Vertical Decomposition in 3D and 4D with Applications to Line Nearest-Neighbor Searching in 3D *

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November 6, 2023

Abstract

Vertical decomposition is a widely used general technique for decomposing the cells of arrangements of semi-algebraic sets in \mathbb{R}^d into constant-complexity subcells. In this paper, we settle in the affirmative a few long-standing open problems involving the vertical decomposition of substructures of arrangements for d = 3, 4: (i) Let \mathscr{S} be a collection of n semi-algebraic sets of constant complexity in \mathbb{R}^3 , and let U(m) be an upper bound on the complexity of the union $\mathscr{U}(\mathscr{S}')$ of any subset $\mathscr{S}' \subseteq \mathscr{S}$ of size at most m. We prove that the complexity of the vertical decomposition of the complement of $\mathscr{U}(\mathscr{S})$ is $O^*(n^2 + U(n))$ (where the $O^*(\cdot)$ notation hides subpolynomial factors). We also show that the complexity of the vertical decomposition of the entire arrangement $\mathscr{A}(\mathscr{S})$ is $O^*(n^2 + X)$, where X is the number of vertices in $\mathscr{A}(\mathscr{S})$. (ii) Let \mathscr{F} be a collection of n trivariate functions whose graphs are semi-algebraic sets of constant complexity. We show that the complexity of the vertical decomposition of the portion of the arrangement $\mathscr{A}(\mathscr{F})$ in \mathbb{R}^4 lying below the lower envelope of \mathscr{F} is $O^*(n^3)$.

These results lead to efficient algorithms for a variety of problems involving these decompositions, including algorithms for constructing the decompositions themselves, and for constructing (1/r)-cuttings of substructures of arrangements of the kinds considered above. One additional algorithm of interest is for output-sensitive point enclosure queries amid semi-algebraic sets in three or four dimensions.

In addition, as a main domain of applications, we study various proximity problems involving points and lines in \mathbb{R}^3 : We first present a linear-size data structure for answering nearest-neighbor queries, with points, amid *n* lines in \mathbb{R}^3 in $O^*(n^{2/3})$ time per query. We also study the converse problem, where we return the nearest neighbor of a query line amid *n* input points, or lines, in \mathbb{R}^3 . We obtain a data structure of $O^*(n^4)$ size that answers a nearest-neighbor query in $O(\log n)$ time. Finally, We study batched, or offline, variants of these problems, and obtain improved algorithms for such scenarios.

^{*}Work by Pankaj Agarwal has been partially supported by NSF grants IIS-18-14493, CCF-20-07556, and CCF-22-23870. Work by Esther Ezra has been partially supported by Israel Science Foundation Grant 800/22, and also by US-Israel Binational Science Foundation under Grant 2022131. Work by Micha Sharir has been partially supported by Israel Science Foundation Grant 260/18.

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1 Introduction

Let \mathscr{S} be a family of *n* semi-algebraic sets¹ of constant complexity in \mathbb{R}^d . The *arrangement* of \mathscr{S} , denoted by $\mathscr{A}(\mathscr{S})$, is the decomposition of \mathbb{R}^d into maximal connected relatively open cells of all dimensions, so that all points within a cell lie in the relative interior or boundary of the same subfamily of sets of \mathscr{S} . Because of their wide range of applications, arrangements of semi-algebraic sets have been extensively studied [13, 19]. The combinatorial complexity of a cell in $\mathscr{A}(\mathscr{S})$ can be quite large, and its topology can be quite complex [13], so a fundamental problem in the area of arrangements, for both combinatorial and algorithmic applications, is to decompose a cell of $\mathscr{A}(\mathscr{S})$ into constant-complexity subcells, each homeomorphic to a ball. In some applications, we wish to decompose all cells of $\mathscr{A}(\mathscr{S})$ while in others only a subset of cells of $\mathscr{A}(\mathscr{S})$.

Vertical decomposition is a popular general technique (and perhaps the only general-purpose technique) for constructing such a decomposition. Roughly speaking, vertical decomposition recurses on the dimension *d*. Let *C* be a cell of $\mathscr{A}(\mathscr{S})$. For d = 2, the vertical decomposition of *C* is obtained by erecting a *y*-vertical segment up and down from each vertex of C and from each point of vertical tangency on the boundary of C, and extending these segments till they hit another edge of C, or else all the way to infinity. This results in a decomposition of C into vertical *pseudo-trapezoids* (trapezoids, for short). For d = 3, we first erect, upwards and downwards, z-vertical curtains from each edge of C and from the silhouette (the locus of points with z-vertical tangency) of each 2-face of C, and extend them until they hit ∂C (or else all the way to infinity). The resulting subcells have a unique pair of faces as their "floor" and "ceiling," but their complexity can still be large. In the second decomposition phase, we project each subcell onto the xy-plane, apply planar vertical decomposition to the projection, and lift each resulting subcell (trapezoid) vertically up to \mathbb{R}^3 to the range between the floor and ceiling of the original subcell. This results in a decomposition of C into vertical *pseudo-prisms* (prisms for short), each bounded by up to six facets. This recursive scheme (on the dimension) can be generalized to higher dimensions, but it becomes more involved as the dimension grows. In this work, though, we only use the three- and four-dimensional scenarios. See [23, 35, 44].

Vertical decompositions, similar to some other geometric decomposition schemes, provide a mechanism for constructing geometric *cuttings* of various substructures of arrangements of semialgebraic sets [13], which in turn leads to an efficient divide-and-conquer mechanism for solving a variety of combinatorial and algorithmic problems, as well as for constructing data structures for geometric searching problems [9]. The performance of these algorithms and data structures depends on the complexity (number of prisms) of the vertical decomposition. For d = 2, the size of the vertical decomposition of a cell *C* is proportional to the combinatorial complexity of *C*, but already for d = 3, the size of the vertical decomposition of *C* can be $\Omega(n^2)$ even when the complexity of *C* is O(n). A challenging problem is thus to obtain sharp bounds on the complexity of the vertical decomposition of (the cells of) various substructures of $\mathscr{A}(\mathscr{S})$ for $d \ge 3$. Despite extensive work on this problem, see, e.g., [4, 5, 12, 21, 23, 35, 43] for a sample of results, several basic problems remain open. In this paper we settle some of these problems in the affirmative, obtaining sharp bounds on the complexity of the vertical decomposition of various substructures of arrangements, and full arrangements, for d = 3, 4; see below for a list of our results. As a major application of these results, we study proximity problems involving lines and points in \mathbb{R}^3 ; see

¹Roughly speaking, a semi-algebraic set in \mathbb{R}^d is the set of points in \mathbb{R}^d that satisfy a Boolean formula over a set of polynomial inequalities; the complexity of a semi-algebraic set is the number of polynomials defining the set and their maximum degree. See [19] for formal definitions of a semi-algebraic set and its dimension.

below.

Related work. Collins [28] (see also [19,42]) had proposed *cylindrical algebraic decomposition* (CAD) as a general technique for decomposing the cells of $\mathscr{A}(\mathscr{S})$ into pseudo-prisms, in any dimension *d*. However, the number of cells produced is $n^{2^{O(d)}}$. Vertical decomposition can be viewed as an optimized version of CAD, with much smaller complexity. Although vertical decompositions for d = 2, 3 have been used since the 1980's [25,27], Chazelle *et al.* [23] described the construction of vertical decomposition in general, for arrangements of semi-algebraic sets in \mathbb{R}^d , and proved a bound of $O^*(n^{2d-3})$ for $d \ge 3$ (where the $O^*(\cdot)$ notation hides subpolynomial factors). They also showed that the vertical decomposition of $\mathscr{A}(\mathscr{S})$ can be computed in $O^*(n^{2d-3})$ expected time. The bound was improved to $O^*(n^{2d-4})$, for $d \ge 4$, by Koltun [35]. These bounds are nearly optimal for $d \le 4$, and are strongly suspected to be far from optimal for $d \ge 5$. Improving the bound, for $d \ge 5$, is a major 30-years-old open problem in this area (which we do not address in this work).

In many applications, one is interested in computing the vertical decomposition of (the cells of) only a substructure of $\mathscr{A}(\mathscr{S})$. In this case, the goal is to show that if the substructure under consideration has asymptotic complexity $o(n^d)$, then so should be the complexity of its vertical decomposition. This statement is true in the plane, as already mentioned, and has been shown to hold for arrangements of triangles in 3D [21,46]. Notwithstanding a few results on the vertical decompositions of substructures of 3D and 4D arrangements, see, e.g., [4,5,12,43], the aforementioned fundamental problem has remained largely open for $d \ge 3$. For example, even though the complexity of the union of a set of objects in \mathbb{R}^3 in many interesting cases—such as a set of cylinders or a set of fat objects—is known to be $O^*(n^2)$ [14,17,29,30], no subcubic bound was known on the size of the vertical decomposition of the complement of their union. In \mathbb{R}^4 , the complexity of the lower envelope of *n* trivariate functions (whose graphs are semi-algebraic sets of constant complexity) is $O^*(n^3)$ (see, e.g., [44]), however, no $o(n^4)$ bound was known on the complexity of the lower envelope.

We conclude this discussion by noting that special-purpose decomposition schemes have been proposed for decomposing cells in arrangements of hyperplanes, boxes, or simplices, using triangulations, binary space partitions, or variants of vertical decomposition; see, e.g., [13,15,18,32] and references therein. Some of these methods also work for arrangements of semi-algebraic sets using the so called linearization technique [9], albeit yielding in general much weaker bounds.

Our contributions. The paper contains three sets of main results — (i) sharp bounds on the complexity of vertical decompositions of substructures of arrangements in \mathbb{R}^3 and \mathbb{R}^4 , (ii) efficient algorithms for constructing these decompositions and related structures, and (iii) as a major application domain, efficient data structures for line-point proximity problems in \mathbb{R}^3 .

Vertical decomposition. We make significant progress on bounding the size of the vertical decomposition of substructures of arrangements in \mathbb{R}^3 and \mathbb{R}^4 , by establishing the following combinatorial bounds.

Union of semi-algebraic sets. Let \mathscr{S} be a family of n semi-algebraic sets of constant complexity in \mathbb{R}^3 , and let U(m) be an upper bound on the complexity of the union $\mathscr{U}(\mathscr{S}')$ of any subset $\mathscr{S}' \subseteq \mathscr{S}$ of size at most m, for any m > 0. (Note that, by definition, U(m) is monotone increasing in m.) We show that the complexity of the vertical decomposition of the complement of $\mathscr{U}(\mathscr{S})$ is $O^*(n^2 + U(n))$ (Section 2).

Lower envelopes. Let \mathscr{F} be a collection of n trivariate functions whose graphs are semi-algebraic sets of constant complexity, and let $\mathscr{A}(\mathscr{F})$ denote the arrangement (in \mathbb{R}^4) of their graphs. The *lower envelope* $E_{\mathscr{F}}$ of \mathscr{F} is defined as $E_{\mathscr{F}}(x) = \min_{F \in \mathscr{F}} F(x)$, for $x \in \mathbb{R}^3$. We show that the complexity of the vertical decomposition of the cell of² $\mathscr{A}(\mathscr{F})$ lying below (the graph of) $E_{\mathscr{F}}$ is $O^*(n^3)$, thereby matching the general upper bound on the complexity of lower envelopes in \mathbb{R}^4 [44] (Section 3).

Sparse arrangements. Let \mathscr{S} be a collection of *n* semi-algebraic sets of constant complexity in \mathbb{R}^3 , and let *X* denote the number of vertices in $\mathscr{A}(\mathscr{S})$. We show that the complexity of the vertical decomposition of the entire arrangement $\mathscr{A}(\mathscr{S})$ is $O^*(n^2 + X)$ (Section 4).

Algorithms. There are a few immediate algorithmic consequences of our combinatorial results:

Computing vertical decompositions. All these vertical decompositions can be constructed, namely, the set of pseudo-prisms in the vertical decomposition can be computed, in time comparable with their respective complexity bounds. Section 5.2 describes the construction for the complement of the union of semi-algebraic sets in \mathbb{R}^3 , as well as for the lower envelopes (or rather minimization diagrams) of trivariate functions (whose graphs are semi-algebraic sets of constant complexity); the same approach extends to sparse arrangements. We note that Agarwal *et al.* [4] described a randomized algorithm for constructing the vertices, edges, and 2-faces of the minimization diagram of a set of trivariate (constant-complexity semi-algebraic) functions in $O^*(n^3)$ expected time. In addition, with $O^*(n^3)$ preprocessing, their technique can also compute, in $O(\log n)$ time, the function that appears on the lower envelope for a query point $\xi \in \mathbb{R}^3$. (Their algorithm can also compute, in $O^*(n^2 + U(n))$ expected time, the vertices, edges, and 2-faces of the union of a collection \mathscr{S} of semi-algebraic sets in \mathbb{R}^3 , where U(m), as above, is the maximum complexity of the union of a subset of \mathscr{S} of size m.) However, their algorithm does not compute three-dimensional cells of the minimization diagram, nor does it compute the vertical decomposition of the minimization diagram. See also [12].

Geometric cuttings. Let \mathscr{S} be a collection of n semi-algebraic sets of constant complexity in \mathbb{R}^d . Let Π be a substructure of $\mathscr{A}(\mathscr{S})$, defined by a collection of cells of $\mathscr{A}(\mathscr{S})$ that satisfy certain properties (e.g., lying in the complement of the union or lying below the lower envelope). For a parameter r > 1, a (1/r)-*cutting* of Π (with respect to \mathscr{S}) is a set Ξ of pseudo-prisms with pairwise-disjoint relative interiors that cover Π such that the relative interior of each pseudo-prism $\tau \in \Xi$ is crossed by (intersected by but not contained in) at most n/r sets of \mathscr{S} . The subset of \mathscr{S} crossed by τ is called the *conflict list* of τ . Our combinatorial results lead to the construction of small-size (1/r)-cuttings of Π . Their size is dictated by our new bounds for the complexity of the vertical decomposition of Π . For the case of the complement of the union of sets in \mathbb{R}^3 , the bound is $O^*(r^2 + U(r))$. For the case of an entire three-dimensional arrangement of complexity X, we obtain a (1/r)-cutting of $\mathscr{A}(\mathscr{S})$, for any parameter $r \leq n$, of total complexity $O^*(r^2 + r^3X/n^3)$. The cuttings along with the conflict lists of all of its cells can be constructed in O(n) expected time if r is a constant (Section 5.1).

