emptyset$, it must be that $j - 1 \in A_i$. Combining this with the fact that $v_{\ell} \in X(u)$, we know that $X^{j-1}(u) \subset T_{v_{\ell}} \subset W_i(u)$. (See Algorithm 1 for the notation.) Thus there are at least $|X^{j-1}(u)| = \frac{L}{2\mu}$ points from Y' in $T_{v_{\ell}}$. Since, $\operatorname{load}_{Y_i}(W_i(u)) \leq \frac{L}{32\mu}$, there must be at least $\frac{L}{2\mu} - \frac{L}{32\mu} > \frac{L}{5\mu}$ unscheduled points left in $T_{v_{\ell}}$ after iteration *i*. Since we are dealing with a type 1 intersection, $T_{v_{\ell}} \subset W_j^2(x)$, and thus $W_j^2(x)$ will contain at least $\frac{L}{5\mu}$ unscheduled points after iteration *i* and the lemma holds. See Figure 12 for an illustration.

Now suppose that the intersection between $W_i(u)$ and $W_j^2(x)$ is a type 2 intersection. Consider the region $T'_{v_\ell} = W_j^2(x) \setminus H_i(v_\ell)$. Since we are assuming $\ell > \frac{L}{10}$, it must be that $\operatorname{load}_{Y'}(T'_{v_\ell}) \ge \frac{L}{10}$. Since we are dealing with a type 2 intersection, it must be that $T'_{v_\ell} \subset W_i(u)$. Since $\operatorname{load}_{Y_i}(W_i(u)) \le \frac{L}{32\mu}$, we have that $\operatorname{load}_{Y_i}(T'_{v_\ell}) \le \frac{L}{32\mu}$ and thus there will be at least $\frac{L}{10} - \frac{L}{32\mu} > \frac{L}{5\mu}$ unscheduled points left in T'_{v_ℓ} after iteration *i*. Since $T'_{v_\ell} \subseteq W_j^2(x)$, there must be (unscheduled) load at least $\frac{L}{5\mu}$ in $W_j^2(x)$ after iteration *i*. See Figure 12 for an illustration.



Figure 12: Illustration for case 2(b): (a) An illustration of $T_{v_{\ell}}$. (b) An illustration of $T'_{v_{\ell}}$.

4 Restricted Strip Cover

We now describe our algorithm for the RSC which takes an instance consisting of sensors **S** and universe $U = \{1, 2, ..., m\}$ and returns a schedule S of the sensors. We assume without loss of generality that $m \leq 2n$. For a sensor $s \in \mathbf{S}$, we denote the range of s to be $R(s) = \{\ell(s), \ell(s) + 1, ..., r(s)\}$ where $\ell(s), r(s) \in U$. We will later show that the schedule produced by the algorithm has duration at least L/5, where L is the load. The reader may wish to consult Section 1 for additional notation used in the context of RSC. The algorithm starts with the empty schedule where no sensor is assigned, and assigns a start time to one sensor in each iteration. We will also denote the current schedule of the algorithm at any stage of its execution by S. We sometimes refer to the elements of U as coordinates. We think of these coordinates lying on a horizontal line and use the natural notion of a coordinate being to the left or right of another coordinate.

With respect to a schedule S, we say the sensor s dominates coordinate x to the right if s extends as far to the right as possible (maximizes r(s)) among all sensors that have not been assigned and are live at x. In the event of a tie, we take the sensor that extends as far to the left as possible. Further ties are broken arbitrarily. The sensor that dominates coordinate x to the left is defined similarly. Recall that for any $x \in U$, we denote $M(S, x) = max\{j : \forall j' \leq j, \exists s \in S, s \text{ covers } x \text{ at time } j'\}$ to be the duration of x in the schedule S, and the duration of the schedule is $M(S) = \min_x M(S, x)$. For ease of description, define $M(S, 0) = M(S, m + 1) = \infty$.

Algorithm 2

- 1: $t \leftarrow 0$
- 2: $S \leftarrow \emptyset$
- 3: while TRUE do
- 4: $t \leftarrow \mathcal{M}(S) + 1$
- 5: Let *i* be the first uncovered coordinate at time *t* and let *j* be max $\{x \in U \mid \text{all coordinates} in the interval [$ *i*,*x*] are uncovered at time*t* $}.$
- 6: Let s' be the sensor that dominates i to the right. If s' does not exist, go to step 9.

7: If s' is not live at $j, t(s') \leftarrow t$ and $S \leftarrow S \cup \{s'\}$.

- 8: If s' is live at j, let s'' be the sensor that dominates j to the left. If $M(S, i-1) \ge M(S, j+1)$, $t(s') \leftarrow t$ and $S \leftarrow S \cup \{s'\}$. Otherwise, $t(s'') \leftarrow t$ and $S \leftarrow S \cup \{s''\}$.
- 9: Return S.

