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ALGORITHMS FOR COVERING BARRIER POINTS BY MOBILE SENSORS WITH  
LINE CONSTRAINT

by

Princy Jain

A thesis submitted in partial fulfillment  
of the requirements for the degree

of

MASTER OF SCIENCE

in

Computer Science

Approved:

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Haitao Wang, Ph.D.  
Major Professor

---

Curtis Dyreson, Ph.D.  
Committee Member

---

Dan Watson, Ph.D.  
Committee Member

---

D. Richard Cutler, Ph.D.  
Interim Vice Provost of Graduate Studies

UTAH STATE UNIVERSITY  
Logan, Utah

2021

## ABSTRACT

Algorithms for Covering Barrier Points by Mobile Sensors with Line Constraint

by

Princy Jain, Master of Science

Utah State University, 2021

Major Professor: Haitao Wang, Ph.D.

Department: Computer Science

In this thesis, we study the problem of covering barrier points by mobile sensors. Each sensor is represented by a point in the plane with the same covering range  $r$  so that any point within distance  $r$  from the sensor can be covered by the sensor. Given a set  $B$  of  $m$  points (called “barrier points”) and a set  $S$  of  $n$  points (representing the “sensors”) in the plane, the problem is to move the sensors so that each barrier point is covered by at least one sensor and the maximum movement of all sensors is minimized. The problem is NP-hard. In this thesis, we consider two line-constrained variations of the problem and present efficient algorithms that improve the previous work. In the first problem, all sensors are given on a line  $\ell$  and are required to move on  $\ell$  only while the barrier points can be anywhere in the plane. We propose an  $O((n + m) \log(n + m))$  time algorithm for the problem. We also consider the weighted case where each sensor has a weight; we give an  $O((m + n) \log^2(m + n))$  time algorithm for this case. In the second problem, all barrier points are on  $\ell$  while all sensors are in the plane but are required to move to  $\ell$  to cover all barrier points. We solve the weighted case in  $O(m \log m + n \log^2 n)$  time.

(38 pages)

## PUBLIC ABSTRACT

Algorithms for Covering Barrier Points by Mobile Sensors with Line Constraint

Princy Jain

In this thesis, we develop efficient algorithms for the problem of covering barrier points by mobile sensors. Each sensor is represented by a point in the plane with the same covering range  $r$  so that any point within distance  $r$  from the sensor can be covered by the sensor. Given a set  $B$  of  $m$  points (called “barrier points”) and a set  $S$  of  $n$  points (representing the “sensors”) in the plane, the problem is to move the sensors so that each barrier point is covered by at least one sensor and the maximum movement of all sensors is minimized. The problem is NP-hard. In this thesis, we consider two line-constrained variations of the problem and present efficient algorithms that improve the previous work. In the first problem, all sensors are given on a line  $\ell$  and are required to move on  $\ell$  only while the barrier points can be anywhere in the plane. We propose an  $O((n + m) \log(n + m))$  time algorithm for the problem. We also consider the weighted case where each sensor has a weight; we give an  $O((m + n) \log^2(m + n))$  time algorithm for this case. In the second problem, all barrier points are on  $\ell$  while all sensors are in the plane but are required to move to  $\ell$  to cover all barrier points. We solve the weighted case in  $O(m \log m + n \log^2 n)$  time.

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Princy Jain

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CHAPTER 1  
INTRODUCTION

### 1.1 The Problem Definition

Let  $B$  be a set of  $m$  points and  $D$  be a set of  $n$  disks of the same radius  $r$  in the plane. We consider the problem of moving the disks of  $D$  to cover all points of  $B$  so that the maximum moving distance of all disks is minimized. The problem is NP-hard.<sup>1</sup> In this thesis, we consider two line-constrained variations of the problem and present efficient algorithms for them.

Due to its potential applications in barrier coverage of mobile sensors in wireless sensor networks [3–5], we consider the problem from the barrier coverage point of view. We call the points of  $B$  the *barrier points*. Let  $S$  be the set of centers of all disks of  $D$ , and points of  $S$  are called *sensors*. All sensors have the same *covering range* (or *sensing range*)  $r$  so that any point within distance  $r$  from a sensor  $s$  can be covered by  $s$  (i.e.,  $s$  covers all points in the disk centered at  $s$  with radius  $r$ ). Hence, our problem becomes the following: move sensors of  $S$  to cover all barrier points of  $B$  such that the maximum moving distance of all sensors is minimized.

We study a line-constrained variation of the problem where all sensors are given on a line  $\ell$  and are required to move on  $\ell$  only while the barrier points can be anywhere in the plane. We also consider its *weighted case* where each sensor  $s_i$  has a weight  $w_i > 0$  and the *moving cost* of  $s_i$  is defined to be its moving distance times  $w_i$ .

To the best of our knowledge, we are not aware of any previous work on this particular problem. If all barrier points are all on  $\ell$ , which becomes a 1D problem (our original problem can be considered as a 1.5D problem), the algorithm of Li and Wang [6] can solve the unweighted case in  $O(m \log m + n \log m \log n)$  time. In this thesis, we present

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<sup>1</sup>This can be proved by an easy reduction from the minimum disk coverage problem [1]; e.g., see [2] for a reduction for a similar problem.



an  $O((n + m) \log(n + m))$  time for the unweighted case and an  $O((n + m) \log^2(n + m))$  time algorithm for the weighted case. Hence, our algorithm for the unweighted case, albeit solving the 1.5D problem, improves the algorithm of [6] by roughly a logarithmic factor.

We also consider another problem variation in which all barrier points are on a line  $\ell$  while sensors can be anywhere in the plane. We want to move all sensors to  $\ell$  to cover all barrier points so that the maximum moving cost of all sensors is minimized. Previously, Huang et al. [3] studied the unweighted case and gave an  $O(mn \log(m + n))$  time algorithm. Our techniques solve the weighted case in  $O(m \log m + n \log^2 n)$  time. This improves the algorithm of Huang et al. [3] by almost a linear factor. Note that we do not have a faster algorithm for the unweighted case. As all barrier points are on  $\ell$  and all sensors will finally move to  $\ell$ , once a sensor  $s$  moves to  $\ell$ , the portion of the covering disk of  $s$  that is relevant is an interval of  $\ell$ . For this reason, we refer to this problem as the *mobile interval coverage problem*; for differentiation, we refer to the first problem above as the *mobile disk coverage problem*. Note that if sensors have different ranges, even the 1D problem (i.e., all sensors and barrier points are on  $\ell$ ) is NP-hard [3].

## 1.2 Related Work

Many variations of mobile sensor barrier coverage problem have been studied in the literature.

Czyzowicz et al. [7] studied the problem of covering a barrier segment on a line  $\ell$  by moving a set of  $n$  sensors on  $\ell$  (the sensors are initially given on  $\ell$ ); they gave an  $O(n^2)$  time algorithm. Chen et al. [8] presented a more efficient  $O(n \log n)$  time algorithm. Chen et al. [8] also studied the case where sensors may have different covering ranges and proposed an  $O(n^2 \log n)$  time algorithm. For the weighted case where the sensors have weights as defined in our problems (but sensors have the same range), Lee et al. [9] derived an algorithm of  $O(n^2 \log n \log \log n)$  time.

Li and Shen [5] studied the same problem as our interval coverage problem except that their barrier is not a set of points but a single line segment on  $\ell$ . They proposed an  $O(n^3 \log n)$  time algorithm. The algorithm was later improved to  $O(n^2 \log n \log \log n)$

time by Li and Wang [6]. Li and Wang [6] also studied a more general problem setting where the barrier is a set of disjoint line segments on  $\ell$  (and the sensors are still in the plane and are required to move to  $\ell$ ); they gave an  $O(n^2 \log n \log \log n + nm \log m)$  time algorithm. Further, for the 1D case where all sensors are initially on  $\ell$ , the algorithm of Li and Wang [6] solves the problem in  $O(m \log m + n \log n \log m)$  time. These results are for the case where sensors have the same range; if sensors have different ranges, even the 1D problem is NP-hard by a simple reduction from the Partition Problem as in [7].

The min-sum version of the line-constrained barrier coverage was also studied in the literature where sensors are given on  $\ell$  and a barrier segment is also on  $\ell$ , and the goal is to move sensors to cover the barrier segment such that the total sum of the moving distances of all sensors is minimized. If sensors have different ranges, the problem is NP-hard [10]. Otherwise, Czyzowicz et al. [10] solved the problem in  $O(n^2)$  time. Later Andrews and Wang [11] proposed a faster algorithm of  $O(n \log n)$  time.

A circular barrier coverage problem was also considered, where the barrier is a circle and sensors are initially located inside the circle and the goal is to move all sensors to the circle to form a regular  $n$ -gon (to form a coverage) so that the maximum moving distance of all sensors is minimized. Bhattacharya [12] first gave an algorithm of  $O(n^{3.5} \log n)$  time. An improved algorithm of  $O(n \log^3 n)$  time was later derived by Chen et al. [13].

There are also other variations of the barrier coverage problem, e.g., see [14–17].

### 1.3 Our Approach

We first discuss the mobile disk coverage problem. Let  $\lambda^*$  denote the optimal moving cost, i.e., the maximum moving cost of all sensors in an optimal solution. In both the unweighted and weighted cases, we first consider the *decision problem*: Given any value  $\lambda$ , determine whether  $\lambda \geq \lambda^*$ .

For the unweighted case, a critical property is an *order-preserving property*: There exists an optimal solution in which the order of the sensors are consistent with their order in the input. Due to the property, we can solve the decision problem in linear time by a simple greedy algorithm (after all barrier points and all sensors are sorted). Next, we use

the decision algorithm to compute  $\lambda^*$ . To this end, we define  $2m$  arrays of size  $n$  each and we show that  $\lambda^*$  must be an element of one of the arrays. To search  $\lambda^*$  in these arrays in an efficient way, we form these arrays implicitly. A helpful observation is that each of these arrays is sorted. Consequently, by using our decision algorithm, we apply a *sorted matrix searching* technique [18–20] (or a simpler implementation called *binary search on sorted arrays* in [21]) to find  $\lambda^*$  in these arrays in  $O((n+m)\log(n+m))$  time.