Point-enclosure queries. Let \mathscr{S} be a family of *n* semi-algebraic sets in \mathbb{R}^3 , and let $U(\cdot)$ denote a bound on its union complexity, as above. We obtain a data structure of size and preprocessing cost $O^*(n^2 + U(n))$ that, for a query point $q \in \mathbb{R}^3$, returns all *k* sets of \mathscr{S} containing *q* in $O^*(1 + k)$

²Even though this vertical decomposition is in \mathbb{R}^4 , it is effectively obtained from the vertical decomposition of the *minimization diagram* of $E_{\mathscr{F}}$ in \mathbb{R}^3 ; see below for details.

time. Similarly, for a given family \mathscr{F} of n semi-algebraic trivariate functions, we can construct a data structure of size $O^*(n^3)$ that, for a query point $q \in \mathbb{R}^4$, can report, in $O^*(1+k)$ time, all the k functions of \mathscr{F} whose graphs lie below q.

Proximity problems for points and lines in \mathbb{R}^3 . In the third part, building on our verticaldecomposition and geometric-cutting results, we present efficient data structures and algorithms for various proximity problems involving points and lines in \mathbb{R}^3 .

Nearest line-neighbor to a query point. A set *L* of *n* lines in \mathbb{R}^3 can be preprocessed, in $O(n \log n)$ expected time, into a data structure of size O(n), so that for a query point $q \in \mathbb{R}^3$, the nearest neighbor of *q* in *L* can be returned in $O^*(n^{2/3})$ time (Section 7). We note that a linear-size data structure with $O^*(n^{3/4})$ query time can be obtained by mapping each line of *L* to a point in \mathbb{R}^4 and using four-dimensional semi-algebraic range searching techniques [11]. We also note that a data structure of $O^*(n^3)$ size and $O(\log n)$ query time can be obtained by constructing and preprocessing the Voronoi diagram of the lines in *L* for point-location queries, following an approach similar to that in [41].

Our data structure constructs a partition tree, as in [9,45], using geometric cuttings. The main challenge in adapting these preceding approaches to our setting is the construction of a so-called *test set*, namely, a small set of representative queries (typically more involved than the usual queries) so that if the data structure can answer those queries efficiently then it can answer efficiently the query for any point in \mathbb{R}^3 . Our new results on vertical decomposition of the lower envelope of trivariate functions and on geometric cuttings provide the missing ingredients needed for constructing such test sets. See Section 7 for details.

Nearest point-neighbor to a query line. We can preprocess a set *P* of *n* points in \mathbb{R}^3 , in expected $O^*(n^4)$ time, into a data structure of $O^*(n^4)$ size, so that, for a query line ℓ in \mathbb{R}^3 , its nearest neighbor in *P* can be returned in $O(\log n)$ time (Section 8.1). The standard tools would yield a data structure of size $O^*(n^5)$ for answering fast queries.

Roughly speaking, after applying some geometric transformations, we reduce the nearestneighbor query to a point-location query in a sandwich region enclosed between two envelopes of trivariate functions. As we do not know how to perform this task efficiently in a direct manner, due to the lack of a good bound on the complexity of the vertical decomposition of such a region (see [37], where this is stated as a major open problem), we use a more involved scheme that achieves the desired efficiency.

We note that a linear-size data structure with $O^*(n^{2/3})$ query time can be obtained by using known results on 3D semi-algebraic range searching [11]. Our new results on vertical decomposition of the complement of the union of objects in \mathbb{R}^3 leads to a faster solution to a restricted version of this problem. That is, we can preprocess a set of *n* points in \mathbb{R}^3 into a linear-size data structure that returns, in $O^*(n^{1/2})$ time, a point within distance at most 1 from a query line, if there exists one. This problem was recently studied in Agarwal and Ezra [7], and they had obtained a more involved data structure with a similar bound. By combining our vertical-decomposition result with some of their ideas, we obtain a significantly simpler data structure.

Nearest line-neighbor to a query line. We can preprocess a set *L* of *n* lines in \mathbb{R}^3 , in $O^*(n^4)$ expected time, into a data structure of size $O^*(n^4)$, so that the nearest neighbor in *L* of a query line can be computed in $O(\log n)$ time (Section 8.2). Again, we note that a linear-size data structure with $O^*(n^{3/4})$ query time can be obtained by using standard four-dimensional semi-algebraic range searching techniques [11], and that a structure of size $O^*(n^5)$ for the fast query regime can also be

obtained by standard methods.

Off-line nearest-neighbor queries. Let us now consider the case when all queries are given in advance. That is, we have a set *L* of *n* lines and a set *P* of *m* points in \mathbb{R}^3 , and the goal is to compute the nearest neighbor in *P* of each line of *L*. We present a randomized algorithm with $O^*(m^{4/7}n^{6/7} + m + n)$ expected running time (Section 9). We note that by plugging our on-line algorithm with the standard space/query-time trade-off techniques would lead to an algorithm with $O^*(m^{8/11}n^{9/11} + m + n)$ expected running time.

2 Vertical Decomposition of the Complement of the Union

Let \mathscr{S} be a collection of n semi-algebraic sets of constant complexity in \mathbb{R}^3 . For any subset \mathscr{S}' of \mathscr{S} , let $\mathscr{U}(\mathscr{S}')$ denote the union of \mathscr{S}' , and let $\mathscr{C}(\mathscr{S}')$ denote the complement of $\mathscr{U}(\mathscr{S}')$. Let U(m) denote the maximum complexity of $\mathscr{U}(S')$ —namely, the number of vertices, edges and 2-faces of the union boundary—over all subsets \mathscr{S}' of size at most m. Clearly $U(m) = O(m^3)$, but as mentioned in the introduction, $U(m) = O^*(m^2)$ in many interesting cases. Let $VD(\mathscr{S})$ denote the *vertical decomposition* of $\mathscr{C} = \mathscr{C}(\mathscr{S})$, and let C(n) denote the maximum complexity of $VD(\mathscr{S})$, where the maximum is taken over all collections of n semi-algebraic sets of constant complexity. Our goal is to obtain a sharp bound on C(n).

A pair (e, e') of edges of $\mathscr{A}(\mathscr{S})$ is called *vertically visible* if there exists a vertical line λ that meets both e and e', so that the relative interior of the segment of λ connecting e and e' does not meet the boundary of any set of \mathscr{S} , and we refer to the pair of points $(\lambda \cap e, \lambda \cap e')$ as a *vertical visibility*. A pair (e, e') of edges can give rise to more than one but at most O(1) vertical visibilities. It is well known (see, e.g., [44]) that C(n) is proportional to U(n) plus the number of vertical visibilities between pairs of edges of $\partial \mathscr{U}$ that occur within \mathscr{C} , so it suffices to bound the latter quantity.

To bound the number of vertical visibilities, we fix an edge e of $\partial \mathscr{U}$, regarding e as the lower edge in the vertical visibilities that we seek,³ and erect a *vertical curtain* V(e) over e, which is the (two-dimensional) union of all *z*-vertical rays emanating upwards from the points of e. The boundary of each set $S \in \mathscr{S}$ (ignoring the two that form e) intersects V(e) in a one-dimensional curve γ_S , which can be empty or disconnected, but is of constant complexity. Note that none of the curves γ_S cross e, for such an intersection would be a vertex of the arrangement of \mathscr{S} and, by definition, e cannot contain such a vertex.

We form the lower envelope E_e of the curves γ_S , and note that each breakpoint a of E_e , at which two curves meet, lies on some edge e' of $\partial \mathscr{U}$ which forms a vertically visible pair with e, with the vertical visibility taking place between a and e. The other breakpoints, formed at endpoints of connected portions of the curves, occur when a vertical line (supporting a ray of the curtain V(e)) is tangent to some $S \in \mathscr{S}$; that is, the breakpoint occurs on the vertical silhouette of S. It is easy to show that the overall number of vertical visibilities involving silhouettes is only $O^*(n^2)$. Indeed, there are O(n) silhouettes, each of constant complexity, and the vertical visibilities that they are involved in correspond to breakpoints of lower or upper envelopes within the vertical curtains that they span. As each envelope can be regarded as the lower envelope of univariate functions, it has $O^*(n)$ complexity [44], and the claim follows.

To facilitate the forthcoming analysis, we turn the problem into a bipartite problem, where

³We assume that the two sets whose boundaries intersect at *e* lie locally below *e*, for otherwise *e* cannot play the role of the bottom edge of a vertically visible pair in the complement of the union.

each set of \mathscr{S} is assigned at random a color red or blue, yielding a partition $\mathscr{S} = \mathscr{R} \cup \mathscr{B}$, where \mathscr{R} (resp., \mathscr{B}) is the set of all red (resp., blue) sets, and our goal is to bound the number of vertical visibilities between red-red edges (edges formed by the intersection of the boundaries of two red sets) and blue-blue edges (those formed by the intersection of the boundaries of two blue sets). Note that a red-red edge *e* on the boundary of the union of \mathscr{R} is not necessarily an original edge of the boundary of $\mathscr{U}(\mathscr{S})$, as *e* may contain red-red-blue vertices (or even be fully contained in a blue set). Still, if there exists a vertical visibility in $\mathscr{C}(\mathscr{S})$ whose lower endpoint *b* lies on *e*, then *b* lies on a portion of *e* that forms an edge of $\partial \mathscr{U}(\mathscr{S})$. Of course, not all vertically visible pairs are captured in this coloring scheme. Nevertheless, it is easily checked that the expected number of visible pairs with this coloring is 1/8 of the overall number of visible pairs, so, up to this factor, there is no loss of generality in using this coloring scheme.

So the setup that we face is: We are given a set \mathscr{R} of m red sets and a set \mathscr{R} of n blue sets (in the above scheme, both m and n are half the size of \mathscr{S} in expectation), and our goal is to bound the number C(m, n) of vertical visibilities between pairs (e, e') of edges, where e is a red-red edge and e' is a blue-blue edge, and the vertical visibility takes place in the complement of $\mathscr{U}(\mathscr{R} \cup \mathscr{B})$.

We estimate C(m, n) using an extension of the recursive analysis in [37, Section 2].⁴ We fix some sufficiently large constant parameter k, and partition \mathscr{B} arbitrarily into k subsets $\mathscr{B}_1, \ldots, \mathscr{B}_k$, each of size n/k (ignoring rounding issues). We solve the problem recursively for \mathscr{R} and each \mathscr{B}_i . Each subproblem yields at most C(m, n/k) vertical visibilities. Note that these vertical visibilities are not necessarily vertical visibilities in the full red-blue setup, because sets in other subsets \mathscr{B}_j may show up between the edges in such a pair and destroy the vertical visibility between them. Nevertheless, each original vertical visibility is either one of these recursively obtained visibilities, or arises at a pair (e, e') where e is a red-red edge and e' is a blue-blue edge formed by the intersection of two boundaries of sets in different subsets $\mathscr{B}_i, \mathscr{B}_j$. We now proceed to bound the number of pairs of the latter kind.

To do so, fix a red-red edge e, and assume that e plays the role of the bottom edge in a vertically visible pair. Consider the upward vertical curtain V(e) of e, and form within V(e) the k blue envelopes $E_e^{(1)}, \ldots, E_e^{(k)}$, where $E_e^{(i)}$ is the lower envelope of the curves γ_S , for $S \in \mathcal{B}_i$, for $i = 1, \ldots, k$. The breakpoints of the envelopes (ignoring silhouette breakpoints) correspond to recursively obtained pairs (e, e') (as noted, not all breakpoints yield visibilities in the full setup), but we are also interested in the additional breakpoints of the overall lower envelope E_e of these k envelopes.

Let $M_e^{(i)}$ denote the number of breakpoints of $E_e^{(i)}$, for i = 1, ..., k, and put $M_e = \sum_i M_e^{(i)}$. Notice that $\sum_e M_e^{(i)}$ is the number of vertical visibilities between \mathscr{R} and \mathscr{B}_i , so it is at most C(m, n/k). Thus $\sum_e M_e \leq kC(m, n/k)$.

Inspired by the analysis in [37], we follow a technique similar to one used by Har-Peled [33] in a different context. Specifically, we partition V(e) into vertical sub-curtains $V_1(e), \ldots, V_t(e)$ by upward vertical rays, so that the overall number of breakpoints of the individual envelopes within each sub-curtain is k, except possibly for the last sub-curtain, where the number is at most k, so $t \le 1 + M_e/k$. Within each sub-curtain $V_j(e)$ there are only at most 2k blue curves γ_S that participate in the envelopes $E_e^{(i)}$, of which k show up on the envelopes at an extreme ray of $V_j(e)$, and at most k others replace them along the various envelopes, within the sub-curtain. Hence, within any

⁴We credit this work for providing us the initial inspiration that their technique can be adapted to apply in our settings too.

fixed $V_j(e)$, E_e is the lower envelope of at most 2k connected subarcs of boundary curves γ_S , so its combinatorial complexity is at most $\lambda_s(2k)$, where $\lambda_s(m)$ is the near-linear maximum length of Davenport-Schinzel sequences of order *s* on *m* symbols, for some constant parameter *s* that depends on the complexity of the sets of \mathscr{S} [44]. We write this bound as $k\beta(k)$, for an appropriate nearconstant extremely slowly growing function $\beta(k)$, and conclude that the number of breakpoints of E_e within each sub-curtain is at most $k\beta(k)$, for a total of at most $kt\beta(k) = (k + M_e)\beta(k)$ breakpoints. Summing over all red-red edges *e*, we obtain

$$C(m,n) \leq \left(\sum_{e} (k+M_{e})\right) \beta(k) \leq k\beta(k)C(m,n/k) + k\beta(k)U(m).$$

We next switch the roles of red and blue, and apply the same analysis to each pair \mathscr{R} , \mathscr{B}_i of sets, keeping \mathscr{B}_i fixed and partitioning \mathscr{R} into k subsets of size m/k each. (We now reverse the direction of the *z*-axis, considering downward-directed vertical curtains erected from the edges formed by the sets of \mathscr{B}_i .) The analysis proceeds more or less verbatim, and yields the following bound on the number of vertical visibilities:

$$C(m,n) \le k^2 \beta^2(k) C(m/k,n/k) + k^2 \beta^2(k) U(n/k) + k\beta(k) U(m)$$

If $U(m) = O^*(m^2)$, we obtain the recurrence

$$C(m,n) \le k^2 \beta^2(k) C(m/k,n/k) + k\beta(k) O^*(m^2) + \beta^2(k) O^*(n^2).$$

Note that the right-hand side of this recurrence also subsumes the number of $O^*(m^2 + n^2)$ vertical visibilities that involve the silhouettes of the red and blue sets.