The algorithm for RSC is Algorithm 2. Let us denote by t_f the duration of the final schedule produced by the algorithm. At termination, there is a point $x \in U$ so that $M(S, x) = t_f$ and there is no unassigned sensor that is live at x. **Running Time** We will iterate through the while loop at most n times because we schedule a sensor in each iteration of the while loop. Each iteration of the while is readily implemented in O(m+n) = O(n) time. Thus the algorithm runs in $O(n^2)$ time. It may be possible to improve the running time by using data structures such as segment trees.

4.1 Approximation Ratio

For an instance \mathbf{S} of RSC, let *OPT* denote the duration of an optimal solution for \mathbf{S} . We have the following theorem which we will prove in the remainder of this section.

Theorem 9. Given any instance S of Restricted Strip Cover, our algorithm returns a schedule S such that $M(S) \ge OPT/5$.

Lemma 10. Given some instance of Restricted Strip Cover S, let S be the schedule returned by our algorithm. Let $u, v \in S$ be any two, distinct sensors. If R(u) is strictly contained in R(v), then u is scheduled after v and in fact $t(u) \ge t(v) + d(v)$.

Proof. Suppose that u and v are two unscheduled sensors such that R(u) is strictly contained in R(v). Sensors are only scheduled when they dominate some coordinate to the left or to the right. Suppose we want to find the sensor that dominates some coordinate $i \in [\ell(u), r(u)]$. We will consider both u and v, but will always prefer v to u from the definition of domination. Therefore, we will schedule v before u and will not consider another sensor to dominate a coordinate in $[\ell(u), r(u)]$ until after time t(v) + d(v).

For $x \in U$ and t > 0, we define coverage(x, t) to be the number of sensors that cover x at time t in the schedule output by our algorithm.

We need the following observation.

Lemma 11. If $coverage(x,t) \leq c$ for each $x \in U$ and t > 0, then the duration t_f of the schedule we output is at least L/c.

Proof. At termination, there is a point $x \in U$ so that $M(S, x) = t_f$ and there is no unassigned sensor that is live at x. Thus, $ct_f \geq L(x) \geq L$, and so $t_f \geq L/c$.

We will now show that $coverage(x,t) \leq 5$ for each $x \in U$ and t > 0. Theorem 9 then follows immediately from this and Lemma 11.

In each iteration the algorithm schedules (assigns) a sensor s which is either s' or s''. Let us call the corresponding interval [i, j] the *interval for which* s *is scheduled*. (Please refer to the algorithm for what i and j stand for.) If s = s', we call s a *right going* sensor to remember that it was chosen to dominate i to the right. In this case, i was not covered at time t(s) before s was scheduled, but i was covered at time t(s) after s was scheduled. We say that s = s' closes i at time t(s). Similarly, if s = s'' we call s a *left going* sensor and say that it closes j at time t(s).

Lemma 12. For any $x \in U$ and t > 0, $coverage(x, t) \le 5$.

Proof. Fix an $x \in U$ and t > 0. If no sensor in the output schedule covers (x, t), then coverage(x, t) is 0. Let us therefore suppose that some sensor covers (x, t), and let s_0 denote the first scheduled sensor that covers (x, t). Let us classify any other sensor s that covers (x, t) into exactly one of the following four types: (1) s closes some i < x and is left going; (2) s closes some i < x and is right



Figure 13: There are 3 sensors covering (x,t). The first scheduled sensor to cover (x,t) is s_0 . The next sensor to cover (x,t) is a type 2 sensor s_1 . Finally, (x,t) is covered by a type 4 sensor s_2 .

going; (3) s closes some i > x and is left going; (4) s closes some i > x and is right going. We show that there are at most two sensors of types 1 and 2 put together. A symmetric argument shows that there are at most two sensors of types 3 and 4 put together.

Suppose that at some point the algorithm adds a sensor l of type 1. We claim that after l is added no more sensors of types 1 or 2 are added. Suppose l closed i < x at time t(l). Consider some sensor l' that is live at x and that closes some i' < x when it is later added by the algorithm. Since l was chosen because it dominated i to the left, we can conclude that $\ell(l') \ge \ell(l)$. (If this were not the case, then l' would necessarily be live at i and would have been preferred to l.) Observe that the interval $[\ell(l), x]$ is covered by l for all times between t(l) and t(l) + d(l) - 1. Since $i' \in [\ell(l'), x] \subseteq [\ell(l), x]$, we must have $t(l') > t(l) + d(l) - 1 \ge t$. Thus l' will not cover x at time t. We conclude that once we schedule a sensor of type 1, we do not schedule any more sensors of types 1 or 2.

We will therefore consider the case where the first sensor of type 1 or 2 is a type 2 sensor which we denote r_1 . We need the following claim.

Claim 13. Let v be a sensor scheduled after r_1 such that (a) v is live at x, (b) $t(v) \leq t$, and (c) v closes some z < x at time t(v). Let [x', y'] be the interval for which v is scheduled. Then $y' + 1 = \ell(r_1)$.