For the weighted case, unfortunately the order-preserving property does not hold anymore. In fact, the major difficulty is to find the correct order for sensors in an optimal solution. This is also the case for solving the decision problem. So we have to use a different approach to solve the decision problem. The runtime of the algorithm is  $O((n+m)\log(n+m))$ . To compute the optimal cost  $\lambda^*$ , we implicitly form  $2n$  arrays of size  $m$  each such that  $\lambda^*$  is one of the array elements. To apply the sorted matrix searching technique, we manage to find a way to order the array elements implicitly so that the arrays are still sorted. Then, with the decision algorithm, the value  $\lambda^*$  can be found in  $O((n+m)\log^2(n+m))$  time.

For the mobile interval coverage problem, we solve the weighted cases directly (without having a faster algorithm for the unweighted case). As above, we also solve the decision problem first, and then form sorted arrays and apply the sorted array searching technique. To solve the decision algorithm, we use an algorithm similar to the weighted case of the above mobile disk coverage problem, but with a simpler and slightly faster implementation. The runtime of our decision algorithm is  $O(m+n\log n)$  after  $O((n+m)\log(n+m))$  time preprocessing for sorting all sensors and barrier points. The time of the overall algorithm (for computing the optimal value  $\lambda^*$ ) is  $O(m\log m+n\log^2 n)$ .

CHAPTER 2  
PRELIMINARIES

For each problem we consider, we use  $\lambda^*$  to denote the optimal moving cost. Given any  $\lambda$ , the *decision problem* is to decide whether  $\lambda \geq \lambda^*$ , i.e., whether it is possible to move sensors to cover all barrier points so that the moving cost of each sensor is at most  $\lambda$ . If  $\lambda \geq \lambda^*$ , we say that  $\lambda$  is a *feasible value*. We use *feasibility test* to refer to the procedure for determining whether  $\lambda \geq \lambda^*$ . For differentiation, we refer to our original problem for computing  $\lambda^*$  as the *optimization problem*.

Without loss of generality, we simply assume that the line  $\ell$  is the  $x$ -axis. Let  $S = \{s_1, s_2, \dots, s_n\}$  be the set of sensors (unless otherwise stated, the order is arbitrary). For each  $s_i$ , we use  $(x_i, y_i)$  to denote its coordinate in the input. For differentiation, for each barrier point  $b \in B$ , we use  $(x_b, y_b)$  to denote its coordinate.

In each problem, we use a *configuration* to refer to a specification on where each sensor  $s_i$  is located. For example, in the input configuration, each sensor  $s_i$  is at  $(x_i, y_i)$ .

For each sensor  $s$ , we use  $D(s)$  to refer to its covering disk, i.e., the disk of radius  $r$  centered at  $s$ . For any disk  $D$ , we use  $\partial D$  to denote its boundary, which is a circle. The *left half-circle* of  $\partial D$  refers to the portion of  $\partial D$  to the left of the vertical line through the center of  $D$ ; the *right half-circle* is defined similarly.

For the mobile disk coverage problem, for simplicity of discussion, we assume that all barrier points are above or on  $\ell$  since if a barrier point is below  $\ell$ , then we can use its symmetric point about  $\ell$  to replace it and that does not affect the solution of the problem.

For any point  $p$  on  $\ell$ , for convenience, sometimes we also use  $p$  to refer to its  $x$ -coordinate. For example, for two points  $p$  and  $q$  on  $\ell$ ,  $p \leq q$  means that  $p$  is to the left of  $q$  (including the case where  $p$  and  $q$  are coincident) and  $p < q$  means that  $p$  is *strictly* to the left of  $q$ .

For each problem, for ease of exposition, we assume that it is always possible to cover all barrier points by moving sensors (i.e., the covering range  $r$  is big enough). Our algorithm can actually determine whether the assumption is true or not. This implies that in the mobile disk coverage problem, for each barrier point  $b$ ,  $y_b \leq r$  must hold since otherwise no sensor on  $\ell$  can cover  $b$ .

For a barrier point  $b$  and the covering disk  $D(s)$  of a sensor  $s$ , we say that  $D(s)$  is *strictly to the left (resp., right)* of  $b$  if  $D(s)$  does not cover  $b$  and the intersection between  $D(s)$  and the horizontal line through  $b$  is strictly to the left (resp., right) of  $b$ .

## CHAPTER 3

## THE MOBILE DISK COVERAGE PROBLEM: THE UNWEIGHTED CASE

In this chapter, we consider the unweighted case of the mobile disk coverage problem. In this problem, all sensors of  $S$  are on the line  $\ell$  while each barrier of  $B$  can be anywhere in the plane. We first present an algorithm to solve the decision algorithm. Consider a value  $\lambda$ . If  $\lambda \geq \lambda^*$ , we use a *feasible solution* to refer to a configuration in which all barrier points are covered and the moving cost of each sensor is no more than  $\lambda$ . As all sensors have the same range, it is not difficult to see that *the order-preserving property* in the following observation holds.

**Observation 1** (The order-preserving property) *If  $\lambda \geq \lambda^*$ , then there exists a feasible solution in which the order of sensors is the same as in the input.*

Due to the order-preserving property, we can solve the decision problem by a simple greedy algorithm in linear time (after sensors and barrier points are sorted).

**Lemma 1** *After  $O(n \log n + m \log m)$  time preprocessing, given any  $\lambda$ , whether  $\lambda \geq \lambda^*$  can be decided in  $O(m + n)$  time.*

**Proof:** In the preprocessing, we sort all sensors of  $S$  from left to right on  $\ell$ ; let  $S = \{s_1, s_2, \dots, s_n\}$  be the sorted list. We also sort all barrier points of  $B$  by their  $x$ -coordinates from left to right; let  $B = \{b_1, b_2, \dots, b_m\}$  be the sorted list. Given any  $\lambda$ , in what follows we describe our  $O(n + m)$  time algorithm for deciding whether  $\lambda \geq \lambda^*$ , which is based on the greedy strategy.

We first move each sensor rightwards on  $\ell$  by distance  $\lambda$  and we use  $C_0$  to refer to the configuration, i.e., in  $C_0$ , the location of each  $s_i$  is  $x_i + \lambda$ . Then, during the algorithm, each sensor will not be allowed to move rightwards anymore but can move leftwards by  $2\lambda$ .

Starting from  $i = 1$  and  $j = 1$ , we process sensors  $s_i$  and barrier points  $b_j$  incrementally. We first check whether  $b_j$  is covered by  $s_i$ . If yes, we increase  $j$  by one (if  $j = m$  before

the increase, then all barrier points are covered and we have found a feasible solution; in this case, we can stop the algorithm and report that  $\lambda$  is a feasible value, i.e.,  $\lambda \geq \lambda^*$ ). Otherwise, either  $b_j$  is to the right of the covering disk  $D(s_i)$  of  $s_i$  or  $b_j$  is to the left of  $D(s_i)$ . In the former case, we increase  $i$  by one and proceed as above (if  $i = n$  before the increase, then we can stop the algorithm and report that  $\lambda$  is not a feasible value, i.e.,  $\lambda < \lambda^*$ ). In the latter case, we check whether it is possible to move  $s_i$  leftwards by distance at most  $2\lambda$  to cover  $b_j$ . If not, then we can stop the algorithm and report that  $\lambda$  is not a feasible value. Otherwise, we move  $s_i$  leftwards until  $b_j$  is covered (i.e.,  $b_j$  is on the left half-circle of  $\partial D(s_i)$ ); we then increase  $j$  by one and proceed as above (if  $j = m$  before the increase, then all barrier points are covered and thus we can stop the algorithm and report that  $\lambda$  is a feasible value). This finishes the description of the algorithm.

The correctness of the algorithm is based on the order-preserving property. It is not difficult to see that the running time of the algorithm is  $O(n + m)$ .  $\square$

We next tackle the optimization problem for computing  $\lambda^*$ , by making use of our decision algorithm in Lemma 1 as a subroutine. For this, we have the following lemma.

**Lemma 2**  $\lambda^*$  is equal to  $x_i - \sqrt{r^2 - y_b^2} - x_b$  or  $x_b - \sqrt{r^2 - y_b^2} - x_i$  for a sensor  $s_i$  and a barrier point  $b$ .

**Proof:** Consider an optimal solution  $OPT$ , where  $\lambda^*$  is the maximum moving distance of all sensors. Then,  $\lambda^*$  is equal to the moving distance of a sensor  $s_i$ . Let  $x'_i$  be the position of  $s_i$  in  $OPT$ . If  $x'_i < x_i$ , then  $s_i$  has been moved leftwards. In this case, there must be a barrier point  $b$  on the left half-circle of  $\partial D(s_i)$  since otherwise we could move  $D(s_i)$  rightwards slightly so that  $D(s_i)$  still covers the same set of barrier points as before but the moving distance of  $s_i$  is strictly smaller than  $\lambda^*$ , a contradiction to the definition of  $\lambda^*$ . Thus, we have  $x'_i = \sqrt{r^2 - y_b^2} + x_b$ . Hence,  $\lambda^* = x_i - x'_i = x_i - \sqrt{r^2 - y_b^2} - x_b$ . If  $x'_i > x_i$ , then by similar analysis as above, we can show that  $\lambda^* = x_b - \sqrt{r^2 - y_b^2} - x_i$ .  $\square$

We sort all sensors of  $S$  from left to right on  $\ell$ ; let  $S = \{s_1, s_2, \dots, s_n\}$  be the sorted list. For each barrier point  $b \in B$ , we define two arrays  $A_b[1 \dots n]$  and  $A'_b[1 \dots n]$  of size  $n$  each as follows: For each  $i \in [1, n]$ , define  $A_b[i] = x_i - \sqrt{r^2 - y_b^2} - x_b$  and  $A'_b[i] = x_b - \sqrt{r^2 - y_b^2} - x_i$ .