We solve this recurrence for the original setup, where *m* and *n* are both roughly half the total number of sets, which we continue to denote by *n*, with some abuse of notation. By choosing *k* to be a sufficiently large constant, the solution of the resulting recurrence is $O^*(n^2)$. We thus conclude that the number of vertical visibilities between pairs of edges of $\mathscr{U}(\mathscr{S})$ is $O^*(n^2)$. A similar analysis applies when U(n) is superquadratic. In this case the bound on the complexity of the vertical decomposition is $O^*(U(n))$, as is easily checked. Putting everything together, we obtain the following main result of this section.

Theorem 2.1 Let \mathscr{S} be a collection of *n* constant-complexity semi-algebraic sets in \mathbb{R}^3 , with an upper bound U(m) on the combinatorial complexity of the union of any subset of \mathscr{S} of size *m*. Then the size of the vertical decomposition of the complement of the union of \mathscr{S} is $O^*(n^2 + U(n))$.

3 Vertical Decomposition of Lower Envelopes in \mathbb{R}^4

Let \mathscr{F} be a collection of n trivariate semi-algebraic functions of constant complexity, let $E = E_{\mathscr{F}}$ denote the lower envelope of \mathscr{F} , let $E^- = E_{\mathscr{F}}^-$ denote the portion of \mathbb{R}^4 below E, and let $M = M_{\mathscr{F}}$ denote the minimization diagram of E, namely the projection of E onto the *xyz*-space. Our goal is to estimate the combinatorial complexity of the vertical decomposition of M. This three-dimensional decomposition can then be lifted up in the *w*-direction to induce a suitable decomposition of E^- , which we refer to as the vertical decomposition of E. We note that the complexity of (the undecomposed) E and of M is $O^*(n^3)$ [44]. The main result of this section yields the same asymptotic bound for their vertical decomposition:

Theorem 3.1 The complexity of the vertical decomposition of the lower envelope (that is, of the minimization diagram) of a collection of n trivariate semi-algebraic functions of constant complexity is $O^*(n^3)$.

Proof. We assume that the functions of \mathscr{F} are in general position, continuous and totally defined. None of these assumptions are essential, but they simplify the analysis. We identify each function of \mathscr{F} with its three-dimensional graph. We recall the way in which the vertical decomposition VD of M is constructed. We fix a function a in \mathscr{F} . For each function $b \in \mathscr{F} \setminus \{a\}$, we use $\sigma_{ab} = \sigma_{ba}$ to denote the *xyz*-projection of the two-dimensional intersection surface $a \cap b$. The surface σ_{ab} partitions the *xyz*-space into the regions σ_{ab}^+ and σ_{ab}^- , where σ_{ab}^+ (resp., σ_{ab}^-) consists or those points (x, y, z) for which $a(x, y, z) \ge b(x, y, z)$ (resp., $a(x, y, z) \le b(x, y, z)$). We observe that the complement \mathscr{C}_a of the union $\mathscr{U}_a := \bigcup \{\sigma_{ab}^+ \mid b \in \mathscr{F} \setminus \{a\}\}$ is precisely the portion of the *xyz*-space over which a attains the envelope E.

We now construct the three-dimensional vertical decomposition, denoted as VD_a, of C_a , and repeat this construction to each complement C_a , over $a \in \mathcal{F}$, observing that the regions C_a are pairwise openly disjoint. The union of all these decompositions yields the vertical decomposition of $M_{\mathcal{F}}$, and, as mentioned above, the vertical decomposition of $E_{\mathcal{F}}$ is obtained by lifting this decomposition to $E_{\mathcal{F}}$ (or to $E_{\mathcal{F}}^-$, see below), in a straightforward manner.

We comment that, as already noted, we can also obtain by this approach the vertical decomposition of E^- . Each cell τ in the decomposition of M is lifted to the semi-unbounded region

$$\{(x, y, z, w) \mid (x, y, z) \in \tau \text{ and } w \le E(x, y, z)\}.$$

We have thus (almost) reduced the problem to that studied in Section 2. The difference is that there we assumed that the complexity of the union of any subcollection of at most *m* of the given objects is $O^*(m^2)$, or at least that we have some (subcubic) bound U(m) on that complexity. Here, though, this no longer holds. That is, considering the entire collection \mathscr{F} , and denoting by M_a the complexity of \mathscr{U}_a , all we know is that $\sum_a M_a = O^*(n^3)$, so we have the bound $O^*(n^2)$ only for the *average* value of M_a . To overcome this technicality, we modify the previous analysis as follows.

Recall that in Section 2 we have reduced the problem to a bichromatic problem by assigning to each object the color red or blue at random. Here we extend this technique to obtain a trichromatic reduction, by assigning to each function the color red, blue or green at random. We now consider only unions \mathcal{U}_a for green functions *a*, and within the complement \mathcal{C}_a of any of these unions, we only consider vertical visibilities between red-red edges and blue-blue edges (technically, they are green-red-red and green-blue-blue edges), exactly as in Section 2. Again, any vertical visibility that arises in the original decomposition has a constant probability to show up as a green-red-red vs. green-blue-blue visibility in the trichromatic version.

For each green function *a*, the overhead terms that appear in the analysis can be written as $M(\{a\}, \mathcal{R}, \mathcal{B})$ and $M(\{a\}, \mathcal{R}, \mathcal{B}_i)$, where, for arbitrary sets $\mathcal{G}, \mathcal{R}, \mathcal{B}$ of green, red, and blue objects, respectively, $M(\mathcal{G}, \mathcal{R}, \mathcal{B})$ denotes the number of the green-red-red and green-blue-blue edges of the undecomposed envelope of $\mathcal{G} \cup \mathcal{R} \cup \mathcal{B}$. Here \mathcal{R}, \mathcal{B} , and the \mathcal{B}_i 's may be recursively obtained subsets of the original sets. Summing these quantities over *a*, we obtain $M(\mathcal{G}, \mathcal{R}, \mathcal{B})$ and $M(\mathcal{G}, \mathcal{R}, \mathcal{B}_i)$, respectively. We also use the notation M(u, v, w) to denote the maximum value of $M(\mathcal{G}, \mathcal{R}, \mathcal{B})$ for $|\mathcal{G}| \leq u$, $|\mathcal{R}| \leq v$ and $|\mathcal{B}| \leq w$.

Consider, say, a green-red-red edge *e* that appears on the boundary of (the complement \mathcal{C}_a of) the union \mathcal{U}_a for some green function *a* (the same argument holds for green-blue-blue edges). If we replace \mathcal{G} by a subset \mathcal{G}' that contains *a*, \mathcal{C}_a can only grow, since fewer regions σ_{ab}^+ form the union

 \mathscr{U}_a . Hence *e* does not disappear, and can only extend, possibly even merge with other edges formed by the same triple of functions. In particular, the number of vertical visibilities in \mathscr{C}_a between green-red-red edges and green-blue-blue edges can only increase.

We use this observation as follows. In the first two-step recursive round, as described in Section 2, we first partition \mathscr{G} into k subsets $\mathscr{G}_1, \mathscr{G}_2, \ldots, \mathscr{G}_k$, each of size n/k, apply the analysis to each \mathscr{G}_i and \mathscr{R} and \mathscr{B} , and then sum up the resulting bounds for $i = 1, \ldots, k$. Denote by C(u, v, w) the maximum number of vertical visibilities for sets of at most u green, v red, and w blue functions. The overhead term will be at most $O(M(u, v, w)) = O^*((u + v + w)^3)$, and the recursive term will be at most C(u/k, v/k, w/k) at each recursive subproblem. Therefore, by applying the recursive relation from Section 2 on the number of red-blue vertical visibilities, we obtain the recurrence:

$$C(u,v,w) \leq \sum_{i=1}^{k} k^2 \beta^2(k) C(u/k,v/k,w/k) + k\beta(k) M(u/k,v,w),$$

which leads to the recursive relation:

$$C(u, v, w) \le k^{3}\beta^{2}(k)C(u/k, v/k, w/k) + k^{2}\beta(k)O^{*}((u+v+w)^{3})$$

The recurrence terminates when one of $u, v, w \le k$. It can be verified that $C(u, v, w) = O^*((u + v + w)^3)$. It then follows that $C(u, v, w) = O^*((u + v + w)^3)$ for any values of u, v, w, and this completes the proof of Theorem 3.1. \Box

4 Vertical Decomposition of Arrangements in \mathbb{R}^3

Let \mathscr{S} be a set of *n* surfaces or surface patches in \mathbb{R}^3 in general position, each of which is semialgebraic of constant complexity, and let *X* denote the number of vertices of $\mathscr{A}(\mathscr{S})$. For simplicity, and with no loss of generality, we assume that the surfaces are graphs of possibly partially defined continuous functions. This can be ensured by cutting surfaces into surface patches at their silhouettes and at their curves of singularity. We show that the complexity of the vertical decomposition of $\mathscr{A}(\mathscr{S})$ is $O^*(n^2 + X)$.

As in Section 2, it suffices to bound the number of vertical visibilities between pairs of edges of $\mathscr{A}(\mathscr{S})$. Again, we randomly color each surface as either red or blue, and only consider visibilities between red-red edges and blue-blue edges, in which the red-red edge lies below the blue-blue edge. An original vertical visibility has 1/8 probability to appear as a visibility of the desired kind under the coloring scheme. That is, up to a constant factor, the bound that we seek is also an upper bound for the original uncolored case. Here too, each monochromatic edge *e* may in general be the union of several original edges of $\mathscr{A}(\mathscr{S})$. Therefore the number of these monochromatic edges is at most O(X). As before, we denote the subsets of red surfaces and blue surfaces as \mathscr{R} and \mathscr{B} , respectively, and put $m := |\mathscr{R}|$, $n := |\mathscr{B}|$, slightly abusing the notation, as above.

The high-level analysis proceeds more or less as in Section 2. That is, we apply a two-step partitioning scheme, in which we first partition the blue surfaces into k subsets $\mathscr{B}_1, \ldots, \mathscr{B}_k$, each of n/k surfaces (in fact, the number of these surfaces in each subcell is at most 2n/k—see below for the details of the analysis). Then, for each red-red edge e, we form k separate lower envelopes of the blue surfaces, one for each \mathscr{B}_i , within the (upward) vertical curtain erected from e, and analyze the complexity of the lower envelope of all these envelopes.

Denote by $C(m, n, X_1, X_2)$ the maximum number of vertical visibilities between red-red edges and blue-blue edges in an arrangement of a set \mathscr{R} of at most m red surfaces and a set \mathscr{B} of at most nblue surfaces, so that the complexity (number of vertices) of $\mathscr{A}(\mathscr{R})$ is at most X_1 and the complexity of $\mathscr{A}(\mathscr{B})$ is at most X_2 . Observe that $X_1 + X_2 \leq X$.

A major new aspect of the analysis is in handling the parameter X, now replaced by X_1 and X_2 . The issue is that we have no control on how X_1 and X_2 are distributed over the subproblems that arise when we partition \mathscr{B} into k arbitrary subsets, and then do the same for \mathscr{R} , as we did in Section 2.

We overcome this issue by partitioning each of \mathscr{R} , \mathscr{B} into k random subsets, say by choosing the subset to which a surface belongs independently and uniformly at random. Specifically, consider the first partitioning step, where \mathscr{B} is split. We form a random partition of \mathscr{B} into k subsets $\mathscr{B}_1, \ldots, \mathscr{B}_k$, where a surface $\sigma \in \mathscr{B}$ is assigned to a subset \mathscr{B}_i , $1 \le i \le k$, which is chosen with probability 1/k, independent of the assignment of the remaining surfaces in \mathscr{B} . This probabilistic model obeys the multinomial distribution with k "categories". In particular, this implies that the size of each \mathscr{B}_i is a binomial random variable with parameters n and 1/k. Similarly, when we apply such a random partition to \mathscr{R} at the second partitioning step, we obtain a partition into k subsets $\mathscr{R}_1, \ldots, \mathscr{R}_k$, where the size of each \mathscr{R}_j is a binomially distributed random variable with parameters m and 1/k. Similarly, then we apply such a random partition to \mathscr{R} at the second partitioning step, we obtain a partition into k subsets $\mathscr{R}_1, \ldots, \mathscr{R}_k$, where the size of each \mathscr{R}_j is a binomially distributed random variable with parameters m and 1/k. We clearly have $E[|\mathscr{B}_i|] = n/k$, for each $1 \le i \le k$, and $E[|\mathscr{R}_j|] = m/k$, for each $1 \le j \le k$.

Using standard probabilistic arguments, exploiting the multiplicative Chernoff bound [16], we conclude that, with high probability,

$$|\mathscr{B}_{i}| \leq n/k \left(1 + O\left(\sqrt{\frac{k}{n}\log n}\right) \right), \quad \text{for each } 1 \leq i \leq k, \text{ and}$$
$$|\mathscr{R}_{j}| \leq m/k \left(1 + O\left(\sqrt{\frac{k}{m}\log m}\right) \right), \quad \text{for each } 1 \leq j \leq k.$$

By choosing *k* appropriately, we can assume that, with high probability, these upper bounds do not exceed 2n/k, and 2m/k, respectively.

Moreover, at the first partitioning step, a blue-blue edge e' is assigned to a specific subset \mathscr{B}_i with probability at most $1/k^2$ (here too, a blue-blue edge of $\mathscr{A}(\mathscr{B}_i)$ may be the union of several original edges of $\mathscr{A}(\mathscr{B})$). Specifically, e' is defined by at most four surfaces. That is, if e' contains two endpoints (each of which is a vertex of the arrangement obtained by the intersection of a triple of surfaces) then this number is four, if it has only one endpoint then e' is defined by three surfaces, otherwise, it is defined by a pair of surfaces (recall that we exclude silhouette and singularity edges, in which case there is only a single surface defining an edge).