We prove the claim after completing the rest of the proof of the lemma. If the next sensor of type 1 or 2 that we schedule after r_1 is a type 1 sensor, we do not schedule any more sensors of types 1 and 2. So let us assume that the next sensor of types 1 or 2 that we schedule after r_1 is a type 2 sensor r_2 . Since $t \ge t(r_2) \ge t(r_1)$, and r_2 closes some i' < x at time $t(r_2)$, we must have $i' < \ell(r_1)$, and thus $\ell(r_2) < \ell(r_1)$. Now assume for the sake of a contradiction that there is some sensor r_3 of type 1 or 2 that is scheduled after r_2 . Reasoning as above, the interval [x'', y''] that it is scheduled for has $y'' < \ell(r_2)$. Thus $y'' + 1 \le \ell(r_2) < \ell(r_1)$, a contradiction to Claim 13.

Thus we have completed the proof of the lemma and we now prove Claim 13.

Proof of Claim 13. First, we clarify to the reader that in the statement of the claim condition (a) does not require v to cover (x, t), but only requires v to be live at x. Let v_1, \ldots, v_k be the sensors satisfying the hypothesis of the claim, ordered in the sequence in which they were chosen by the algorithm. Let $[x_j, y_j]$ be the interval for which v_j is scheduled. Since $t(r_1) \leq t(v_j) \leq t$ and v_j closes some point strictly less than x, we must have $y_j < \ell(r_1)$. We have argued that $y_j \leq \ell(r_1) - 1$, and we want to show $y_j = \ell(r_1) - 1$. Suppose for the sake of contradiction that $y_j < \ell(r_1) - 1$ for some j, and consider the first j for which this happens.

When v_j was being scheduled, $y_j + 1$ is covered at time $t(v_j)$ by a sensor w. Clearly, it must be that $y_j + 1 = \ell(w)$. So we have $\ell(v_j) < \ell(w) < \ell(r_1)$.

If w was scheduled before r_1 , then r(w) < i' < x where i' is the point that r_1 closes. Thus $R(v_j)$ properly contains R(w) but v_j is scheduled after w, a contradiction to Lemma 10.

If w was scheduled after r_1 , then w must be live at x, for otherwise $R(v_j)$ properly contains R(w) and we derive a contradiction as above. Also, we must have $r(w) < r(r_1)$ for otherwise R(w) properly contains $R(r_1)$ and we reach a contradiction. Since $r(w) < r(r_1)$, w closes some $i < \ell(r_1)$. Thus w is scheduled after r_1 , $t(w) \le t(v_j) \le t$, w is live at x, and w closes some point strictly to the left of x. Thus $w = v_{j'}$ for some j' < j. If j = 1, we have reached a contradiction. We therefore assume j > 1. We observe that w cannot be a left going sensor, because v_j is also live at the point i that w closes, and would have been preferred to w otherwise since $\ell(v_j) < \ell(w)$. Since j' < j, we have $y_{j'} + 1 = \ell(r_1)$. Thus $M(S, y_{j'} + 1) \ge t$ at the time $w = v_{j'}$ is being scheduled. Since w is right going, we must have $M(S, x_{j'} - 1) \ge M(S, y_{j'} + 1) \ge t$ at the time w is being scheduled. Let s denote the sensor that covers $x_{j'} - 1$ at times $t(w), t(w) + 1, \ldots, t$ when w is being scheduled. We have $r(s) = x_{j'} - 1 < x_{j'} < x \le r(v_j)$. Now v_j closes some point $i'' \in [x_j, y_j]$ at time $t(v_j)$, and since $t \ge t(v_j) \ge t(w)$, i'' cannot be in R(s). Since $i'' \le y_j = \ell(w) - 1 \le x_{j'} - 1 = r(s)$, it must be that $i'' < \ell(s)$. So $\ell(v_j) \le i'' < \ell(s)$ and we have already argued that $r(v_j) > r(s)$. So $R(v_j)$ properly contains R(s) but v_j is scheduled after s, a contradiction to Lemma 10.

The following observation about our algorithm for RSC is evident from the analysis.

Observation 14. Suppose that we stop our algorithm once the duration of the schedule becomes greater than equal to t. Then the total load of all the scheduled sensors that are live at some point x of the universe is at most $5(t + d_{max})$, where d_{max} is the maximum duration of any input sensor.

4.2 Implication for Planar Sensor Cover

Here we generalize Theorem 1 to show that given an instance of the planar sensor cover problem, we can compute a schedule whose duration is within a constant factor of the load. The proof proceeds along similar lines, and we only need an analog in the non-uniform duration case of the procedure computeCover() in Section 2.1. Now our algorithm for RSC furnishes just such an analog, with Lemma 10 and Observation 14 being the equivalent of Observation 5. The rest of the proof follows from a careful but fairly mechanical modification to the proof of Theorem 1. We conclude with a statement of our constant factor approximation for planar sensor cover:

Theorem 15. For any given convex polygon, there is a polynomial time algorithm for the planar sensor cover problem (with ranges being translates of the convex polygon) that computes a schedule whose duration is within a constant factor of the load of the instance.

Acknowledgment

The work on this paper was partially supported by NSF CAREER award CCR 0237431.

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