According to Lemma 2,  $\lambda^*$  is an element in one of the  $2m$  arrays  $A_b$  and  $A'_b$  for all  $b \in B$ . We next find  $\lambda^*$  in these arrays. Computing these arrays explicitly will take  $\Omega(nm)$  time. Below, we present a near linear time algorithm without computing these arrays explicitly. Indeed, given an index  $i \in [1, n]$  and a barrier point  $b \in B$ , we can obtain the values  $A_b[i]$  and  $A'_b[i]$  in constant time.

An easy observation is that elements of the array  $A_b$  are sorted in ascending order and elements of  $A'_b$  are sorted in descending order. Therefore, we are searching  $\lambda^*$  in  $2m$  sorted arrays of size  $n$  each. Note that  $\lambda^*$  is actually the smallest feasible value in these  $2m$  arrays. We can use the sorted matrix searching techniques [18–20] (or a simpler implementation, called *binary search on sorted arrays*, in [21]) to search sorted arrays with the following lemma.

**Lemma 3** [18–21] *Suppose we have a set of  $M$  sorted arrays of size at most  $N$  each such that each array element can be evaluated in  $O(1)$  time (i.e., given the index of an array, the element of the array can be obtained in  $O(1)$  time). Then, the smallest feasible value in these arrays can be computed by  $O(\log(N + M))$  feasibility tests and the total time of the algorithm excluding the feasibility tests is  $O(M \log N)$ .*

Applying the algorithm of Lemma 3 and using our decision algorithm in Lemma 1,  $\lambda^*$  can be found in  $O((m + n) \log(m + n))$  time. We summarize our result in the following theorem.

**Theorem 1** *Given a set of  $m$  barrier points in the plane and a set of  $n$  sensors on a line  $\ell$ , the problem of moving sensors on  $\ell$  to cover all barrier points such that the maximum moving cost of all sensors is minimized can be solved in  $O((m + n) \log(m + n))$  time.*

Note that after  $\lambda^*$  is computed, we can apply our decision algorithm in Lemma 1 with  $\lambda = \lambda^*$  to find a way to move sensors on  $\ell$  so that all barrier points are covered and the maximum moving cost of all sensors is at most  $\lambda^*$ .



## CHAPTER 4

## THE MOBILE DISK COVERAGE PROBLEM: THE WEIGHTED CASE

In this chapter, we solve the weighted case of the mobile disk coverage problem. Here also, we start with the decision problem and later solve the optimization problem by applying sorted array searching techniques in Lemma 3. In the weighted case, each sensor  $s_i$  is associated with a weight  $w_i > 0$ .

**4.1 The Decision Problem**

Given any  $\lambda$ , the problem is to decide whether  $\lambda \geq \lambda^*$ . Although our algorithm is similar in spirit to those in the previous work [6, 8, 9], our algorithm is for a more general problem setting in that the barrier points are in the plane while the barriers in all previous work [6, 8, 9] are on  $\ell$ . In the following, we first describe our algorithm, and then prove its correctness; finally, we will discuss how to efficiently implement the algorithm in  $O((n + m) \log(n + m))$  time.

**4.2 The Algorithm Description**

For each sensor  $s_i$ , define  $x_i^l = x_i - \lambda/w_i$  and  $x_i^r = x_i + \lambda/w_i$ , i.e.,  $x_i^l$  is the leftmost location on  $\ell$  where  $s_i$  can move to and  $x_i^r$  is the rightmost location on  $\ell$  where  $s_i$  can move to with respect to  $\lambda$ . We call  $x_i^l$  (resp.,  $x_i^r$ ) the *leftmost* (resp., *rightmost*)  $\lambda$ -reachable location.

For each barrier point  $b$ , we use  $c(b)$  to denote the center of the circle of radius  $r$  whose center is at  $\ell$  and whose left half-circle contains  $b$ , i.e.,  $c(b) = x_b + \sqrt{r^2 - y_b^2}$ . We sort all barrier points  $b \in B$  in the order of the values  $c(b)$ . Alternatively, it is also the order of the barrier points of  $B$  encountered by sweeping a left half-circle centered at  $\ell$  from left to right. Let  $B = \{b_1, b_2, \dots, b_m\}$  be the sorted list.

Initially, we move each sensor  $s_i$  to  $x_i^r$  and thus  $s_i$  will not be allowed to move rightwards

anymore but can move leftwards by  $2\lambda/w_i$ . Let  $C_0$  denote the resulting configuration. If  $\lambda \geq \lambda^*$ , our algorithm will find a subset of sensors with their new locations such that all barrier points are covered and the maximum moving cost of each sensor is at most  $\lambda$  (sensors not in the subset are still in their positions of  $C_0$ ).

Consider the  $i$ -th iteration of the algorithm (initially,  $i = 1$ ). Let  $C_{i-1}$  be the configuration right before the iteration. Our algorithm maintains the following invariants.

1. A subset of sensors  $S_{i-1} = \{s_{g_1}, \dots, s_{g_{i-1}}\}$  has been computed, where  $g_j$  is the index of the sensor  $s_{g_j}$  for each  $j \in [1, i-1]$ .
2. In  $C_{i-1}$ , each sensor  $s_k$  of  $S_{i-1}$  is at a location, denoted by  $x'_k$ , which may not be equal to  $x_k^r$ , while sensors of  $S \setminus S_{i-1}$  are still in their locations of  $C_0$  (i.e., each sensor of  $S \setminus S_{i-1}$  is at its rightmost  $\lambda$ -reachable location).
3. An index  $h_{i-1}$  of a barrier point is maintained such that in the configuration  $C_{i-1}$ , the barrier point  $b_{h_{i-1}}$  is not covered by any sensor of  $S_{i-1}$  while  $b_k$  is covered by a sensor in  $S_{i-1}$  for each  $k < h_{i-1}$  (note that it is possible that  $b_k$  for some  $k > h_{i-1}$  is also covered by a sensor in  $S_{i-1}$ , which cannot happen in the problem settings of the previous work [6, 8, 9]; this case makes our problem more challenging to solve).
4. Each sensor of  $S_{i-1}$  covers at least one barrier point  $b_j$  with  $j < h_{i-1}$  in  $C_{i-1}$ .
5. The locations of the sensors  $s_{g_1}, s_{g_2}, \dots, s_{g_{i-1}}$  in  $C_{i-1}$  are sorted from left to right on  $\ell$ .
6. The barrier point  $b_{h_{i-1}}$  is strictly to the right of the covering disk  $D(s_{g_{i-1}})$  of  $s_{g_{i-1}}$  if  $S_{i-1} \neq \emptyset$ .

Initially when  $i = 1$ , we have  $S_0 = \emptyset$  and we set  $h_0 = 1$ ; thus, all algorithm invariants trivially hold. The  $i$ -th iteration of the algorithm finds a sensor  $s_{g_i}$  from  $S \setminus S_{i-1}$  and move it to a new location  $x'_{g_i} \in [x_{g_i}^l, x_{g_i}^r]$  to obtain a new configuration  $C_i$  with  $S_i = S_{i-1} \cup \{s_{g_i}\}$ . The details of the  $i$ -th iteration of the algorithm are described below.

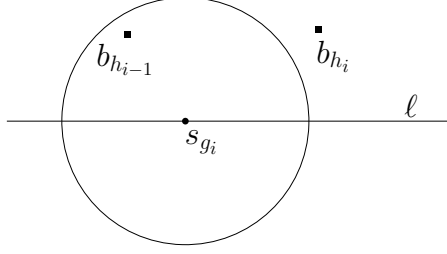


Fig. 4.1: Illustrating the Invariant (6) in the proof of Lemma 4: the circle is the boundary of  $D(s_{g_i})$ .

Define  $S_{i1}$  to be the set of sensors that cover the barrier point  $b_{h_{i-1}}$  in the configuration  $C_{i-1}$ . According to our algorithm invariants,  $b_{h_{i-1}}$  is not covered by any sensor in  $S_{i-1}$ . Hence,  $S_{i1} \subseteq S \setminus S_{i-1}$ .

If  $S_{i1} \neq \emptyset$ , we pick an arbitrary sensor from  $S_{i1}$  as  $s_{g_i}$  and set  $x'_{g_i} = x^r_{g_i}$  (i.e., the sensor does not move from its position in  $C_{i-1}$ ); thus  $C_i = C_{i-1}$ . We set  $h_i = k + 1$ , where  $k$  is the largest index in  $[h_{i-1}, n]$  such that barrier points  $b_j$  for all  $j \in [h_{i-1}, k]$  are covered by sensors of  $S_i$ . If  $h_i = n + 1$ , all barrier points  $b_j$  for all  $j \in [h_{i-1}, n]$  are covered, and thus we can stop the algorithm and report  $\lambda \geq \lambda^*$ .

**Lemma 4** *All algorithm invariants hold.*

**Proof:** We go through every invariant. Invariant (1) trivially holds. Invariant (2) holds because  $C_i = C_{i-1}$ . Invariant (3) follows immediately from how our algorithm computes  $h_i$ . Invariant (4) holds because  $s_{g_i}$  covers  $b_{h_{i-1}}$  in  $C_i$ . For Invariant (5), it suffices to show that  $s_{g_{i-1}}$  is to the left of the  $s_{g_i}$  in  $C_i$ . Indeed, according to Invariant (6) in  $C_{i-1}$ ,  $b_{h_{i-1}}$  is strictly to the right of the covering disk  $D(s_{g_{i-1}})$ . Since  $b_{h_{i-1}}$  is covered by  $s_{g_i}$  in  $C_i$ , we obtain that  $s_{g_{i-1}}$  must be to the left of  $s_{g_i}$  in  $C_i$ . For Invariant (6), since the sensor  $s_{g_i}$  covers  $b_{h_{i-1}}$  but does not cover  $b_{h_i}$  and  $h_{i-1} < h_i$ , according to the definition of the indices of the barrier points, we can obtain that  $b_{h_i}$  must be strictly to the right of the covering disk  $D(s_{g_i})$  of  $s_{g_i}$  (e.g., see Fig. 4.1). This proves Invariant (6).  $\square$

If  $S_{i1} = \emptyset$ , we define  $S_{i2} = \{s_k \mid x^l_k \leq c(b_{h_{i-1}}) < x^r_k, s_k \in S \setminus S_{i-1}\}$ , i.e., the set of sensors  $s_k$  that do not cover  $b_{h_{i-1}}$  in  $C_{i-1}$  but can be moved leftwards to cover  $b_{h_{i-1}}$ ; e.g.,

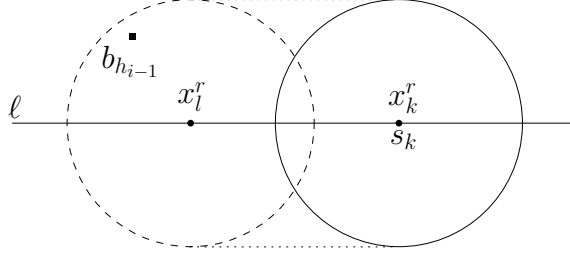


Fig. 4.2: Illustrating the definition of  $S_{i2}$ : The solid circle shows the position of  $s_k$  in  $C_{i-1}$ , i.e., at  $x_k^r$ , and the dashed circle shows its leftmost  $\lambda$ -reachable location, i.e.,  $x_l^l$ .

see Fig. 4.2. Note that each sensor of  $S_{i2}$  is currently at its rightmost  $\lambda$ -reachable location in  $C_{i-1}$ .