In the first two scenarios \mathscr{B}_i has to contain the triple of surfaces defining an endpoint of e' (or the quadruple defining both endpoints), which occurs with probability at most $1/k^3$. In the latter scenario the pair of surfaces defining e' has to be assigned to \mathscr{B}_i , which happens with probability $1/k^2$. Therefore the expected complexity of the arrangement $\mathscr{A}(\mathscr{B}_i)$ is $O(n^2/k^2 + X_2/k^3)$. We comment that the events that edges show up in a specific subset are not independent. However, we claim below that, with high probability, the complexity of $\mathscr{A}(\mathscr{B}_i)$ is $O(n^2/k^2 + X_2/k^2)$, for each $1 \le i \le k$. This bound is slightly worse than the expected complexity, but it suffices for the analysis to proceed.

Indeed, since we have, with high probability, $|\mathscr{B}_i| \leq 2n/k$, for each $1 \leq i \leq k$, we immediately

conclude that the number of edges of $\mathscr{A}(\mathscr{B}_i)$ that are formed by pairs of surfaces is $O(n^2/k^2)$ (with high probability). Regarding the number of edges that are formed by a triple (or a quadruple) of surfaces, their expected number *Y* is $O(X_2/k^3)$, as observed above. Using Markov's inequality we conclude that the probability that the actual number of such edges exceeds 2kY is at most 1/(2k). That is, with probability at least 1 - 1/(2k), the number of such edges in $\mathscr{A}(\mathscr{B}_i)$ is at most $O(X_2/k^2)$. Using the probability union bound, we obtain that this bound holds for all sets B_i , $1 \le i \le k$, with probability at least 1/2. We comment that this event is conditioned on the event that $|\mathscr{B}_i| \le 2n/k$, for each $1 \le i \le k$ (which occurs with very high probability), so using the rule of conditional probability, we can assume that with probability at least 1/4 the overall complexity of $\mathscr{A}(\mathscr{B}_i)$ is at most $O(n^2/k^2 + X_2/k^2)$, for each $1 \le i \le k$. By the probabilistic method [16] this implies that there exists such a partition $\mathscr{B}_1, \ldots, \mathscr{B}_k$.

Hence, a suitable adaptation of the analysis in Section 2 yields the first-level recurrence (where c > 0 below is an absolute constant):

$$C(m, n, X_1, X_2) \le k\beta(k)C(m, 2n/k, X_1, c(n^2/k^2 + X_2/k^2)) + k\beta(k)X_1 + O^*(mn),$$

for a suitable near-constant extremely slowly growing function $\beta(k)$. The overhead term $O^*(mn)$ comes from vertical visibilities that involve silhouettes and singularities, and follows by an argument similar to that in Section 2.

We next switch the roles of red and blue, and apply the same analysis to each pair \mathscr{R} , \mathscr{B}_i of surfaces, keeping \mathscr{B}_i fixed and partitioning \mathscr{R} into k random subsets, as above, each of which is of size at most 2m/k (with high probability). The analysis proceeds in a similar manner, and yields the bound

$$k^{2}\beta^{2}(k)C(2m/k,2n/k,c(m^{2}/k^{2}+X_{1}/k^{2}),c(n^{2}/k^{2}+X_{2}/k^{2}))+O_{k}(X_{1}+X_{2})+O_{k}^{*}(mn)$$

on the number of vertical visibilities, where the $O_k(\cdot)$ notation indicates that the constant of proportionality depends on *k*. That is, we obtain the recurrence

 $C(m, n, X_1, X_2) \leq k^2 \beta^2(k) C(2m/k, 2n/k, c(m^2/k^2 + X_1/k^2), c(n^2/k^2 + X_2/k^2)) + O_k(X_1 + X_2) + O_k^*(mn)$

By choosing *k* to be a sufficiently large constant, the solution of the recurrence is easily seen to be

$$C(m, n, X_1, X_2) = O^*(m^2 + n^2 + X_1 + X_2).$$

That is, replacing *m* and *n* by the original value of *n*, and X_1 , X_2 by the original quantity *X*, we obtain the following:

Theorem 4.1 Let \mathscr{S} be a collection of n constant-complexity semi-algebraic surfaces or surface patches in \mathbb{R}^3 , and let X be the number of vertices in $\mathscr{A}(\mathscr{S})$. Then the complexity of the vertical decomposition of $\mathscr{A}(\mathscr{S})$ is $O^*(n^2 + X)$.

5 Constructing Cuttings and Decompositions

5.1 Constructing cuttings

Let \mathscr{S} be a collection of *n* semi-algebraic sets of constant complexity in \mathbb{R}^d . Let Π be a substructure of $\mathscr{A}(\mathscr{S})$, say, defined by a collection of cells of $\mathscr{A}(\mathscr{S})$ that satisfy certain properties (e.g., lying

in the complement of the union or lying below the lower envelope). For a parameter r > 1, a (1/r)-*cutting* of Π is a set Ξ of pseudo-prisms with pairwise-disjoint relative interiors that cover Π , such that the relative interior of each pseudo-prism $\tau \in \Xi$ is crossed by (intersected by but not contained in) at most n/r sets of \mathscr{S} . The subset of \mathscr{S} crossed by τ is called the *conflict list* of τ .

It is well known that the random-sampling paradigm can be used to construct a (1/r)-cutting [1, 22, 34, 38]. Namely, set $s = cr \log r$, where c is a sufficiently large constant. Let $\mathscr{R} \subseteq \mathscr{S}$ be a random subset of \mathscr{S} of size s, and let $VD(\mathscr{R})$ be the vertical decomposition of $\mathscr{A}(\mathscr{R})$. For each cell $\tau \in VD(\mathscr{R})$, let $\mathscr{S}_{\tau} \subset \mathscr{S}$ be the subset of \mathscr{S} that crosses τ . By construction, $\mathscr{S}_{\tau} \cap \mathscr{R} = \emptyset$ and τ is a semi-algebraic set of constant complexity, therefore using a standard random-sampling argument [26, 34], it can be shown that $|\mathscr{S}_{\tau}| \leq n/r$ for all $\tau \in VD(\mathscr{R})$ with probability at least 1/2 assuming the constant c is chosen sufficiently large. Therefore, to construct a (1/r)-cutting Ξ of Π , we only have to decide which of the cells of $VD(\mathscr{R})$ should be included in Ξ to ensure that they cover Π .

If \mathscr{S} is a set of semi-algebraic sets in \mathbb{R}^3 and we wish to compute a (1/r)-cutting of $\mathscr{C}(\mathscr{S})$, the complement of the union of \mathscr{S} , we set $\Xi = \{\tau \in \mathrm{VD}(\mathscr{R}) \mid \tau \subseteq \mathscr{C}(\mathscr{R})\}$. Since $\mathscr{R} \subseteq \mathscr{S}$, $\mathscr{C}(\mathscr{S}) \subseteq \mathscr{C}(\mathscr{R})$, and thus Ξ is guaranteed to cover $\mathscr{C}(\mathscr{S})$. By Theorem 2.1, $|\Xi| = O^*(r^2 + U(r))$. In contrast, if we want to construct a (1/r)-cutting of the entire $\mathscr{A}(\mathscr{S})$, we set $\Xi = \mathrm{VD}(\mathscr{R})$. If $\mathscr{A}(\mathscr{S})$ has X vertices, then the expected number of vertices in $\mathscr{A}(\mathscr{R})$ is $O(r^2 + Xr^3/n^3)$, and thus, by Theorem 4.1, the expected size of Ξ is $O^*(r^2 + Xr^3/n^3)$. (If the size of Ξ is more than twice its expected size, we discard Ξ and repeat the construction.) Finally, if \mathscr{S} represents graphs of a set of trivariate functions in \mathbb{R}^4 and we wish to construct a (1/r)-cutting of the portion of $\mathscr{A}(\mathscr{S})$ lying below the lower envelope of \mathscr{S} , we set Ξ to be the set of cells of $\mathrm{VD}(\mathscr{R})$ that lie below the lower envelope of \mathscr{R} . By Theorem 3.1, $|\Xi| = O^*(r^3)$. Hence, we conclude the following:⁵

- **Theorem 5.1** (*i*) Let \mathscr{S} be a collection of n semi-algebraic sets of constant complexity in \mathbb{R}^3 , and let U(m) be an upper bound on the complexity of the union of at most m objects of \mathscr{S} . There exists a (1/r)-cutting of $\mathscr{C}(\mathscr{S})$, the complement of the union of \mathscr{S} , of size $O^*(r^2 + U(r))$.
 - (ii) Let \mathscr{F} be a collection of n trivariate semi-algebraic functions of constant complexity. There exists a (1/r)-cutting of the region below the lower envelope of \mathscr{F} of size $O^*(r^3)$.
- (iii) Let \mathscr{S} be a collection of *n* constant-complexity semi-algebraic surfaces or surface patches in \mathbb{R}^3 , so that the number of vertices in $\mathscr{A}(\mathscr{S})$ is X. Then there exists a (1/r)-cutting for \mathscr{S} of size $O^*(r^2 + r^3X/n^3)$.

For contestant values of r, these cuttings, along with the conflict lists of their cells, can be computed in O(n) expected time (where the constant of proportionality depends on r).

5.2 Constructing vertical decompositions

We now describe algorithms for constructing vertical decompositions for the cases studied in Sections 2–4.

⁵It is possible to reduce the size of the cuttings by a polylogarithmic factor using a two-level sampling scheme as described in [10, 22, 24, 38]. Since we are using $O^*()$ notation and are ignoring subpolynomial factors, we described a simpler, albeit slightly weaker, construction.

Complements of unions in \mathbb{R}^3 . Let \mathscr{S} be a collection of *n* semi-algebraic sets (each of constant complexity) in \mathbb{R}^3 such that the maximum complexity of the union of any subset \mathscr{S}' of \mathscr{S} of at most $m \leq n$ sets is U(m). Let $\mathscr{C}(\mathscr{S}')$ denote the complement of $\mathscr{U}(\mathscr{S}')$.

We present below an algorithm that constructs, in $O^*(n^2 + U(n))$ expected time, the vertical decomposition of $\mathscr{C}(\mathscr{S})$. More precisely, it constructs the set of pseudo-prisms in the vertical decomposition of $\mathscr{C}(\mathscr{S})$. As a main step of the algorithm, we perform the subtask of reporting all the vertical visibilities, within $\mathscr{C}(\mathscr{S})$, between pairs of edges (e, e') that lie on $\partial \mathscr{U}(\mathscr{S})$. By Theorem 2.1, the number of these vertical visibilities is $O^*(n^2 + U(n))$. We also compute the vertices, edges, and 2-faces of $\mathscr{U}(\mathscr{S})$ in $O^*(n^2 + U(n))$ expected time, e.g., using the randomized incremental algorithm described in [4]. Then the pseudo-prisms in VD(\mathscr{S}) can be computed in a fairly standard (though somewhat tedious) manner by traversing all the faces and edges of $\partial \mathscr{U}(\mathscr{S})$ and tracking their vertical visibilities. We omit the details from here in the interest of brevity, and refer the reader to [21], where a similar method was used for computing the vertical decomposition of an arrangement of triangles in \mathbb{R}^3 .

We follow a randomized divide-and-conquer scheme to compute vertical visibilities. Let $1 \le r \le n$ be a sufficiently large constant parameter. If $|\mathscr{S}| \le n_0$, where n_0 is a constant that depends on r, we report all pairs of vertical visibilities between the edges on $\partial \mathscr{C}(\mathscr{S})$ in a brute-force manner. Otherwise, we recursively construct a (1/(2r))-cutting Ξ of $\mathscr{C}(\mathscr{S})$ of size $O^*(r^2 + U(r))$, using Theorem 5.1 (i). (We comment that the actual reporting is done only at the bottom of the recurrence.) For each cell $\tau \in \Xi$, let $\mathscr{I}_{\tau} \subset \mathscr{S}$ be its conflict list, the family of input sets that cross the relative interior of τ , plus the O(1) input sets that define the cell τ . By construction, $|\mathscr{I}_{\tau}| \le n/(2r) + O(1) \le n/r$. As is easily verified, any edge pair (e, e') (that lie on $\partial \mathscr{C}(\mathscr{S})$) of vertical visibility within $\mathscr{C}(\mathscr{S})$ must be reported during this process, since the vertical segment ρ connecting e and e' must be contained in some prism cell of Ξ . Otherwise, this would imply that one of the input sets crosses ρ , but this violates the definition of vertical visibility. The overall expected running time T(n) to report all pairs of vertical visibility obeys the recurrence:

$$T(n) = O^*(r^2 + U(r))T(n/r) + O^*(n),$$

where the overhead term accounts for computing Ξ and the conflict lists of all the cells of Ξ . Using induction, it can be verified that the solution is $T(n) = O^*(n^2 + U(n))$. We have thus shown:

Theorem 5.2 Let \mathscr{S} be a collection of n constant-complexity semi-algebraic sets in \mathbb{R}^3 , such that the complexity of the union of any subset of \mathscr{S} of size m is U(m). Then the vertical decomposition of $\mathscr{C}(\mathscr{S})$ can be constructed in $O^*(n^2 + U(n))$ randomized expected time.

Arrangements in \mathbb{R}^3 . Let \mathscr{S} be a collection of *n* semi-algebraic sets (each of constant complexity) in \mathbb{R}^3 such that $\mathscr{A}(\mathscr{S})$ has *X* vertices. The above approach for computing the vertical decomposition of $\mathscr{C}(\mathscr{S})$ can be extended to compute the vertical decomposition of $\mathscr{A}(\mathscr{S})$. The only difference is that we now compute a (1/(2r))-cutting of $\mathscr{A}(\mathscr{S})$ of size $O^*(r^2 + r^3X/n^3)$ using Theorem 5.1 (iii). Omitting the straightforward details, we conclude the following result.

Theorem 5.3 Let \mathscr{S} be a collection of *n* constant-complexity semi-algebraic sets in \mathbb{R}^3 such that the arrangement $\mathscr{A}(\mathscr{S})$ has X vertices. Then the vertical decomposition of $\mathscr{A}(\mathscr{S})$ can be constructed in $O^*(n^2 + X)$ randomized expected time.

Lower envelopes in four dimensions. Let \mathscr{F} be a collection of *n* trivariate semi-algebraic functions of constant complexity. Our goal is to construct the vertical decomposition of E^- , the portion of $\mathscr{A}(\mathscr{F})$ lying below the lower envelope *E* of \mathscr{F} .

We briefly recall how the vertical decomposition is defined. We iterate over the functions of \mathscr{F} . For each function $a \in \mathscr{F}$, we form the 2D intersection surfaces $a \cap b$, for $b \in \mathscr{F} \setminus \{a\}$, which we denote for short as ab. We project these surfaces onto the *xyz*-space, and construct the vertical decomposition of the complement \mathscr{C}_a of the union \mathscr{U}_a as defined in Section 3. As in the basic construction in Section 2, the key step is to find all the vertical visibilities within \mathscr{C}_a . Each such visibility is between two edges, each of which is the intersection of two of the surfaces ab (for *a* fixed). We denote for short the intersection curve of ab and ac as abc. That is, we need to find all the 5-tuples (a, b, c, d, e) of distinct functions of \mathscr{F} , such that abc and ade form a vertical visibility (in the *z*-direction) within \mathscr{C}_a . Once we have found all these 5-tuples, completing the representation of the vertical decomposition can be carried out in a routine manner, similar to that used in the three-dimensional case reviewed earlier, which, for this setting, takes overall $O^*(n^3)$ time.

To construct the above visibilities, we proceed as above. Namely, we construct a (1/(2r))cutting Ξ of E^- of size $O^*(r^3)$ using Theorem 5.1 (ii). For each prism $\tau \in \Xi$, let \mathscr{F}_{τ} be its conflict
list plus the O(1) functions that define τ . We process recursively each prism cell τ , where at the
bottom of the recursion we report all pairs of vertical visibilities between the edges of \mathscr{F}_{τ} in a brute
force manner.

We claim that, for each vertical visibility (in the full collection \mathscr{F}) defined by a 5-tuple (a, b, c, d, e), all five functions appear in the conflict list of the same prism $\tau \in \Xi$, so the visibility will be found in the corresponding recursive step (in fact, as just described, it will be found at some leaf of the recursion). Indeed, let ζ be the *z*-vertical segment in the *xyz*-space that defines the visibility, with endpoints on *abc* and on *ade*. Let ζ^+ be the lifting of ζ to the graph of *a*. Then ζ^+ is fully contained in E_a , and in fact no function graph crosses the downward vertical curtain erected (in the *w*-direction) from ζ^+ .

We claim that ζ^+ is fully contained in a prism $\tau \in \Xi$, from which the previous claim follows readily. Suppose to the contrary that this is not the case, so ζ^+ crosses the boundary of such a prism. Since ζ^+ , or rather ζ , is in the *z*-direction, it follows that ζ must hit the floor or the ceiling, in the *z*-direction, of a prism of the three-dimensional decomposition of the minimization diagram, which, by construction, lies on some (*xyz*-projection of an) intersection surface, say *uv*. This however is impossible, since no such surface can cross the interior of ζ , which is fully contained in C_a , which is disjoint from all such surface projections. This establishes the correctness of the procedure and yields the following:

Theorem 5.4 Let \mathscr{F} be a collection of *n* trivariate semi-algebraic functions of constant complexity. Then the vertical decomposition of portion of $\mathscr{A}(\mathscr{F})$ lying below the lower envelope of \mathscr{F} can be constructed in randomized expected time $O^*(n^3)$.

6 Output-Sensitive Point-Enclosure Reporting in \mathbb{R}^3

In the problem considered in this section we have a set \mathscr{S} of n semi-algebraic regions of constant complexity in \mathbb{R}^3 , with a bound U(m) on the complexity of the union of any subset of at most m regions of \mathscr{S} . As in the earlier sections we assume here that $U(m) = O^*(m^2)$.

The goal is to preprocess \mathscr{S} into a data structure that can support *output-sensitive point enclosure reporting* queries, where a query specifies a point p and seeks to report all the regions of \mathscr{S} that contain p. We present an algorithm that uses $O^*(n^2)$ preprocessing and storage, and answers a query is $O^*(1 + k)$ time, where k is the output size.

The technique that we present bears some resemblance to the original technique of Matoušek [39], which has been developed for the case where \mathscr{S} consists of halfspaces, but is different in several key aspects.

Let *k* be a parameter. We take a random sample \mathscr{R} of $\frac{\alpha n}{k}$ regions from \mathscr{S} (in expectation), by choosing each region independently with probability $q = \frac{\alpha}{k}$, for some small constant $0 < \alpha < 1$, and construct the vertical decomposition $VD(\mathscr{R})$ of the complement $\mathscr{K} = \mathscr{K}(\mathscr{R})$ of the union of \mathscr{R} . As shown in Section 5.2, this takes time $O^*((n/k)^2)$. In addition, we associate with each cell τ of $VD(\mathscr{R})$ its *conflict list* \mathscr{S}_{τ} , which is the set of those regions of \mathscr{S} whose boundary crosses τ , and the set \mathscr{S}_{τ}^0 of those regions of \mathscr{S} that fully contain τ . By random sampling theory, with high probability,

$$|\mathscr{S}_{\tau}| = O(k \log(n/k)) = O(k \log n)$$

for every cell τ .

To obtain an efficient construction of the conflict lists, as well as an efficient procedure for locating the points of *P* in VD(\mathscr{R}) (see below), we modify the construction of VD(\mathscr{R}) and make it *hierarchical*, as follows. We construct a hierarchical tree structure of decompositions. At each recursive step we take a random sample \mathscr{R}_0 of r_0 regions from the current set \mathscr{S}' , for a sufficiently large constant parameter r_0 , and construct the vertical decomposition VD(\mathscr{R}_0) of the complement of the union of \mathscr{R}_0 . For each cell τ of VD(\mathscr{R}_0) we construct its conflict list \mathscr{S}'_{τ} , and the set \mathscr{S}'_{τ} of regions that fully contain τ . Since r_0 is constant, this takes $O(|\mathscr{S}'|)$ time over all cells τ . We recursively repeat the construction for each conflict list \mathscr{S}'_{τ} . The construction terminates when we reach subproblems with $O(k \log n)$ regions.

A single recursive step in this hierarchy with *n* input regions generates $O^*(r_0^2)$ subproblems, each with $O^*(n/r_0)$ regions. The overhead nonrecursive cost of the step is O(n), where the constant of proportionality depends on r_0 . Hence, at level *j* of the recursion, we have $O^*(r_0^{2j})$ subproblems, each of size $O^*(n/r_0^j)$, and the total cost of constructing the whole structure, taking also into account the overhead costs, is therefore

$$O^*\left(\sum_j r_0^{2j} \cdot \frac{n}{r_0^j}\right) = O^*\left(n\sum_j r_0^j\right) = O^*\left(nr_0^{j_{\max}}\right),$$

where the constant of proportionality is the product of two factors, one depending on r_0 but not on j, and one of the form c^j for some absolute constant, independent of r, and where j_{max} is the maximum level of recursion, which satisfies $n/r_0^{j_{\text{max}}} \approx k \log n$, or $r_0^{j_{\text{max}}} = O^*(n/k)$. That is, the overall cost of the construction is $O^*(n^2/k)$.

Note that the output of the hierarchical construction is not necessarily VD(\mathscr{R}), but it suffices for our need. Specifically, we now locate the query point p in the structure. At each node τ that the search reaches, we find, in brute force, the cell τ' of the local vertical decomposition at τ that contains p, and continue the search recursively at τ' . At each step of the search, at any node τ , we can report all the regions of \mathscr{S}^0_{τ} , as they certainly contain p. If at some step we detect that p does not lie in any cell of the local vertical decomposition, we conclude that p does not belong to \mathscr{K} , and terminate the search (see below for the rationale of this termination). Otherwise the search reaches a leaf τ . We then report all the regions in $\mathscr{S}_{\tau'}^0$, over all nodes τ' along the search path. The only unreported regions that might contain p are those in \mathscr{S}_{τ} . As will follow from the overall structure of the algorithm, we can afford to inspect all the regions of \mathscr{S}_{τ} , and output those among them that contain p. The cost of the query is $O(\log n)$ plus a cost that, as we will show, is larger than the number of regions that have been reported, by at most a logarithmic factor.

The full reporting procedure. Let us first consider the offline problem, where we are given *m* query points. Define the *depth* of a point *p* to be the number of regions of \mathscr{S} that contain *p*. Let *p* be a point of depth $j \le k$. Then the probability that *p* belongs to $\mathscr{K}(\mathscr{R})$ is

$$(1-q)^j \ge (1-q)^k \approx e^{-qk} = e^{-\alpha}.$$

We can make this probability very close to 1 by independently drawing $c \ln m$ random samples \Re . The probability that p avoids the complement of the union for all these samples is at most

$$(1-e^{-\alpha})^{c\ln m} \approx e^{-ce^{-\alpha}\ln m} = \frac{1}{m^{ce^{-\alpha}}}.$$

By choosing *c* sufficiently large, we can ensure that, with high probability, all query points, taken from some set of *m* possible queries, are captured in this manner (i.e., belong to $\mathcal{K}(\mathcal{R})$ for at least one sample \mathcal{R}).

We now construct a geometric sequence of these structures, for $k = 2^j$ with j = 1, 2, ... For a point $p \in P$, let j be the first index for which p lies in a cell τ of one of the vertical decompositions constructed for $k = 2^j$. (Informally, as j increases, the size of the sample \mathscr{R} decreases, so $\mathscr{K}(\mathscr{R})$ increases, making it 'easier' for p to belong to $\mathscr{K}(\mathscr{R})$. In the worst case, p may stay inside the union for every k, but the analysis will handle this case too.) The preceding analysis implies that, with high probability, the depth of p is larger than k/2 (otherwise p would have been captured earlier, with high probability). But then we can afford to inspect all the $O(k \log n)$ regions in the conflict list of τ and report those that contain p, in the sense that the size of the list is larger than the output size by at most a logarithmic factor.

The cost of constructing all these structures is $\sum_j O^*(n^2/2^j) = O^*(n^2)$, and the cost of locating the query point in the respective vertical decompositions, ignoring the reporting part of the cost, is $O^*(1)$. For the reporting part, we do not report anything when we find out that the query point pis not in the current vertical decomposition. At the first time when p lies in VD(\mathscr{R}), for each cell τ' that it visits, all the regions of $\mathscr{S}^0_{\tau'}$ are reported. Then at the leaf τ that the search reaches, we iterate over its conflict list and report those regions that contain p. The overall reporting cost is proportional to the output size, up to a logarithmic factor, which may arise when we iterate over the conflict list of the leaf, which may be larger than the output size by a logarithmic factor. That is, we have a data structure of size $O^*(n^2)$, where each point-enclosure query costs $O^*(1+k)$. Hence, if we want to perform m point-enclosure reporting queries, the overall cost, including preprocessing, is $O^*(n^2 + m + K)$, where K is the overall output size.

Returning to the online problem (where queries are given online), we observe that there are at most $O(n^3)$ combinatorially different queries, each of which corresponds to a cell in the arrangement $\mathscr{A}(\mathscr{S})$. Therefore, we follow verbatim the above analysis with $m = O(n^3)$. This results in a data structure of overall storage and preprocessing $O^*(n^2)$, for the case where $U(n) = O^*(n^2)$, or $O^*(U(n))$ otherwise, which answers point-enclosure reporting queries in $O^*(1+k)$ time.

Point enclosure reporting in 4D. The same machinery can be used for performing outputsensitive point-enclosure reporting queries in \mathbb{R}^4 . In this setup we have a collection \mathscr{F} of nsemi-algebraic trivariate functions of constant complexity, and we want to preprocess \mathscr{F} into a data structure, so that, for a query point $q \in \mathbb{R}^4$, it reports all the functions of \mathscr{F} whose graphs pass below q. A more or less identical analysis shows that this can be done with $O^*(n^3)$ storage and preprocessing time, so that a query of the above kind can be answered in $O^*(1 + k)$ time, where k is the output size, namely the number of functions below the query point. Hence, in an offline version, m queries can be answered in $O^*(n^3 + m + K)$ time, including preprocessing, where K is the overall output size.

In conclusion, we have shown:

Theorem 6.1 (a) Let \mathscr{S} be a set of n semi-algebraic regions of constant complexity in \mathbb{R}^3 , so that the complexity of the union of any subset of at most m regions of \mathscr{S} is $O^*(m^2)$. Then \mathscr{S} can be preprocessed into a data structure of size $O^*(n^2)$, in $O^*(n^2)$ randomized expected time, which supports point-enclosure reporting queries in time $O^*(1 + k)$, where each query is with a point $q \in \mathbb{R}^3$, and seeks to report all regions of \mathscr{S} that contain q, and k is the output size.

(b) Let \mathscr{F} be a set of n semi-algebraic trivariate functions of constant complexity. Then \mathscr{F} can be preprocessed into a data structure of size $O^*(n^3)$, in $O^*(n^3)$ randomized expected time, which supports point-enclosure queries in time $O^*(1+k)$, where each query is with a point $q \in \mathbb{R}^4$, and seeks to report all functions of \mathscr{F} whose graphs pass below q, and k is the output size.

7 Nearest Neighbor Searching amid Lines in \mathbb{R}^3

We now turn our attention to nearest-neighbor-searching problems involving points and lines in \mathbb{R}^3 . In this section, we present a linear-size data structure for preprocessing a set *L* of *n* lines in \mathbb{R}^3 into a data structure so that for a query point $p \in \mathbb{R}^3$, the line of *L* nearest to *p* can be reported quickly (more quickly than what can be obtained by the standard machinery). Using standard techniques (e.g., parametric search) [1,8], a nearest-neighbor query, referred to as an NN query on *L*, can be reduced to answering $O^*(1)$ sphere-intersection-detection queries on *L*. That is, we want to preprocess *L* into a data structure that can efficiently determine whether a query sphere σ intersects any of the lines in *L*.

Overall data structure. Our overall data structure is based on the following technical property, originally proved by Mohaban and Sharir [41]. Let ℓ be a line in \mathbb{R}^3 , and let σ_p be a sphere, centered at a point p. Let V_{ℓ} be the vertical plane that contains ℓ , and let H_{ℓ} be the plane that contains ℓ and is orthogonal to V_{ℓ} . We say that ℓ is *lower* (resp., *higher*) than σ_p if p lies above (resp., below) H_{ℓ} ; see Figure 1.

Lemma 7.1 ([41]) Assuming that ℓ is lower than σ_p (using the above notation), ℓ intersects σ_p if and only if the following two conditions hold:

- (i) The xy-projections of ℓ and of σ_p intersect, and
- (ii-) ℓ lies above the parallel line ℓ^- that lies in V_ℓ and is tangent to σ_p from below.