If  $S_{i2} \neq \emptyset$ , then among all sensors of  $S_{i2}$ , we choose the leftmost one (with respect to their positions in  $C_{i-1}$ ) as  $s_{g_i}$  and add it to  $S_{i-1}$  to obtain  $S_i$ . We move  $s_{g_i}$  leftwards until  $b_{h_{i-1}}$  is covered (i.e., it is on the left half-circle of  $\partial D_{g_i}$ ); this obtains the configuration  $C_i$ . Next, we set  $h_i = k + 1$ , where  $k$  is the largest index in  $[h_{i-1}, n]$  such that barrier points  $b_j$  for all  $j \in [h_{i-1}, k]$  are covered by sensors of  $S_i$ . If  $h_i = n + 1$ , then all barrier points are covered and thus we can stop the algorithm and report  $\lambda \geq \lambda^*$ . Following the similar analysis as Lemma 4, we can show that all algorithm invariants hold.

If  $S_{i2} = \emptyset$ , then we terminate the algorithm and report that  $\lambda < \lambda^*$ .

In summary, if  $S_{i1} = S_{i2} = \emptyset$ , then the algorithm will terminate and report  $\lambda < \lambda^*$ . Otherwise, a sensor  $s_{g_i}$  is found from either  $S_{i1}$  (if it is not empty) or  $S_{i2}$  and added to  $S_{i-1}$  to obtain  $S_i$ . In either case,  $h_i = k + 1$ , where  $k$  is the largest index in  $[h_{i-1}, n]$  such that barrier points  $b_j$  for all  $j \in [h_{i-1}, k]$  are covered by sensors of  $S_i$ . If  $h_i = n + 1$ , then the algorithm will terminate and report  $\lambda \geq \lambda^*$ ; otherwise, the algorithm will proceed to the next iteration  $i + 1$  and all algorithm invariants hold. As there are  $m$  barrier points and a new barrier point is covered in each iteration, the algorithm has at most  $m$  iterations. On the other hand, as there are  $n$  sensors and each iteration finds a new sensor to form  $S_i$ , the algorithm has at most  $n$  iterations. Hence, the algorithm will stop in  $\min\{n, m\}$  iterations.

### 4.3 The Algorithm Correctness

We now prove the correctness of the algorithm. The high-level idea of the proof is

similar to the previous work [6, 8, 9], although the details are quite different because in our problem barrier points are in the plane while the barriers in the previous work [6, 8, 9] are all on  $\ell$ .

Suppose the algorithm reports  $\lambda \geq \lambda^*$ , say, in the  $i$ -th iteration of the algorithm. Then, according to our algorithm, the configuration  $C_i$  is a feasible solution. Thus, it suffices to show that if the algorithm reports  $\lambda < \lambda^*$ , then no feasible solution exists.

For any index  $i \in [0, m]$  for the barrier points, we say that  $[0, i]$  is a *prefix interval* of  $[0, m]$ . For convenience, depending on the context, we may also use  $[0, i]$  to represent the subset of barrier points  $b_j$  for all  $j \in [0, i]$  (the subset is  $\emptyset$  if  $i = 0$ ). For example, we say that the interval  $[0, i]$  is *covered* by a set of sensors if all barrier points  $b_j$ ,  $0 \leq j \leq i$ , are covered by the set of sensors. We say that another prefix interval  $[0, i']$  is *larger than*  $[0, i]$  if  $i' > i$ .

**Lemma 5** *Consider the configuration  $C_i$  produced in the  $i$ -th iteration of our algorithm with  $i \geq 1$ . Suppose  $S'_i$  is the set of sensors of  $S$  whose covering disks are strictly to the left of  $b_{h_i}$  in  $C_i$ . Then,  $[0, h_i - 1]$  is the largest possible prefix interval that can be covered by sensors of  $S'_i$  with respect to  $\lambda$  (i.e., the moving cost of each sensor of  $S'_i$  is at most  $\lambda$ ).*

Before proving Lemma 5, we use it to prove the correctness of our algorithm, i.e., we prove that if the algorithm reports  $\lambda < \lambda^*$ , then no feasible solution exists.

Suppose our algorithm reports  $\lambda < \lambda^*$  in the  $i$ -th iteration. Then, according to our algorithm,  $b_{h_{i-1}}$  is not covered by any sensor in  $C_{i-1}$  and  $S_{i1} = S_{i2} = \emptyset$ . By Lemma 5 (replacing the index  $i$  in the lemma by  $i - 1$ ),  $[0, h_{i-1} - 1]$  is the largest prefix interval that can be covered by sensors of  $S'_{i-1}$ . According to our algorithm invariants, the covering disk of each sensor of  $S_{i-1}$  is strictly to the left of  $b_{h_{i-1}}$  in  $C_{i-1}$ . Hence,  $S_{i-1}$  is a subset of  $S'_{i-1}$ . Since both  $S_{i1}$  and  $S_{i2}$  are empty in  $C_{i-1}$ , no sensor in  $S \setminus S'_{i-1}$  can cover the barrier point  $b_{h_{i-1}}$ . Therefore, it is not possible to cover all barrier points in the interval  $[0, h_{i-1}]$  using the sensors of  $S$  (with respect to the maximum moving cost  $\lambda$ ). This implies that no feasible solution exists.

#### 4.4 Proof of Lemma 5

We now prove Lemma 5. We follow the notation in Lemma 5. Note that according to our algorithm invariants,  $S_i = \{s_{g_1}, s_{g_2}, \dots, s_{g_i}\}$  is a subset of  $S'_i$ .

We first prove the following lemma and then use the lemma to prove Lemma 5.

**Lemma 6** *If  $C$  is a configuration in which a prefix interval  $[0, t]$  is covered by the sensors of  $S'_i$ , then there also exists a configuration  $C^*$  in which  $[0, t]$  is covered and the location of each sensor  $s_{g_j}$  of  $S_i$  in  $C^*$  is the same as its location in  $C_i$ .*

**Proof:** We prove the lemma by induction. We assume that the lemma statement holds for  $k - 1$ ,  $1 \leq k \leq i$ , i.e., there exists a configuration  $C'$  in which the interval  $[0, t]$  is covered and the location of each sensor  $s_{g_j}$  of  $S_i$  with  $1 \leq j \leq k - 1$  in  $C^*$  is the same as its location in  $C_i$  (i.e.,  $x'_{g_j}$ ). The assumption trivially holds for  $k = 1$ . Below we show that the lemma statement holds for  $k$ .

Our goal is to find a configuration  $C''$  in which barrier points of the interval  $[0, t]$  are also covered and the location of each sensor  $s_{g_j}$  of  $S_i$  with  $1 \leq j \leq k$  in  $C''$  is  $x'_{g_j}$ . We refer to such a configuration that satisfies the above condition as a *satisfying configuration*.

According to our algorithm, in the configuration  $C_k$ ,  $s_{g_j}$  is at  $x'_{g_j}$  for all  $1 \leq j \leq k$ , and the interval  $[0, h_k - 1]$  is covered by sensors of  $S_k$ . Hence, if  $t \leq h_k - 1$ , then we can simply let  $C'' = C_k$ , which is a satisfying configuration. In the following, we assume that  $t \geq h_k$ . Let  $x_{C'}(s_{g_k})$  be the location of  $s_{g_k}$  in the configuration  $C'$ . If  $x_{C'}(s_{g_k}) = x'_{g_k}$ , then let  $C'' = C'$ , which is a satisfying configuration. In what follows, we assume that  $x_{C'}(s_{g_k}) \neq x'_{g_k}$ . According to our algorithm,  $s_{g_k}$  is either from  $S_{k1}$  or from  $S_{k2}$ . We discuss the two cases below.

The case  $s_{g_k} \in S_{k1}$  If  $s_{g_k}$  is from  $S_{k1}$ , then according to our algorithm,  $x'_{g_k} = x^r_{g_k}$ . As  $x_{C'}(s_{g_k}) \neq x'_{g_k}$ , it must be that  $x_{C'}(s_{g_k}) < x'_{g_k}$ . Let  $C''$  be the configuration obtained from  $C'$  by moving  $s_{g_k}$  from  $x_{C'}(s_{g_k})$  rightwards to  $x'_{g_k}$ . In the following, we show that  $C''$  is a satisfying configuration.

Indeed, in light of the induction hypothesis, the location of each sensor  $s_{g_j}$  of  $S_i$  with  $1 \leq j \leq k$  in  $C''$  is  $x'_{g_j}$  (i.e., the same as its location in  $C_i$ ). Thus, it suffices to show that the interval  $[0, t]$  is covered by sensors of  $S'_i$  in  $C''$ . Consider any barrier point  $b_l$  with  $l \in [1, t]$ .