Figure 1: Illustration of condition (ii-) of Lemma 7.1. Here ℓ is lower than σ_p .

Symmetrically, assuming that ℓ *is higher than* σ_p *,* ℓ *intersects* σ_p *if and only if (i) holds and*

(ii+) ℓ lies below the parallel line ℓ^+ that lies in V_{ℓ} and is tangent to σ_p from above.

We describe a linear-size data structure that, for a query sphere σ , determines whether any line of *L* that is lower than σ intersects σ . (A similar data structure can be constructed for detecting whether any line of *L* that is higher than σ intersects σ .) We thus need a data structure that, for a query sphere σ , returns YES if a line in ℓ satisfies the following three conditions, as in Lemma 7.1:

- (C1) the *xy*-projections of ℓ and σ intersect,
- (C2) ℓ is lower than σ , and
- (C3) ℓ lies above the parallel line ℓ^- that lies in V_{ℓ} and is tangent to σ_p from below.

We use a multi-level partition tree [1,2] for answering queries of this kind. In particular, we construct a 3-level partition tree, each of whose nodes v stores a "canonical" subset $L_v \subseteq L$. The first-level tree identifies the subset of lines that satisfy condition (C1) for the given query. Since a line in \mathbb{R}^2 requires two parameters, (C1) can be formulated as a two-dimensional semi-algebraic range query of a very simple nature-the inequality that we need to test just involves the absolute value of a linear expression. Thus the first level is a 2-dimensional partition tree for semi-algebraic range queries of this simple kind [11,40]. As shown in [41], and easy to see, (C2) just amounts to testing whether the center of the sphere lies above the respective planes H_{ℓ} , so it can be formulated as a 3-dimensional halfspace range query. For each node *u* of the first-level tree, we construct a 3-dimensional partition tree for halfspace range searching, on the subset of lines L_u associated with u, as a second-level tree. Finally, for each node v of every second-level tree, we construct a third-level partition tree on L_v , the subset of lines associated with v, which tests for (C3). We present below a linear-size data structure that can test condition (C3) in $O^*(n^{2/3})$ time (actually, in $O^*(|L_v|^{2/3})$ time). For a query sphere σ , the first two levels of the partition tree return the subset of lines that satisfy conditions (C1) and (C2) as the union of a few canonical subsets (see below for a precise statement). For each of these canonical subsets L_v , the third-level tree constructed on L_v is used to test whether any line in L_v satisfies (C3). If the answer is YES, then we conclude that σ intersects a line of L_v and return YES. Since the query time at each level is $O^*(n^{2/3})$ (it is actually smaller for the first level), the properties of multi-level partition trees (see, e.g., Theorem A.1 in the appendix of [2]), imply that the overall query time is also $O^*(n^{2/3})$. The overall size of the data structure is O(n).⁶

Sphere-intersection query for lines lower than the sphere. Let *L* be a set of *n* lines in \mathbb{R}^3 . We wish to preprocess *L* into a linear-size data structure that, for a query sphere σ satisfying conditions (C1) and (C2) for all lines in *L*, can determine in $O^*(n^{2/3})$ time whether σ intersects any line of *L*. We work in the 4-dimensional parametric space of lines, denoted by \mathbb{L} , where a line ℓ is represented by the point $\ell^* = (a, b, c, d)$ and the equations defining ℓ are y = ax + c, z = bx + d; \mathbb{L} is thus identified⁷ with \mathbb{R}^4 . Put $L^* = \{\ell^* \mid \ell \in L\}$. A sphere σ is associated with a surface (patch) $\gamma_{\sigma} \subset \mathbb{L}$, which is the locus of points ℓ^* such that the corresponding line ℓ is tangent to σ from below. Let γ_{σ}^+ be the set of points lying on or above γ_{σ} in the *d*-direction; γ_{σ}^+ is a semi-algebraic set of constant complexity. It is easily seen that a line ℓ satisfying conditions (C1) and (C2) intersects σ if and only if ℓ^* lies in γ_{σ}^+ . Let Γ be the collection of all sets γ_{σ}^+ such that σ satisfies (C1) and (C2) for all lines in *L*. Thus the sphere-intersection query for a sphere σ in our setting reduces to semi-algebraic range-emptiness query in L^* with $\gamma_{\sigma}^+ \in \Gamma$. Using the known and standard partition tree mechanism [11,40], this query can be answered in $O^*(n^{3/4})$ time, but we show how to improve the query time to $O^*(n^{2/3})$.

We follow the approach of Matoušek [39] and of Sharir and Shaul [45] for answering the rangeemptiness query. We need a couple of definitions. Let $P \subset \mathbb{L}$ be a set of n points. For a parameter $k \geq 0$, we call a semi-algebraic set $\gamma \subset \mathbb{L}$, which semi-unbounded in the negative d-direction, k-shallow if $|P \cap \gamma| \leq k$. For a parameter $r \geq 1$, we call a family $\Pi = \{(P_1, \Delta_1), \ldots, (P_u, \Delta_u)\}$ a (1/r)-partition for P if (i) $\{P_1, \ldots, P_u\}$ is a partition of P, (ii) $n/2r \leq |P_i| \leq n/r$, and (iii) $P_i \subset \Delta_i$ where $\Delta_i \subseteq \mathbb{L}$ is a semi-algebraic set of constant complexity, referred to as a cell of Π . The *crossing number* of Π for a semi-algebraic set τ , denoted by $\chi(\Pi, \tau)$, is the number of cells of Π intersected by the boundary of τ . The crossing number of Π for a family Ξ of semi-algebraic sets, denoted by $\chi(\Pi, \Xi)$, is defined as $\max_{\tau \in \Xi} \chi(\Pi, \tau)$.

A major ingredient of the approach in [39, 45] is to construct a so-called *test set* Φ of a small number of semi-algebraic sets, which represent well all query semi-algebraic sets that are shallow. The following lemma of Sharir and Shaul [45, Theorem 3.2] summarizes the key property:

Lemma 7.2 ([45]) Let P be a set of n points in \mathbb{R}^d , for some $d \ge 1$, and let Γ be a (possibly infinite) family of semi-algebraic sets of constant complexity. Let $r \ge 1$ be a parameter, and let Φ be another finite collection (not necessarily a subset of Γ) of semi-algebraic sets of constant complexity with the following properties:

- (i) Every set in Φ is (n/r)-shallow with respect to P.
- (ii) The complement of the union of any m sets of Φ can be decomposed into at most $\zeta(m)$ "elementary cells" (semi-algebraic sets of constant complexity) for any $m \ge 1$, where $\zeta(m)$ is a suitable monotone increasing superlinear function of m.
- (iii) Any (n/r)-shallow set $\gamma \in \Gamma$ can be covered by the union of at most δ ranges of Φ , where δ is a constant (independent of r).

⁶A straightforward application of the multi-level data-structure framework leads to a data structure of size $O^*(n)$. But, using well known machinery, the size can be improved to O(n) while keeping the query time $O^*(n^{2/3})$ by constructing secondary structures only at some of the nodes.

⁷For convenience (and with no loss of generality if one assumes general position), we ignore the fact that this space is actually projective.

Then there exists a (1/r)-partition Π of P such that for any (n/r)-shallow range $\gamma \in \Gamma$, $\chi(\Pi, \gamma) = O(r/\zeta^{-1}(r) + \log r \log |\Phi|)$ if $\zeta(r)/r^{1+\varepsilon}$ is monotonically increasing for some (arbitrarily small) constant $\varepsilon > 0$, and $\chi(\Pi, \gamma) = O(r \log r/\zeta^{-1}(r) + \log r \log |\Phi|)$ otherwise. Furthermore, Π can be constructed in $(|\Phi| + n)r^{O(d)}$ expected time assuming Φ is given.

As shown in [39, 45], using Lemma 7.2 and assuming that $|\Phi| = r^{O(d)}$, one can construct a partition tree of linear-size that can determine in $O^*(n/\zeta^{-1}(n))$ time whether $\gamma \cap P \neq \emptyset$, for any query range $\gamma \in \Gamma$. We present an algorithm below for constructing a test set Φ of size $r^{O(1)}$ for our setup so that $\zeta(m) = O^*(m^3)$ and $\delta = 1$, which in turn yields a linear-size data structure for sphere intersection queries with $O^*(n^{2/3})$ query time, as desired.

Constructing a test set. To construct the test set, we also use the 4-dimensional parametric space S of spheres in \mathbb{R}^3 , where a sphere σ of radius r centered at a point p is mapped to the point $\sigma^* = (p, r) \in S$; S can thus be identified with \mathbb{R}^4 . A line ℓ in \mathbb{R}^3 is mapped to a surface ω_{ℓ} , consisting of all points $\sigma^* \in S$ that represent spheres that touch ℓ from above. As is easily verified, these surfaces are monotone over the *xyz*-subspace, so that a point σ^* lies above the surface ω_{ℓ} if and only if ℓ intersects σ , assuming σ and ℓ satisfy (C1) and (C2).⁸

Let $\Omega = \{\omega_{\ell} \mid \ell \in L\}$ denote the collection of these surfaces. We take a random subset $R \subseteq \Omega$ of $s = cr \log r$ surfaces, for some sufficiently large constant r, and construct the vertical decomposition VD(R) of the arrangement $\mathscr{A}(R)$; VD(R) has $O^*(r^4)$ cells [35]. By a standard random-sampling argument [34], each cell of VD(R) is crossed by at most n/r surfaces of Ω with probability at least 1/2. If this is not the case, we discard R and choose another random subset, until we find one with the desired property. We choose a subset Ξ of VD(R), namely, those cells that have at most n/r surfaces of Ω passing *fully below* them. By construction, these cells cover the lowest n/r levels of $\mathscr{A}(\Omega)$, and are contained in the at most 2n/r lower levels of $\mathscr{A}(\Omega)$.

Let τ be a cell of Ξ . We now switch to the parametric line-space \mathbb{L} , where each point $\sigma^* \in \tau$ becomes the surface γ_{σ} . We construct the lower envelope of the (infinitely many) surfaces γ_{σ} over all $\sigma^* \in \tau$. Let $\Phi_{\tau} \subset \mathbb{L}$ be the set of points lying above the lower envelope. Since τ has constant complexity, Φ_{τ} is a semi-algebraic surface of constant complexity. A point $\ell^* \in L^*$ lies in Φ_{τ} if and only if there is a surface γ_{σ} , with $\sigma^* \in \tau$, that passes below ℓ^* . This happens when, back in S, the surface ω_{ℓ} (corresponding to the line ℓ) crosses τ or lies below τ . By construction, there are at most n/r + n/r = 2n/r such surfaces. Consequently, Φ_{τ} is (2n/r)-shallow with respect to the points of L^* .

Set $\Phi = {\Phi_{\tau} | \tau \in \Xi}$. Φ is a family of $O^*(r^4)$ constant-complexity semi-algebraic surfaces⁹ in \mathbb{L} , each of which is (2n/r)-shallow with respect to L^* . This is our desired test set, as stated in the following lemma. The proof of the lemma is an immediate consequence of our construction.

Lemma 7.3 Let σ be a sphere that satisfies (C1) and (C2) with respect to the lines of L and that is (n/r)-shallow with respect to L. Then there exists a semi-algebraic set of Φ that contains σ^* .

Plugging Lemma 7.3 into Lemma 7.2, Φ is a test set for L^* with respect to the semi-algebraic ranges in Γ , with $\delta = 1$ and $\zeta(m) = O^*(m^3)$. The bound on $\zeta(m)$ follows from Theorem 3.1. Putting everything together, we thus obtain:

⁸Informally, this is why we have to distinguish between lines that pass below the sphere and lines that pass above.

⁹By construction, as in [45], these semi-algebraic sets do not correspond to spheres any more, but they are nevertheless semi-algebraic sets of constant complexity.

Theorem 7.4 A set L of n lines in \mathbb{R}^3 can be preprocessed, in $O^*(n)$ expected time, into a data structure of size O(n) so that for any query point $p \in \mathbb{R}^3$, the line of L nearest to p can be computed in $O^*(n^{2/3})$ time.

8 Nearest-Neighbor Queries with Lines in \mathbb{R}^3

In this section we consider the converse situation, where queries are lines in \mathbb{R}^3 . We first consider in Section 8.1 a simpler, yet challenging, case where the input is a set of points in \mathbb{R}^3 , and then, in Section 8.2, consider the case where the input is a set of lines in \mathbb{R}^3 . We are interested in a data structure that answers NN queries in $O^*(1)$ time using as little storage as possible.

8.1 Nearest-point queries with lines in \mathbb{R}^3

Let *P* be a set of *n* points in \mathbb{R}^3 . Since we are aiming for an $O^*(1)$ query time, we work in the 4-dimensional parametric space \mathbb{L} of (query) lines (the same parametric space used in the previous section), where a line ℓ in \mathbb{R}^3 , given by the equations y = ax + c and z = bx + d, is represented as the point $\ell^* = (a, b, c, d) \in \mathbb{L}$. We begin by describing the distance function between a point and a line in \mathbb{R}^3 and the Voronoi diagram that the points of *P* induce in \mathbb{L} .

Distance function, lower envelope, Voronoi diagram. Let $\ell^* = (a, b, c, d) \in \mathbb{L}$. For a fixed pair $a, b \in \mathbb{R}$, the (unnormalized) direction of ℓ , (1, a, b), is fixed. Let H be the plane that is orthogonal to ℓ (i.e., with normal direction (1, a, b)) and passes through the origin. Redefine the representation of ℓ so that (c, d) is actually the intersection of ℓ with H, in a suitable canonical coordinate frame within H (we omit here the easy details of specifying this frame, noting that it does depend on (a, b)). Write u = (1, a, b).

For a point $p \in P$, let p^{\downarrow} denote its projection onto H. Concretely, write $p^{\downarrow} = p + tu$. The condition for p^{\downarrow} to lie in H is that p + tu be orthogonal to u (recall that H passes through the origin). That is, we require that

$$(p+tu) \cdot u = p \cdot u + t|u|^2 = 0$$
, or $t = -\frac{p \cdot u}{|u|^2}$.