- If  $l \leq h_k - 1$ , then according to our algorithm,  $b_l$  is covered by a sensor  $s$  in  $S_k$  in  $C_i$ . As  $S_k \subseteq S_i \subseteq S'_i$ ,  $s$  is in  $S'_i$ . Further, since  $s \in S_k$ , its location position in  $C''$  is the same as in  $C_i$ . Therefore,  $b_l$  is covered by  $s$  in  $C''$  and thus  $b_l$  is covered by sensors of  $S'_i$  in  $C''$  since  $s \in S'_i$ .
- If  $l \geq h_k$ , then depending on whether  $b_l$  is covered by a sensor of  $S_k$  in  $C_i$ , there are two subcases. If  $b_l$  is covered by a sensor of  $S_k$  in  $C_i$ , then following the same analysis as above,  $b_l$  is covered by sensors of  $S'_i$  in  $C''$ . Otherwise, since the locations of the sensors of  $S_{k-1}$  in  $C''$  are the same as in  $C'$ ,  $b_l$  must be covered in  $C'$  by either  $s_{g_k}$  or a sensor in  $S'_i \setminus S_k$ .

We claim that  $b_l$  cannot be covered by  $s_{g_k}$  in  $C'$ . Indeed, according to our algorithm invariants, the covering disk of  $s_{g_k}$  is strictly to the left of  $b_{h_k}$  in  $C_k$ . Since  $x_{C'}(s_{g_k}) < x'_{g_k}$ , i.e., the location of  $s_{g_k}$  in  $C'$  is strictly to the left of its location in  $C_k$ , the covering disk  $D(s_{g_k})$  is also strictly to the left of  $b_{h_k}$  in  $C'$ . Since  $l \geq h_k$ , by our definition of the indices of the barrier points,  $b_l$  cannot be in  $D(s_{g_k})$  in  $C'$ .

The above claim implies that  $b_l$  is covered in  $C'$  by a sensor  $s$  of  $S'_i \setminus S_k$ . Since the location of  $s$  in  $C''$  is the same as its location in  $C'$ ,  $s$  still covers  $b_l$  in  $C''$ . Therefore,  $b_l$  is covered by sensors of  $S'_i$  in  $C''$ .

This proves that  $C''$  is a satisfying configuration.

The case  $s_{g_k} \in S_{k2}$  If  $s_{g_k}$  is from  $S_{k2}$ , then according to our algorithm,  $S_{k1} = \emptyset$  and  $s_{g_k}$  is the leftmost sensor of  $S_{k2}$  in the configuration  $C_{k-1}$  and  $x'_{g_k}$  is the rightmost location for  $s_{g_k}$  to cover  $b_{h_{k-1}}$  (i.e.,  $b_{h_{k-1}}$  is on the left half-circle of  $\partial D(s_{g_k})$ ). If  $x_{C'}(s_{g_k}) < x'_{g_k}$ , then we can use the same argument as the above case to obtain a satisfying configuration. In the following, we assume that  $x_{C'}(s_{g_k}) > x'_{g_k}$ . This also implies that  $s_{g_k}$  does not cover  $b_{h_{k-1}}$

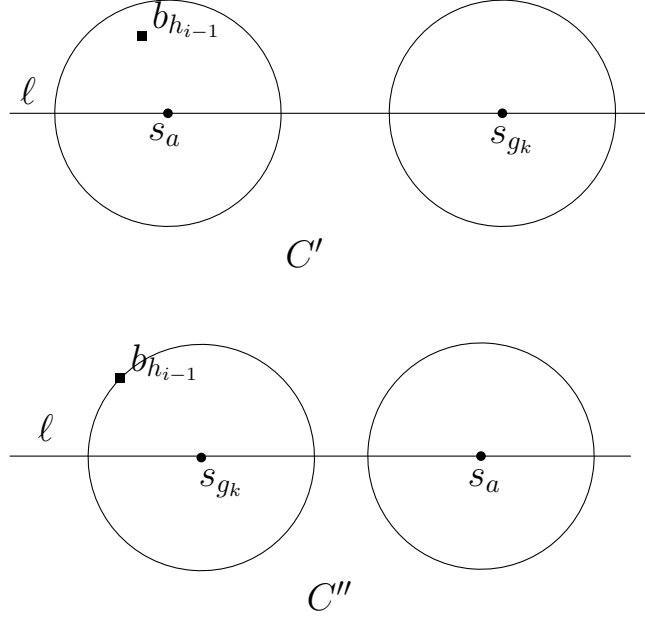


Fig. 4.3: Illustrating the sensors  $s_a$  and  $s_{g_k}$  in the two configurations  $C'$  and  $C''$ .

in  $C'$ . Since  $t \geq h_k > h_{k-1}$ , there must be a sensor  $s_a$  that covers the barrier point  $b_{h_{k-1}}$  in  $C'$ . Also, because  $S_{k1} = \emptyset$  and the positions of the sensors  $s_{g_j}$  for all  $1 \leq j \leq k-1$  in  $C'$  are the same as in  $C_{k-1}$ ,  $s_a$  must be from  $S_{k2}$ . As  $s_{g_k}$  is the leftmost sensor of  $S_{k2}$  in  $C_{k-1}$ , it must hold that  $x_{g_k}^r \leq x_a^r$ .

Let  $C''$  be the configuration obtained from  $C'$  by moving  $s_a$  to  $x_{C'}(s_{g_k})$  and moving  $s_{g_k}$  to  $x'_{g_k}$ , i.e.,  $s_a$  moves to the position of  $s_{g_k}$  in  $C'$  and  $s_{g_k}$  moves to its position in  $C_k$  (e.g., see Fig. 4.3). Below we argue that  $C''$  is a satisfying configuration. For this, we will show the following: (1) The interval  $[0, t]$  is still covered by sensors of  $S'_i$  in  $C''$ ; (2) the moving cost of  $s_a$  is no more than  $\lambda$  (note that since the position of  $s_{g_k}$  in  $C''$  is the same as its position in  $C_k$ , we know that its moving cost in  $C''$  is no more than  $\lambda$ ; other sensors do not change locations from  $C'$  to  $C''$ ).

We first prove the above (1). Since the locations of the sensors of  $s_{g_j}$  for all  $j \in [1, k]$  in  $C''$  are the same as their locations in  $C_k$ , these sensors together cover all barrier points of the interval  $[0, h_k - 1]$ . Consider any other barrier point  $b_l$  with  $l \in [h_k, t]$ . To prove (1), it suffices to show that  $b_l$  is covered by a sensor of  $S'_i$  in  $C''$ . Recall that  $b_l$  is covered by a sensor of  $S'_i$  in  $C'$ ; let  $s$  be such a sensor.



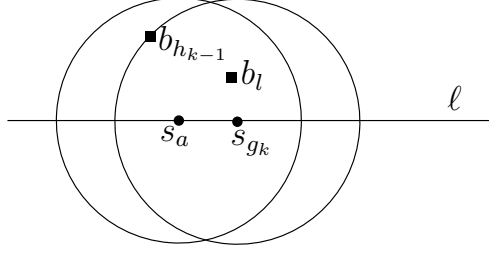


Fig. 4.4: Illustrating the relative positions of  $s_a$ ,  $s_{g_k}$ ,  $b_{h_{k-1}}$ , and  $b_l$ : the locations of  $s_a$  and  $s_{g_k}$  are  $x_{C'}(s_a)$  and  $x'_{g_k}$ , respectively.

1. If  $s$  is  $s_{g_j}$  for any  $j \leq k-1$ , since  $s$  has the same location in  $C'$  and  $C''$ ,  $s$  also covers  $b_l$  in  $C''$ .
2. If  $s$  is  $s_a$ , then we claim that  $b_l$  must be covered by  $s_{g_k}$  in  $C''$ . Indeed, recall that  $b_{h_{k-1}}$  is on the left half-circle of the covering disk of  $s_{g_k}$  when  $s_{g_k}$  is at  $x'_{g_k}$  in  $C''$  (and also in  $C_k$ ). Since  $b_{h_{k-1}}$  is covered by  $s_a$  in  $C'$ , we obtain that  $x_{C'}(s_a) \leq x'_{g_k}$ , where  $x_{C'}(s_a)$  is the location of  $s_a$  in  $C'$  (e.g., see Fig. 4.4). Since  $s_a$  also covers  $b_l$  and  $l \geq h_k > h_{k-1}$ , if we move a disk  $D$  of radius  $r$  centered at  $x_{C'}(s_a)$  rightwards until  $x'_{g_k}$ ,  $D$  starts at the covering disk of  $s_a$  in  $C'$  and stops at the covering disk of  $s_{g_k}$  in  $C''$ . Hence, in the beginning of the movement of  $D$ , it covers  $b_l$ , and at the end of the movement,  $b_{h_{k-1}}$  is on the left half-circle of  $\partial D$ . Since  $l > h_{k-1}$ , during the above movement of  $D$ , its left half-circle cannot encounter the barrier point  $b_l$ . This implies that  $b_l$  is always inside  $D$  during the movement of  $D$ . This further implies that  $b_l$  is covered by  $s_{g_k}$  in  $C''$ .
3. If  $s$  is  $s_{g_k}$ , then since  $s_a$  moves to the position of  $s_{g_k}$  in  $C''$ ,  $s_a$  also covers  $b_l$  in  $C''$ .
4. If  $s$  is not a sensor in the above three cases, then  $s$  does not change its location from  $C'$  to  $C''$ . Hence,  $s$  still covers  $b_l$  in  $C''$ .

In summary, the barrier point  $b_l$  is still covered by sensors of  $S'_i$  in  $C''$ .

We proceed to prove the above (2), i.e., the moving cost of  $s_a$  is no more than  $\lambda$  in  $C''$ .

Let  $x_{C''}(s_a)$  denote the location of  $s_a$  in  $C''$ . It suffices to show that  $x_{C''}(s_a) \in [x_a^l, x_a^r]$ .

According to our definition of  $C''$ ,  $x_{C''}(s_a) = x'_{g_k}$ . Recall that  $x^r_{g_k} \leq x^r_a$ . Since  $x'_{g_k} \leq x^r_{g_r}$ , we obtain that  $x_{C''}(s_a) = x'_{g_k} \leq x^r_{g_r} \leq x^r_a$ .