That is, we have

$$p^{\downarrow} = p - \frac{p \cdot u}{|u|^2} u.$$

Write $p^{\downarrow} = (x_p(a, b), y_p(a, b))$; clearly, these coordinates depend on (a, b). The distance between p and ℓ , denoted by dist (p, ℓ) , is then the distance between p^{\downarrow} and (c, d). That is,

$$dist^{2}(p, \ell) = (x_{p}(a, b) - c)^{2} + (y_{p}(a, b) - d)^{2}$$

= $(x_{p}^{2}(a, b) + y_{p}^{2}(a, b)) - 2cx_{p}(a, b) - 2dy_{p}(a, b) + (c^{2} + d^{2}).$ (1)

For a query line ℓ , our goal is to compute $\arg \min_{p \in P} \operatorname{dist}^2(p, \ell)$, the point $p \in P$ that is closest to ℓ , i.e., minimizes (1). Since $c^2 + d^2$ is common to all points p, we can drop it, and seek the point p that minimizes

$$f_p(a, b, c, d) = g_p(a, b) - 2cx_p(a, b) - 2dy_p(a, b),$$
(2)

where $g_p(a,b) = x_p^2(a,b) + y_p^2(a,b)$. Let $\mathscr{F} = \{f_p \mid p \in P\}$ be the resulting set of *n* 4-variate functions. Consider the lower envelope $E : \mathbb{L} \to \mathbb{R}$ of \mathscr{F} defined as

$$E(a,b,c,d) = \min_{p \in P} f_p(a,b,c,d).$$

The projection of the graph of *E* onto L, denoted by M := M(P), is called the minimization diagram of \mathscr{F} . M induces a partition of L, to which we refer as the Voronoi diagram of *P* in L. Each cell τ of M is associated with a point $p \in P$ that is the nearest neighbor of all lines whose dual points lie in the cell τ . For a query line ℓ , we wish to locate the cell of M containing $\ell^* = (a, b, c, d)$. However, currently we do not know how to preprocess four-dimensional minimization diagrams, like M, into a data structure of size $O^*(n^4)$ for answering point-location queries in $O^*(1)$ time. We manage to address this problem by exploiting the additional structure of the Voronoi cells of M.

Structure of Voronoi cells. For each point $p \in P$, let M_p denote the region of \mathbb{L} where f_p attains E, i.e., the set of cells of M that are associated with p. Let E_p denote the graph of E restricted to M_p , which is a suitable subset of the graph of f_p .

For each $q \in P$, $q \neq p$, let $\sigma_{p,q}$ denote the intersection surface of f_p and f_q , which is a threedimensional surface that is disjoint from the relative interior of E_p , and does not pass below any point on E_p . It is defined by the equation

$$g_p(a,b) - 2cx_p(a,b) - 2dy_p(a,b) = g_q(a,b) - 2cx_q(a,b) - 2dy_q(a,b).$$

Assuming $y_q(a, b) \neq y_p(a, b)$, we define a trivariate function $\psi_{p,q} : \mathbb{L}^{(d)} \to \mathbb{R}$, where $\mathbb{L}^{(d)} \subset \mathbb{L}$ is the 3-dimensional hyperplane d = 0, as follows:

$$d = \psi_{p,q}(a,b,c) := \frac{g_q(a,b) - g_p(a,b)}{2(y_q(a,b) - y_p(a,b))} - \frac{x_q(a,b) - x_p(a,b)}{y_q(a,b) - y_p(a,b)}c.$$
(3)

The surface $\sigma_{p,q}$ partitions \mathbb{L} into the two regions

$$K_{p,q}^{(d+)} = \{\ell^* \in \mathbb{L} \mid f_p(\ell^*) \le f_q(\ell^*)\} \text{ and } K_{p,q}^{(d-)} = \{\ell^* \in \mathbb{L} \mid f_p(\ell^*) \ge f_q(\ell^*)\}.$$

Then $M_p = \bigcap_{q \in P \setminus \{p\}} K_{p,q}^+$. By (3), we can write $K_{p,q}^{(d+)}$ as

$$K_{p,q}^{(d+)} = \{(a,b,c,d) \in \mathbb{L} \mid y_q(a,b) - y_p(a,b) \ge 0, \ d \le \psi_{p,q}(a,b,c)\} \bigcup \{(a,b,c,d) \in \mathbb{L} \mid y_q(a,b) - y_p(a,b) \le 0, \ d \ge \psi_{p,q}(a,b,c)\}.$$

To simplify this representation, we define two functions $\psi_{p,q}^+, \psi_{p,q}^- : \mathbb{L}^{(d)} \to \mathbb{R}$ by:

$$\psi_{p,q}^{(d+)}(a,b,c) = \begin{cases} \psi_{p,q}(a,b,c) & y_q(a,b) - y_p(a,b) \ge 0 \\ +\infty & \text{otherwise} \end{cases} \\
\psi_{p,q}^{(d-)}(a,b,c) = \begin{cases} \psi_{p,q}(a,b,c) & y_q(a,b) - y_p(a,b) \le 0 \\ -\infty & \text{otherwise.} \end{cases}$$
(4)

Then we can write

$$K_{p,q}^{(d+)} = \{(a, b, c, d) \in \mathbb{L} \mid \psi_{p,q}^{(d-)}(a, b, c) \le d \le \psi_{p,q}^{(d+)}(a, b, c)\}.$$
(5)



Figure 2: The structure of the decomposition of the lower envelope and the minimization diagram of the sample. To simplify the figure, the superscripts (d+) and (d-) have been suppressed.

In other words, M_p is the *sandwich region* between the lower envelope (with respect to the *d*-direction) $E_p^{(d-)}$ of the functions $\psi_{p,q}^{(d+)}$ and the upper envelope $E_p^{(d+)}$ of the functions $\psi_{p,q}^{(d-)}$, for $q \in P \setminus \{p\}$. See Figure 2 for an illustration.

We can thus write M_p as $M_p^{(d-)} \cap M_p^{(d+)}$, where $M_p^{(d-)}$ (resp., $M_p^{(d+)}$) is the region below the lower envelope $E_p^{(d-)}$ (resp., above the upper envelope $E_p^{(d+)}$) in the *d*-direction.

Note that the above construction is symmetric in *c* and *d*, as each function f_p is linear in both *c* and *d*. We can therefore repeat the whole construction, switching between *c* and *d*. The analysis is fully symmetric, with obvious modifications, such as having $x_q(a, b) - x_p(a, b)$ in the denominators in (2), and similar straightforward changes. M_p can now be written as $M_p^{(c-)} \cap M_p^{(c+)}$, where $M_p^{(c-)}$ (resp., $M_p^{(c+)}$) is the region below (resp., above), in the *c*-direction, the lower envelope $E_p^{(c-)}$ (resp., upper envelope $E_p^{(c+)}$) of the corresponding set of trivariate functions $\psi_{p,q}^{(c-)}$ (resp., $\psi_{p,q}^{(c+)}$) defined analogously to $\psi_{p,q}^{(d-)}$ (resp., $\psi_{p,q}^{(d+)}$).

We conclude this discussion with the following observation, which will be the key to the performance of our data structure and the query procedure.

Lemma 8.1 Let $\ell^* = (\ell_a, \ell_b, \ell_c, \ell_d) \in \mathbb{L}$, and let p be a point of P. Let $\rho^{(d)}$ (resp., $\rho^{(c)}$) denote the line in the d-direction (resp., c-direction) in \mathbb{L} passing through ℓ^* , and let $\gamma^{(d)}$ (resp., $\gamma^{(c)}$) denote the curve on (the graph of) f_p traced over the line $\rho^{(d)}$ (resp., $\rho^{(c)}$). Let q be a point of P that is nearer to ℓ than p, assuming that such a point exists, i.e., $f_q(\ell^*) < f_p(\ell^*)$. Then f_q intersects either $\gamma^{(d)}$ or $\gamma^{(c)}$. Furthermore if f_q intersects $\gamma^{(d)}$ at a point $w = (w_a, w_b, w_c, w_d)$ such that $w_d > \ell_d$ (resp., $w_d < \ell_d$) then we have $w_d = \psi_{p,q}^{(d-)}(w_a, w_b, w_c)$ (resp., $w_d = \psi_{p,q}^{(d+)}(w_a, w_b, w_c)$). A similar property holds if f_q intersects $\gamma^{(c)}$.

Proof. Suppose f_q does not intersect $\gamma^{(d)}$. Then we would have, using (2),

$$g_q(a,b) - 2cx_q(a,b) - 2dy_q(a,b) < g_p(a,b) - 2cx_p(a,b) - 2dy_p(a,b)$$

for every *d*. Since *a*, *b*, *c* are fixed along $\gamma^{(d)}$, this can happen only when $y_q(a, b) = y_p(a, b)$. Repeating the same argument for $\gamma^{(c)}$, if f_q does not intersect $\gamma^{(c)}$, then $x_q(a, b) = x_p(a, b)$. Therefore, if f_q does not intersect either of these curves then we also have, by definition, $g_q(a, b) = g_p(a, b)$, which implies that $f_q(\ell^*) = f_p(\ell^*)$, i.e., *p* and *q* are equidistant from ℓ . This contradicts the assumption that *q* is (strictly) nearer to ℓ than *p*.

Thus f_q intersects one of the curves, say, for specificity, that it intersects $\gamma^{(d)}$. Again, by (2), f_q intersects $\gamma^{(d)}$ at a unique point $w = (w_a, w_b, w_c, w_d)$, with $w_d = \psi_{p,q}(w_a, w_b, w_c)$. If $w_d > \ell_d$ (resp., $w_d < \ell_d$), then by (4), we must have $w_d = \psi_{p,q}^{(d-)}(w_a, w_b, w_c)$ (resp., $w_d = \psi^{(d+)}(w_a, w_b, w_c)$). This completes the proof of the lemma. \Box

We are now ready to describe the data structure based on the above lemma.

Overall data structure. Fix some sufficiently large constant parameter r > 0. We choose a random subset $R \subseteq P$ of $cr \log r$ points, for a suitable absolute constant c > 0. We construct the Voronoi diagram M(R) of R. For every point $p \in R$, we construct $M_p^{(d-)}, M_p^{(d+)}, M_p^{(c-)}, M_p^{(c+)}$, as defined above (with respect to M(R)). Let $\Xi_p^{(d-)} = VD(M_p^{(d-)})$ be the vertical decomposition of $M_p^{(d-)}$. Similarly define, $\Xi_p^{(d+)}, \Xi_p^{(c-)}, \Xi_p^{(c+)}$. Let Ξ be the set of cells in all these 4|R| vertical decompositions. By Theorem 3.1, $|\Xi| = O^*(r \cdot r^3) = O^*(r^4)$, and by Theorem 5.4, Ξ can be constructed in a total of $O^*(r^4)$ expected time.

We define a *conflict list* L_{τ} for every $\tau \in \Xi$, as follows. For each point $p \in R$ and each cell τ of $\Xi_p^{(d-)}$ (resp., $\Xi_p^{(d+)}$), we define $P_{\tau} \subset P$ to be the subset of points $q \in P$ for which the surface $d = \psi_{p,q}^{(d+)}$ (resp., $d = \psi_{p,q}^{(d-)}$) crosses τ . With a suitable choice of c, the size of each conflict list is at most n/r, with high probability, because, by construction, for a cell τ of $M_p^{(d-)}$ (resp., $M_p^{(d+)}$), none of the surfaces $d = \psi_{p,u}^+$ (resp., $d = \psi_{p,u}^-$), for $u \in R \setminus \{p\}$, intersect τ [34]. Similarly we define the conflict lists of cells in $\Xi_p^{(c-)}, \Xi_p^{(c+)}$; their sizes are also all at most n/r, with high probability.

For each cell $\tau \in \Xi$, we recursively build the data structure on P_{τ} . The recursion stops when the size of a subproblem becomes smaller than some fixed absolute constant n_0 . Since there are $O^*(r^4)$ subproblems of size at most n/r each, a straightforward analysis shows that the size of the overall structure is $O^*(n^4)$, and that it can be constructed in $O^*(n^4)$ expected time.

Query procedure. A query with a line ℓ is processed as follows. We compute the nearest neighbor of ℓ in R, which we call p. Next, we compute the cells $\tau^{(d-)}, \tau^{(d+)}, \tau^{(c-)}, \tau^{(c+)}$ of $M_p^{(d-)}, M_p^{(d+)}, M_p^{(c-)}, M_p^{c+)}$, respectively, that contain ℓ^* . All this is done in brute force and takes $O^*(1)$ time. If P contains a point q that is nearer to ℓ than p, then by Lemma 8.1, f_q intersects either the curve $\gamma^{(d)}$ or $\gamma^{(c)}$. Suppose f_q intersects $\gamma^{(d)}$ at a point $w = (w_a, w_b, w_c, w_d)$. Again, by Lemma 8.1, if $w_d \ge \ell_d$, then $w_d = \psi_{p,q}^{-}(w_a, w_b, w_c)$, implying that $w \in \tau^{d+}$ and thus q belongs to the conflict list $P_{\tau^{d+}}$. Similarly, if $w_d < \ell_d$, then q belongs to the conflict list $P_{\tau^{d-}}$. A symmetric analysis applies when f_q intersects $\gamma^{(c)}$. In summary, if q is closer to ℓ than p then q lies in the conflict lists of one of $\tau^{(d-)}, \tau^{(d+)}, \tau^{(c-)}, \tau^{(c+)}$. Hence, we need to search recursively in these four subproblems, and return the nearest point among p and the points returned by these four recursive subproblems.

Since we recurse in four subproblems, each of size at most n/r (and r can be chosen to be a sufficiently large constant), the total query time is $O^*(1)$ (it is not polylogarithmic, though). We thus obtain the following result:

Theorem 8.2 A given set P of n points in \mathbb{R}^3 can be preprocessed, in $O^*(n^4)$ expected time, into a data

structure of size $O^*(n^4)$, so that, for any query line $\ell \in \mathbb{R}^3$, the point of P nearest to ℓ can be computed in $O^*(1)$ time.

8.2 Nearest-line queries with lines in \mathbb{R}^3

Next, we show that the machinery in the preceding subsection can be extended (with a couple of twists—see below) to obtain a line NN-searching data structure, with the same asymptotics performance, when the input is a set *L* of *n* lines in \mathbb{R}^3 , and we want to find the line nearest to a query line. We first describe the two new challenges we face in dealing with lines as input, and explain how to address them, and then describe the overall data structure.