On the other hand, recall that  $x'_{g_k} < x_{C'}(s_{g_k}) = x_{C''}(s_a)$ . Also,  $x_{C'}(s_a) \geq x^l_a$ , where  $x_{C'}(s_a)$  is the location of  $s_a$  in  $C'$ . Since  $b_{h_{k-1}}$  is on the left half-circle of  $\partial D(s_{g_k})$  when  $s_{g_k}$  is at  $x'_{g_k}$  and  $b_{h_{k-1}}$  is covered by  $s_a$  in  $C'$  when  $s_a$  is at  $x_{C'}(s_a)$ , we obtain that  $x_{C'}(s_a) \leq x'_{g_k}$ . Therefore, we can derive  $x^l_a \leq x_{C'}(s_a) \leq x'_{g_k} < x_{C'}(s_{g_k}) = x_{C''}(s_a)$ .

This proves that  $x_{C''}(s_a) \in [x^l_a, x^r_a]$ . Hence,  $C''$  is a satisfying configuration.  $\square$

Proving Lemma 5 In what follows, we use Lemma 6 to prove Lemma 5.

Let  $[0, t]$  be the largest prefix interval of sensors that can be covered by sensors of  $S'_i$  (with respect to the maximum moving cost  $\lambda$ ). By Lemma 6, there exists a configuration  $C^*$  in which  $[0, t]$  is still covered and the location of each sensor  $s_{g_j}$  of  $S_i$  in  $C^*$  is the same as its location in  $C_i$ , i.e.,  $x'_{g_j}$ .

Consider any sensor  $s_k \in S'_i \setminus S_i$ . According to our algorithm,  $s_k$  is at  $x^r_k$ . By the definition of  $S'_i$ , the covering disk  $D(s_k)$  is strictly to the left of  $b_{h_i}$  in  $C_i$ . Hence,  $s_k$  cannot be used to cover  $b_{h_i}$  in any configuration (with respect to  $\lambda$ ), in particular, in  $C^*$ . On the other hand, according to our algorithm, all barrier points of the interval  $[0, h_i - 1]$  are covered by sensors of  $S_i$  in  $C_i$ . As the sensors of  $S_i$  have the same locations in  $C^*$  as in  $C_i$ , all barrier points of  $[0, h_i - 1]$  are covered by sensors of  $S_i$  in  $C^*$ . Combining the above, we can conclude that  $[0, h_i - 1]$  is the largest prefix interval that can be covered by sensors of  $S'_i$  in  $C^*$ , i.e.,  $t = h_i - 1$ . This proves Lemma 5.

#### 4.5 The Algorithm Implementation

We now provide an efficient way to implement the algorithm in  $O((n + m) \log(n + m))$  time. For differentiation, we use “algorithm implementation” to refer to the algorithm we will discuss below and use “algorithm description” to refer to the algorithm we described before in Section 4.2.

We sweep a point  $p$  on  $\ell$  from left to right. The event point set is  $E = \{c(b) \mid b \in B\} \cup \{x^l_i, x^r_i \mid s_i \in S\}$ . We sort all points of  $E$  from left to right on  $\ell$  and put them in a list,

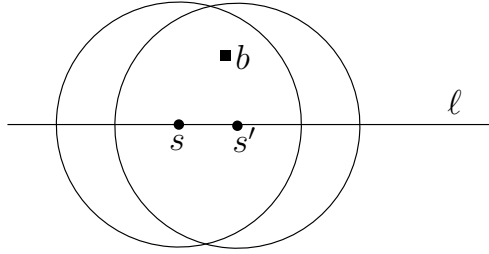


Fig. 4.5: Illustrating Observation 2.

still denoted by  $E$ . Using the sorted list  $E$  as a guide, we sweep  $p$  on  $\ell$  from left to right. When  $p$  encounters a point  $x_k^l$  for some sensor  $s_k$ , we insert  $s_k$  to a balanced binary search tree  $T$  in which the sensors  $s_k$  are ordered by their values  $x_k^r$ . As will be shown later, the tree  $T$  is used to maintain the set  $S_{i2}$ . When  $p$  encounters a point  $x_k^r$ , we remove  $s_k$  from  $T$  and store  $s_k$  at a variable  $s^*$  (if  $s^*$  already stores a sensor, we simply update  $s^*$  to  $s_k$ ). Our algorithm implementation maintains the following invariant: the sensor  $s_k$  stored in  $s^*$  and all sensors of  $T$  are at their positions in  $C_0$ .

Now consider the case where  $p$  encounters  $c(b_j)$  for some barrier point  $b_j$ . We assume that  $j$  is equal to  $h_{i-1}$  for some  $i$  as defined in the algorithm description. The assumption is true initially when  $j = 1$  and  $i = 1$ . This means that we are at the beginning of the  $i$ -th iteration in the algorithm description. We first need to check whether  $S_{i1} = \emptyset$ . To this end, we have the following Lemma 7. But before giving Lemma 7, we prove the following observation, which will be used in the proofs of Lemma 7 and other lemmas.

**Observation 2** *Consider a barrier point  $b$  and two sensors  $s$  and  $s'$ . Suppose the followings hold (e.g., see Fig. 4.5): (1)  $s'$  is to the right of  $s$ ; (2)  $s$  covers  $b$ ; (3)  $b$  is to the right of the left half-circle of  $\partial D(s')$ . Then,  $s'$  also covers  $b$ .*

**Proof:** Assume to the contrary that  $s'$  does not cover  $b$ . Then, since  $b$  is to the right of the left half-circle of  $\partial D(s')$ ,  $b$  must be strictly to the right of the right half-circle of  $\partial D(s')$ . Because  $s'$  is to the right of  $s$ ,  $b$  must also be strictly to the right of the right half-circle of  $\partial D(s)$ . But this means that  $s$  does not cover  $b$ , a contradiction.  $\square$

**Lemma 7** *If the sensor  $s_k$  stored in  $s^*$  covers  $b_j$  when  $s_k$  is at  $x_k^r$ , then  $s_k \in S_{i1}$ ; otherwise (including the case where  $s^*$  does not store any sensor)  $S_{i1} = \emptyset$ .*

**Proof:** Suppose the sensor  $s_k$  stored in  $s^*$  covers  $b_j$  when  $s_k$  is at  $x_k^r$ . To prove the lemma, it suffices to show that if  $S_{i1} \neq \emptyset$ , then  $s_k$  must be in  $S_{i1}$ . In the following, we assume that  $S_{i1} \neq \emptyset$ . Our goal is to prove that  $s_k$  is in  $S_{i1}$ . Since  $s_k$  is stored in  $s^*$ , according to our algorithm implementation invariant,  $s_k$  is at  $x_k^r$ . Hence, to prove  $s_k \in S_{i1}$ , by the definition of  $S_{i1}$ , it is sufficient to show that  $s_k$  covers  $b_j$  (when  $s_k$  is at  $x_k^r$ ).

Let  $s_a$  be a sensor of  $S_{i1}$ . If  $s_a$  is  $s_k$ , then it is vacuously true that  $s_k \in S_{i1}$ . In what follows, we assume that  $s_a$  is not  $s_k$ . Because  $s_a$  is in  $S_{i1}$ , according to our algorithm description,  $s_a$  is at  $x_a^r$  and has never been moved during the algorithm, and further,  $s_a$  covers  $b_j$ . Since the sweeping point  $p$  is at  $c(b_j)$ , which is the rightmost position on  $\ell$  for the center of a circle of radius  $r$  to cover  $b_j$ ,  $p$  must have passed  $x_a^r$ . Therefore, according to our algorithm implementation,  $s_a$  had been stored in  $s^*$  before and later  $s^*$  got updated to  $s_k$ . This implies that  $s_k$  is to the right of  $s_a$  (and both of them are at their rightmost  $\lambda$ -reachable locations). Because  $p$  is now at  $c(b_j)$ ,  $p$  has already passed  $x_k^r$ . Therefore,  $b_j$  is to the right of left half-circle of  $\partial D(s_k)$ . Since  $b_j$  is covered by  $s_a$  and  $s_k$  is to the right of  $s_a$ , by Observation 2,  $b_j$  must be covered by  $s_k$ .  $\square$

By Lemma 7, if  $s^*$  does not store any sensor or if the sensor stored at  $s^*$  does not cover  $b_j$ , then  $S_{i1} = \emptyset$ . Otherwise, the sensor stored at  $s^*$ , denoted by  $s_k$ , covers  $b_j$  and is in  $S_{i1}$ . Depending on whether  $S_{i1} = \emptyset$ , there are two cases to proceed.

**The case  $S_{i1} \neq \emptyset$**  We first consider the case  $S_{i1} \neq \emptyset$ . In this case, according to our algorithm description, we can simply choose  $s_k$  as  $s_{g_i}$  and add it to  $S_{i-1}$  to obtain  $S_i$ . Next, we need to determine  $h_i$ , which is equal to  $l + 1$  with  $l$  as the largest index such that all barrier points  $b_j, b_{j+1}, \dots, b_l$  can be covered by sensors of  $S_i$ . To find  $l$ , we initialize  $l = j$  and then keep sweeping  $p$  rightwards. If  $p$  encounters a point  $x_k^l$  or  $x_k^r$ , we process the event in the same way as before. If  $p$  encounters a point  $c(b_{j'})$ , we know that  $j' = l + 1$ . We need to determine whether  $b_{j'}$  can be covered by sensors of  $S_i$ . For this, we have the following lemma.

**Lemma 8**  $b_{j'}$  can be covered by sensors of  $S_i$  if and only if  $b_{j'}$  can be covered by  $s_{g_i}$ .

**Proof:** If  $b_{j'}$  is covered by  $s_{g_i}$ , then it is vacuously true that  $b_{j'}$  is covered by sensors of  $S_i$  because  $s_{g_i}$  is in  $S_i$ .

Now assume that  $b_{j'}$  is covered by a sensor  $s_{g_a} \in S_i$ . We need to prove that  $s_{g_i}$  also covers  $b_{j'}$ . This is obviously true if  $a = i$ . We now assume  $a \neq i$ , implying that  $a < i$ . According our algorithm implementation,  $b_{j'}$  is to the right of the left half-circle of  $\partial D(s_k)$  and  $s_{g_i} = s_k$ . According to our algorithm invariants in the algorithm description,  $s_{g_a}$  is to the left of  $s_{g_i}$ . Since  $s_{g_a}$  covers  $b_{j'}$ , by Observation 2,  $s_{g_i}$  also covers  $b_{j'}$ .  $\square$

In light of Lemma 8, we check whether  $b_{j'}$  is covered by  $s_{g_i}$ . If yes, we increment  $l$  by one and proceed as above (if  $l = n$ , then all barrier points are covered and we can stop the algorithm and report  $\lambda \geq \lambda^*$ ). Otherwise, we set  $h_i = j'$ ; in this case, we have finished the  $i$ -th iteration of the algorithm and we then proceed to the  $(i + 1)$ -th iteration.

**The case  $S_{i1} = \emptyset$**  We now consider the case  $S_{i1} = \emptyset$ . In this case, we need to know whether  $S_{i2} = \emptyset$ , and if not, we need to find the leftmost sensor in  $S_{i2}$ . For this, we have the following lemma.

**Lemma 9** *The sensors stored in the current tree  $T$  are exactly the sensors of  $S_{i2}$ .*

**Proof:** We prove the lemma by analyzing our algorithm implementation. Recall that the sweeping point  $p$  is now at  $c(b_j)$  and  $j = h_{i-1}$ .

- Let  $s_a$  be a sensor of  $S_{i2}$ . We show that  $s_a$  is stored in  $T$ . Indeed, since  $s_a$  is in  $S_{i2}$ , by the definition of  $S_{i2}$ , we have  $x_a^l \leq c(b_j) < x_a^r$ . According to our algorithm implementation, when  $p$  encounters  $x_a^l$ ,  $s_a$  is inserted to  $T$  and will not be removed from  $T$  until  $p$  counters  $x_a^r$ . Since  $p$  is at  $c(b_j)$  right now and  $c(b_j) < x_a^r$ ,  $s_a$  is still in  $T$ .
- Let  $s_a$  be a sensor stored in  $T$ . We show that  $s_a$  is in  $S_{i2}$ . Indeed, since  $s_a$  is in  $T$ , according to our algorithm implementation,  $p$  has already passed  $x_a^l$  but not encountered  $x_a^r$  yet. Since  $p$  is at  $c(b_j)$  right now, we obtain that  $x_a^l \leq c(b_j) < x_a^r$ .

Further, according to our algorithm implementation invariant,  $s_a$  has not been moved from its position in  $C_0$ , i.e.,  $s_a$  is still at  $x_a^r$ . Therefore,  $s_a$  is in  $S_{i2}$ .

This proves the lemma. □

In light of Lemma 9, we can use  $T$  to find the leftmost sensor of  $T$  in  $O(\log n)$  time; let  $s_k$  denote the sensor. We choose  $s_k$  as  $s_{g_i}$  and add it to  $S_{i-1}$  to obtain  $S_i$ . Then, we move  $s_k$  leftwards to  $c(b_j)$ , i.e., setting  $x_k^l = c(b_j)$ , and remove  $s_k$  from  $T$ . We also remove both events  $x_k^l$  and  $x_k^r$  from the list  $E$  because we do not need to process these two events anymore.<sup>1</sup> Next, we need to determine  $h_i$ . This can be done using the same method as in the above case where  $S_{i1} \neq \emptyset$  (i.e., keep sweeping  $p$  rightwards and making use of Lemma 8, which is still applicable here). After  $h_i$  is found, we finish the  $i$ -th iteration of the algorithm and begin the  $(i + 1)$ -th iteration.

This finishes the description of the algorithm implementation. The proof of the following lemma analyzes the running time of the algorithm.

**Lemma 10** *Given any  $\lambda$ , whether  $\lambda \geq \lambda^*$  can be decided in  $O((m + n) \log(n + m))$  time.*

**Proof:** We analyze the running time of our implementation. In the beginning, computing the sorted list  $E$  takes  $O((m + n) \log(m + n))$  time. There are  $O(n + m)$  operations on  $E$ , each of which takes  $O(1)$  time. The time we spent on the binary search tree  $T$  is bounded by  $O(n \log n)$  as there are  $n$  sensors and each sensor can be inserted and removed from  $T$  at most once (also, there are at most  $n$  operations of “finding the leftmost sensor”). Therefore, the total time of the algorithm is  $O((n + m) \log(n + m))$ . More specifically, after the points of  $E$  are sorted in  $O((m + n) \log(m + n))$  time, the rest of the algorithm takes  $O(m + n \log n)$  time. □

#### 4.6 The Optimization Problem

We now solve the optimization problem, i.e., computing  $\lambda^*$ , by using the algorithm of Lemma 10 as a subroutine. We begin with the following lemma.

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<sup>1</sup>To implement each remove operation in constant time, we can store the list  $E$  by a doubly-linked list and associate each of the values  $x_a^l$  and  $x_a^r$  for all sensors  $s_a \in S$  with a pointer pointing to its location in  $E$ .

**Lemma 11**  $\lambda^*$  is equal to  $(x_i - \sqrt{r^2 - y_{b_j}^2} - x_{b_j})/w_i$  or  $(x_{b_j} - \sqrt{r^2 - y_{b_j}^2} - x_i)/w_i$  for a sensor  $s_i$  and a barrier point  $b_j$ .

**Proof:** The proof is almost the same as that of Lemma 2 except that we have to consider the weight in the last step of the proof. We briefly discuss it below.

Consider an optimal solution  $OPT$ , where  $\lambda^*$  is the maximum moving cost of all sensors. Then,  $\lambda^*$  is equal to the moving cost of some sensor  $s_i$ . Let  $x'_i$  be the  $x$ -coordinate of  $s_i$  in  $OPT$ . If  $x'_i < x_i$ , then  $s_i$  has been moved leftwards and there must be a barrier point  $b_j$  on the left-circle of  $\partial D(s_i)$ . Thus, we have  $x'_i = \sqrt{r^2 - y_{b_j}^2} + x_{b_j}$ . Hence,  $\lambda^* = (x_i - x'_i)/w_i = (x_i - \sqrt{r^2 - y_{b_j}^2} - x_{b_j})/w_i$ . If  $x'_i > x_i$ , by similar analysis, we can show that  $\lambda^* = (x_{b_j} - \sqrt{r^2 - y_{b_j}^2} - x_i)/w_i$ .  $\square$

For each sensor  $s_i$ , we will define two sorted arrays  $A_i[1 \cdots m]$  and  $B_i[1 \cdots m]$  of size  $m$  each. Unlike the unweighted case where defining sorted arrays is relatively straightforward, here the definitions are quite subtle. We define the array  $A_i$  first, which consists of the values  $(x_i - \sqrt{r^2 - y_{b_j}^2} - x_{b_j})/w_i$  for all  $j = 1, \dots, m$ . For each  $j \in [1, m]$ , let  $a_j = \sqrt{r^2 - y_{b_j}^2} + x_{b_j}$ . We sort the values  $a_j$  for all  $j = 1, \dots, m$  in ascending order. For each  $j \in [1, m]$ , we let  $\pi(j) = k$  if  $a_k$  ranks the  $j$ -th place in the above sorted list. Hence,  $\pi(\cdot)$  is a permutation of the indices  $1, 2, \dots, m$ ; note that we can obtain  $\pi(\cdot)$  in  $O(m \log m)$  time. For each  $j \in [1, m]$ , we define  $A_i[j] = (x_i - a_{\pi(j)})/w_i$ . In light of the definition of  $\pi(\cdot)$ ,  $A_i$  is a sorted array. Analogously, we can define a sorted array  $B_i$  for the  $m$  values  $(x_{b_j} - \sqrt{r^2 - y_{b_j}^2} - x_i)/w_i$ ,  $j = 1, \dots, m$ . Note that the permutation  $\pi(\cdot)$  can be used to define  $A_i$  for all  $i = 1, 2, \dots, n$ . Hence, in  $O(n + m \log m)$  time, we can implicitly form  $2n$  sorted arrays  $A_i$  and  $B_i$  for all  $i = 1, 2, \dots, n$ , such that given any index  $j$  and any array  $A_i$  (resp.,  $B_i$ ), we can obtain the array element  $A_i[j]$  (resp.,  $B_i[j]$ ) in  $O(1)$  time. Also, Lemma 11 implies that  $\lambda^*$  is the smallest feasible value of all elements of these arrays. By applying Lemma 3 and using our decision algorithm in Lemma 10, we can find  $\lambda^*$  in  $O((n + m) \log^2(n + m))$  time. We summarize our result in the following theorem.

**Theorem 2** *Given a set of  $m$  barrier points in the plane and a set of  $n$  weighted sensors on a line  $\ell$ , the problem of moving sensors on  $\ell$  to cover all barrier points such that the*

*maximum moving cost of all sensors is minimized can be solved in  $O((m+n)\log^2(m+n))$  time.*



## CHAPTER 5

## THE MOBILE INTERVAL COVERAGE PROBLEM

In this chapter, we consider the mobile interval coverage problem, where the barrier points are on the  $x$ -axis  $\ell$  while the sensors can be anywhere in the plane. The problem is to move all sensors to  $\ell$  to cover all barrier points so that the minimum moving cost of all sensors is minimized.

We first sort all barrier points from left to right on  $\ell$  in  $O(m \log m)$  time; let  $B = \{b_1, b_2, \dots, b_m\}$  be the sorted list. Recall that for each sensor  $s_i \in S$ ,  $(x_i, y_i)$  is its coordinate. In the weighted case, each sensor  $s_i$  has a weight  $w_i > 0$ . In the following, we only give an algorithm for the weighted case because we do not have a faster algorithm for the unweighted case. Our goal is to compute the optimal moving cost  $\lambda^*$ . Note that since we require that all sensors finally move to  $\ell$ , it must hold that  $\lambda^* \geq \max_{1 \leq i \leq n} w_i \cdot y_i$ .

We again first consider the decision problem: Given any  $\lambda$ , decide whether  $\lambda \geq \lambda^*$ . We present an algorithm of  $O(m + n \log n)$  time (not including the time for sorting the barrier points) for the problem. Later we will solve the optimization problem (i.e., computing  $\lambda^*$ ) using Lemma 3 and the decision algorithm.

### 5.1 The Decision Problem

Consider a value  $\lambda$ . We assume that  $\lambda \geq \max_{1 \leq i \leq n} w_i \cdot y_i$  since otherwise it is impossible to move all sensors to  $\ell$  (and thus we immediately report  $\lambda < \lambda^*$ ). For each sensor  $s_i$ , define  $x_i^r = x_i + \sqrt{(\lambda/w_i)^2 - y_i^2}$  and  $x_i^l = x_i - \sqrt{(\lambda/w_i)^2 - y_i^2}$ . We call  $x_i^r$  (resp.,  $x_i^l$ ) the *rightmost* (resp., *leftmost*)  $\lambda$ -reachable location of  $s_i$ .

At the outset, we move each sensor  $s_i$  to  $x_i^r$  on  $\ell$ . Let  $C_0$  denote the resulting configuration. The rest of the algorithm is similar to the one in Section 4.1. In fact, we can basically apply the same algorithm. But since the problem setting here is simpler (because all barrier points are now on  $\ell$ ), below we describe the algorithm in a simpler way (the

running time is also slightly faster if  $m$  is significantly larger than  $n$ ).

Consider the  $i$ -th iteration of the algorithm (initially  $i = 1$ ). Let  $C_{i-1}$  denote the configuration right before the iteration. Our algorithm maintains the following invariants:

1. A subset  $S_{i-1} = \{s_{g(1)}, s_{g(2)}, \dots, s_{g(i-1)}\}$  of sensors has been computed.
2. In  $C_{i-1}$ , each sensor  $s_k$  of  $S_{i-1}$  is at a location, denoted by  $x'_k$ , which may not be equal to  $x_k^r$ , while sensors of  $S \setminus S_{i-1}$  are still in their locations of  $C_0$ .
3. An index  $h_{i-1}$  of a barrier point is maintained such that in the configuration  $C_{i-1}$ , the barrier point  $b_{h_{i-1}}$  is not covered by any sensor of  $S_{i-1}$  while  $b_k$  is covered by a sensor in  $S_{i-1}$  for each  $k < h_{i-1}$ .
4. Each sensor of  $S_{i-1}$  covers at least one barrier point  $b_j$  with  $j < h_{i-1}$  in  $C_{i-1}$ .
5. The locations of the sensors  $s_{g_1}, s_{g_2}, \dots, s_{g_{i-1}}$  in  $C_{i-1}$  are sorted from left to right on  $\ell$ .
6. The barrier point  $b_{h_{i-1}}$  is strictly to the right of the covering disk  $D(s_{g_{i-1}})$  of  $s_{g_{i-1}}$  if  $S_{i-1} \neq \emptyset$ .

Initially when  $i = 1$ , we have  $S_0 = \emptyset$  and set  $h_0 = 1$ ; thus all algorithm invariants hold. The  $i$ -th iteration of the algorithm finds a sensor  $s_{g_i}$  from  $S \setminus S_{i-1}$  and move it to a new location  $x'_{g_i}$ ; we thus obtain a new configuration  $C_i$  with  $S_i = S_{i-1} \cup \{s_{g_i}\}$ . We briefly discuss algorithm below.

Define  $S_{i1}$  be the set of sensors that cover the barrier point  $b_{h_{i-1}}$  in  $C_{i-1}$ . Again, due to our algorithm invariants,  $S_{i1} \subseteq S \setminus S_{i-1}$ .

If  $S_{i1} \neq \emptyset$ , we choose an arbitrary sensor in  $S_{i1}$  as  $s_{g_i}$  and set  $x'_{g_i} = x_{g_i}^r$ . Hence,  $C_i = C_{i-1}$ . Next, we set  $h_i = k + 1$ , where  $k$  is the largest index such that all barrier points of  $[h_{i-1}, k]$  are covered by  $S_i$  (it is easy to see that a barrier point  $b_l$  with  $l \geq h_{i-1}$  is covered by  $S_i$  if and only if  $b_l$  is covered by  $s_{g_i}$ , i.e., Lemma 8 is still applicable). If  $k = m$ , then we stop the algorithm and report  $\lambda \geq \lambda^*$ .

If  $S_{i1} = \emptyset$ , we define  $S_{i2}$  as the set of sensors of  $S \setminus S_{i-1}$  that do not cover  $b_{h_{i-1}}$  in  $C_{i-1}$  but can be moved leftwards to cover  $b_{h_{i-1}}$ . If  $S_{i2} \neq \emptyset$ , we choose the leftmost sensor of  $S_{i2}$  as  $s_{g_i}$  and set  $x'_{g_i} = x_b + r$  to obtain a new configuration  $C_i$ , where  $b = b_{h_{i-1}}$ . Next, we set  $h_i$  in the same way as above. If  $S_{i2} = \emptyset$ , then we terminate the algorithm and report  $\lambda < \lambda^*$ .

The algorithm will terminate in at most  $\min\{m, n\}$  iterations. The correctness of the algorithm can be proved in a similar way as before.

To implement the algorithm, we first sort the barrier points in the preprocessing, which takes  $O(m \log m)$  time. Then, given any  $\lambda$ , we can implement the algorithm in  $O(m + n \log n)$  time using essentially the same implementation as in Section 4.1. We briefly discuss it below.

We first compute  $x_i^r$  and  $x_i^l$  for each sensor  $s_i \in S$ , and sort all these  $2n$  values in  $O(n \log n)$  time. Then, we compute the value  $c(b)$  for each barrier point  $b \in B$ . Unlike in Section 4.1, here the value  $c(b)$  is fixed and does not depend on  $\lambda$ , and the sorted list of  $c(b)$  of all barrier points  $b \in B$  is consistent with the sorted list of all barrier points  $b \in B$ . Since the sorted list of  $B$  is already computed in the preprocessing, we can obtain the sorted list of  $c(b)$  for all barrier points  $b \in B$  in  $O(m)$  time. By merging it with the sorted list of  $x_i^r$  and  $x_i^l$  for all sensors  $s_i \in S$ , we can obtain the sorted list of the event set  $E = \{c(b) \mid b \in B\} \cup \{x_i^l, x_i^r \mid s_i \in S\}$  in additional  $O(n + m)$  time. Using  $E$ , we run the same sweeping algorithm as before. We still use a binary search tree  $T$  to maintain the sensors of  $S_{i2}$  and use a variable  $s^*$  to store a sensor of  $S_{i1}$ . When  $p$  encounters  $x_k^l$  for a sensor  $s_k$ , we insert  $s_k$  to  $T$ . When  $p$  encounters  $x_k^r$ , we remove  $s_k$  from  $T$  and set  $s^*$  to  $s_k$ . When  $p$  encounters a barrier point  $b_j$ , we determine the sensor  $s_{g_i}$  using the variable  $s^*$  and the tree  $T$  in the same way as before. As analyzed in the proof of Lemma 10, the total time of the algorithm is  $O(m + n \log n)$ .

**Lemma 12** *After  $O(m \log m)$  time preprocessing, given any  $\lambda$ , whether  $\lambda \geq \lambda^*$  can be decided in  $O(m + n \log n)$  time.*

## 5.2 The Optimization Problem

We now show how to compute  $\lambda^*$ . We first implicitly form  $2n$  sorted arrays as follows. For each sensor  $s_i$ , we define two sorted arrays  $A_i[1 \dots m]$  and  $B_i[1 \dots m]$  of size  $m$  each: for each  $1 \leq j \leq m$ ,  $A_i[j] = (\sqrt{x_i^2 + y_i^2} - r - x_{b_j})/w_i$  and  $B_i[j] = (x_{b_j} - r - \sqrt{x_i^2 + y_i^2})/w_i$ . One can verify that  $\lambda^*$  must be one of the elements of these arrays (e.g., using analysis similar to Lemmas 2 and 11) and each array is sorted. Then, applying Lemma 3 with our decision algorithm in Lemma 12,  $\lambda^*$  can be computed in  $O(m \log m + (m + n \log n) \log(n + m))$  time, which is bounded by  $O(m \log m + n \log^2 n)$  as shown in the following lemma.

**Lemma 13**  $m \log m + (m + n \log n) \log(n + m) = O(m \log m + n \log^2 n)$ .

**Proof:** To prove the lemma, first it is easy to see that  $m \log m + (m + n \log n) \log(n + m) = O(m \log m + n \log n \log(n + m))$ . Further, if  $m \geq n^2$ , then  $m \log m + n \log n \log(n + m) = O(m \log m)$ ; otherwise,  $\log(n + m) = \Theta(\log n)$  and thus  $m \log m + n \log n \log(n + m) = O(m \log m + n \log^2 n)$ . The lemma thus follows.  $\square$

The following theorem summarizes our result for the mobile interval coverage problem.

**Theorem 3** *Given a set of  $m$  barrier points on a line  $\ell$  and a set of  $n$  weighted sensors in the plane, the problem of moving sensors to  $\ell$  to cover all barrier points such that the maximum moving cost of all sensors is minimized can be solved in  $O(m \log m + n \log^2 n)$  time.*

## CHAPTER 6

## CONCLUDING REMARKS AND FUTURE WORK

In this thesis, we present efficient algorithms for solving line-constrained mobile sensor coverage problems. Future work includes investigating whether a logarithmic factor can be further shaved for the weighted case of the mobile disk coverage problem as well as for the mobile interval coverage problem. In particular, it would be interesting to see whether a faster algorithm exists for the unweighted case of the mobile interval coverage problem.

Note that for the 1D problem, i.e., all sensors and barrier points are given on  $\ell$  and sensors are allowed to move on  $\ell$  only, the algorithm can be simplified as follows. For the unweighted case, we can use the same algorithm as in Section 3 but the algorithm becomes simpler as  $y_b = 0$  for each barrier point  $b \in B$ . The runtime of the algorithm is  $O((m+n)\log(n+m))$ . For the weighted case, we can use the same algorithm as in Section 5 but the algorithm becomes simpler as  $y_i = 0$  for each sensor  $s_i \in S$ . The runtime of the algorithm is  $O(m \log m + n \log^2 n)$ .

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