We use the same representation (a, b, c, d) for the query line ℓ , using the orthogonal plane H as before. Thus ℓ is represented as the same point $\ell^* \in \mathbb{L}$. For a line $\lambda \in L$, let λ^{\downarrow} denote the projection of λ onto H. A crucial observation, which is easy to verify, is that

$$f_{\lambda}(\ell^*) := \operatorname{dist}(\ell, \lambda) = \operatorname{dist}(\ell, \lambda^{\downarrow}) = \operatorname{dist}((c, d), \lambda^{\downarrow}).$$

The equation of λ^{\downarrow} , in the canonical coordinate frame within *H*, is of the form

$$\xi_{\lambda}(a,b)x + \eta_{\lambda}(a,b)y + \zeta_{\lambda}(a,b) = 0,$$

where we normalize the coefficients so that $\xi_{\lambda}^2(a, b) + \eta_{\lambda}^2(a, b) = 1$. Hence,

$$f_{\lambda}(a,b,c,d) = |\xi_{\lambda}(a,b)c + \eta_{\lambda}(a,b)d + \zeta_{\lambda}(a,b)|.$$
(6)

Except for the absolute value, (6) is linear in c and d, as in the preceding analysis, a property that has been crucial for the analysis there, and will be crucial for the analysis here too.

We handle the absolute value as follows. Orient each line $\lambda \in L$ in an arbitrary (but fixed) manner, say in the positive *x*-direction, and similarly orient each query line ℓ . If we know the relative orientation of ℓ and λ , then we also know the sign in the expression for $f_{\lambda}(\ell^*)$. In fact, we can reduce the setup in such a way that allows us to assume that the sign is positive if and only if the relative orientation is positive. For a line $\lambda \in L$, we define the surface $\sigma_{\lambda} \subset \mathbb{L}$, which is the locus of all points $\ell^* \in \mathbb{L}$ such that ℓ touches λ . It partitions \mathbb{L} space into two portions, one consisting of points representing lines that are positively oriented with respect to λ , and the other consists of points with negative orientations. We construct a data structure on these surfaces that, for a query (oriented) line ℓ , partitions the set of all lines of L into $O(\log n)$ "canonical" subsets such that, for every canonical subset, either all its lines are positively oriented with respect to ℓ or all of them are negatively oriented.

In view of the above discussion, let us assume that the query line has positive orientation with respect to all lines in *L*, and that this corresponds to a positive sign of the expression in (6). We construct a data structure on *L* using, more or less, the same machinery as in Section 8.1, exploiting the double linearity (in *c* and *d*) of the distance functions. Here we face the second challenge. Recall that we basically showed in Lemma 8.1 that if f_p and f_q do not cross along the lines ρ_d , ρ_c , then we have $x_p(a, b) = x_q(a, b)$ and $y_p(a, b) = y_q(a, b)$, and thus the free terms $g_p(a, b)$ and $g_q(a, b)$ are also equal, implying that *p* and *q* are equidistant from the query line ℓ . Here, in contrast, if f_{λ} , $f_{\lambda'}$, for two distinct lines λ , $\lambda' \in L$, do not cross along ρ_c , ρ_d , we can show, using the same reasoning as before, but based on (6), that $\xi_{\lambda}(a, b) = \xi_{\lambda'}(a, b)$ and $\eta_{\lambda}(a, b) = \eta_{\lambda'}(a, b)$ (actually, one equality suffices, because of our normalization). However, now it no longer follows that $\zeta_{\lambda}(a, b) = \zeta_{\lambda'}(a, b)$.

That is, the projected lines (on H(a, b)) could be parallel, and λ' could still be (strictly) nearer to ℓ than λ .

To address this issue we proceed as follows. For each pair of lines λ , λ' in L, let $\beta_{\lambda,\lambda'}$ denote the one-dimensional locus of all (a, b) for which the projections of λ and λ' onto H are parallel; this is the curve $\xi_{\lambda}(a, b) = \xi_{\lambda'}(a, b)$. For each λ in the sample R, we construct the two-dimensional arrangement \mathscr{A}_{λ} of the curves in $\{\beta_{\lambda,\lambda'} \mid \lambda' \in L \setminus \{\lambda\}\}$, in the (a, b)-plane. For a query dual point $\ell^* = (\ell_a, \ell_b, \ell_c, \ell_d)$, we locate the point (ℓ_a, ℓ_b) in \mathscr{A}_{λ} and find the set L_{par} of the curves $\beta_{\lambda,\lambda'}$ that contain the point (ℓ_a, ℓ_b) to determine the lines of L whose projections onto H(a, b) are parallel to λ . (See below how the algorithm handles sets L_{par} of large size.)

We now describe the overall data structure and the query procedure by incorporating these observations in the data structure described in Section 8.1.

Overall data structure. We build a three-level data structure. Let $\Sigma = \{\sigma_{\lambda} \mid \lambda \in L\}$. At the top-level, we construct a tree data structure $\mathscr{T}^{(1)}$ for answering point-enclosure queries on Σ , using the algorithm in [3]. Each node u of $\mathscr{T}^{(1)}$ is associated with a *canonical subset* $L_u \subseteq L$ of lines. For a query line ℓ , querying with ℓ^* in $\mathscr{T}^{(1)}$ partitions the lines of L into $O(\log n)$ canonical subsets, each associated with one of its nodes, such that all lines in one subset are either positively oriented with respect to ℓ or all of them are negatively oriented.

For each node v of $\mathscr{T}^{(1)}$, we construct two second-level data structures $\mathscr{T}^{(2+)}_v, \mathscr{T}^{(2-)}_v$ on the canonical subset L_v —one assuming that the sign in (6) is positive and the other assuming that it is negative. These structures are constructed by following and adapting the construction in Section 8.1, using the expressions in (6) (without the absolute value) instead of those in (2), following both the c- and d-directions, and using partial lower envelopes within the minimization diagram. Each of $\mathscr{T}_{v}^{(2+)}$, $\mathscr{T}_{v}^{(2-)}$ essentially consists of several tree data structures. Each node w of $\mathscr{T}^{(2+)}$ or $\mathscr{T}^{(2-)}$ is also associated with a subset $L_w \subseteq L_v$ of lines. We choose a random subset $R_w \subset L_w$ of size $cr \log r$, for some constant $c \ge 1$, and construct, as in Section 8.1, a total of $O^*(r^4)$ subproblems, each of size at most $|L_w|/r$. In addition, we now store the following third-level structure at *w*: For each line $\lambda \in R$, we construct the two-dimensional arrangement \mathscr{A}_{λ} of the curves $\mathscr{B}_{\lambda} = \{\beta_{\lambda,\lambda'} \mid \lambda' \in L_w \setminus R_w\}$ and preprocess it for point-location queries. If the input lines are in general position, then at most two curves of \mathscr{B}_{λ} pass through any point (a, b), and we simply store them. Otherwise, many curves of \mathscr{B}_{λ} may pass through a vertex $\chi = (\chi_a, \chi_b)$ of \mathscr{A}_{λ} . Let $L_{\chi} \subseteq L_w \setminus R_w$ be the subset of lines whose curves are incident on χ . We store L_{χ} in a sorted order (by the ordering of their projections on the plane $H(\chi_a, \chi_b)$ so that for a query line ℓ of the form $\ell^* = (\chi_a, \chi_b, \ell_c, \ell_d)$, we can find the line in L_{χ} nearest to ℓ in $O(\log n)$ time. The total size of this third-level data structure over all lines of *R* is $|R| \cdot O(|L_w|^2) = O(|L_w|^2)$. Using the properties of multi-level data structures, one can show that the overall size of the data structure is $O^*(n^4)$ and that it can be constructed in $O^*(n^4)$ expected time.

Query procedure. For a query line ℓ , we first search in $\mathscr{T}^{(1)}$ with ℓ^* and compute a partition of L into $O(\log n)$ canonical subsets, each associated with a node of $\mathscr{T}^{(1)}$, such that each subset is positively oriented or negatively oriented with respect to ℓ . For each such node v, if the lines in L_v have positive (resp., negative) orientation with respect to ℓ , we search in $\mathscr{T}^{(2+)}_v$ (resp. $\mathscr{T}^{(2-)}_v$) with ℓ^* , as in Section 8.1. At each second-level node w visited by the query procedure, if λ is the nearest neighbor of ℓ in R_w , we recursively search in the four corresponding children of v as in the previous section. In addition, we locate the point (ℓ^*_a, ℓ^*_b) in the arrangement \mathscr{A}_λ to find, in $O(\log n)$

time, the nearest neighbor of ℓ among the line of $L_w \setminus R$ whose projections on $H(\ell_a, \ell_b)$ are parallel to that of λ , if any such lines exist. Following the same analysis as above, the overall query time remains $O^*(1)$. Putting everything together, we obtain the following result:

Theorem 8.3 A given set L of n lines in \mathbb{R}^3 can be preprocessed, in $O^*(n^4)$ expected time, into a data structure of size $O^*(n^4)$, so that, for any query line $\ell \in \mathbb{R}^3$, the line of L nearest to ℓ can be computed in $O^*(1)$ time.

9 All Line-Point Nearest Neighbors in \mathbb{R}^3

Here we consider an offline version of the problem studied in the previous sections.

9.1 A simple offline algorithm

Let *L* be a set of *n* lines and *P* a set of *m* points in \mathbb{R}^3 . Our goal is to compute, for each line $\ell \in L$, the point of *P* that is nearest to ℓ . This is the batched, or offline, version of the line-point nearest-neighbor problem studied in Section 8.

We first present a rather simple algorithm, which we will improve in the next subsection, using a more involved analysis.

Our approach consists of the following steps. We first take a random sample *R* of *t* points of *P*, for a parameter *t* that we will set later. For each line $\ell \in L$ we compute the point $p \in R$ that is nearest to ℓ , and associate with ℓ the cylinder C_{ℓ} that has ℓ as its symmetry axis, and has radius dist (p, ℓ) . The overall cost of this step is O(nt), using a brute-force approach.

By standard random sampling arguments, C_{ℓ} contains at most $O\left(\frac{m}{t}\log t\right) = O^*(m/t)$ points of P, which holds, with high probability, for all lines $\ell \in L$. Let \mathscr{C} denote the set of these n cylinders, and denote by $K = O^*(m/t)$ the total number of point-cylinder containments.

We next perform an offline point-enclosure reporting step, where the cylinders of \mathscr{C} are our input, each query is with a point $p \in P$, and the goal of the query is to report all the cylinders that contain p. We do this using the algorithm presented in Section 6. We apply this step to each point of P. Each line $\ell \in L$ collects the points $p \in P$ for which C_{ℓ} contains p, and outputs the nearest point to ℓ . By the analysis in Section 6, the point enclosure queries take a total of $O^*(n^2 + m + K) = O^*(n^2 + m + mn/t)$ time. Including the cost of the sampling as described above, the overall cost is $O^*(n^2 + m + mn/t + nt)$, which we optimize by choosing $t = m^{1/2}$. The resulting bound, $O^*(n^2 + m + m^{1/2}n)$, can be trivially improved by breaking the set of lines into subsets, each of size at most $m^{1/2}$, and by repeating the above procedure to each subset and all the points. The resulting running time is $O^*(m^{1/2}n + m)$. That is, we have:

Proposition 9.1 Given *m* points and *n* lines in \mathbb{R}^3 , we can compute, for each line ℓ , the point nearest to ℓ in $O^*(m^{1/2}n + m)$ overall randomized expected time.

9.2 An improved algorithm

We next present an improved and faster algorithm. The improvement is in the implementation of the point enclosure procedure amid the cylinders of \mathscr{C} . It is obtained by combining the machinery

of the algorithm in Section 8 with the point enclosure mechanism of Section 6, and proceeds as follows.

We run a modified version of the procedure of Section 6. At each recursive step, we obtain a decomposition of the problem into $O^*(r^4)$ subproblems, for the constant parameter r used there, each involving at most m/r points of P (where m is the size of the current point set). The lines of L are represented as n points in the four-dimensional line space \mathbb{L} (where n is the size of the current line set). By the analysis in Section 8, adapted to the offline setup, each line participates in at most four of the subproblems. From this it easily follows that we can split each subproblem into further subproblems, so that the number of subproblems remains $O^*(r^4)$, and each subproblem involves at most m/r points of P and at most n/r^4 lines of L. Moreover, by construction, if $\ell \in L$ and p is the point of P nearest to ℓ then at least one of the subproblems involves both ℓ and p.

We carry the recursion for *j* levels, for some parameter *j* that we will fix shortly. At the bottom of this prematurely terminated recursion, we have $O^*(r^{4j})$ subproblems, each involving at most m/r^j points of *P* and at most n/r^{4j} lines of *L*.

We now apply to each subproblem the simpler algorithm in Section 9.1. By Proposition 9.1, this costs a total of

$$O^*(r^{4j}) \cdot O^*\left(\left(\frac{m}{r^j}\right)^{1/2} \frac{n}{r^{4j}} + \frac{m}{r^j}\right) = O^*\left(\frac{m^{1/2}n}{r^{j/2}} + mr^{3j}\right).$$

We now set *j* so as to roughly balance these terms, i.e., choose *j* to satisfy $r^{7j/2} = n/m^{1/2}$, or $r^j = n^{2/7}/m^{1/7}$. Substituting this in the above bound, we obtain the overall cost $O^*(m^{4/7}n^{6/7})$. For this to make sense, we require that $m/r^j \ge 1$ and $n/r^{4j} \ge 1$, and that $r^j \ge 1$. As is easily checked, this means that this choice of *j* makes sense when $n^{1/4} \le m \le n^2$. When $m < n^{1/4}$, we only apply the procedure of Section 8.1, which takes a total of $O^*(m^4 + n) = O^*(n)$ time. When $m > n^2$, we only apply the procedure of Section 9.1, which takes a total of $O^*(m^{1/2}n + m) = O^*(m)$ time. Altogether we obtain

Theorem 9.2 Given sets P of m points and L of n lines in \mathbb{R}^3 , we can compute, for each line $\ell \in L$, the point of P nearest to ℓ , in overall $O^*(m^{4/7}n^{6/7} + m + n)$ randomized expected time.

10 Conclusion

In this paper, we settled in the affirmative a few long-standing open problems involving the vertical decomposition of various substructures of arrangements in d = 3, 4 dimensions. In particular, we obtained sharp bounds on the vertical decomposition of the complement of the union of a family of semi-algebraic sets in \mathbb{R}^3 of constant complexity, and of the lower envelope of a family of semi-algebraic trivariate functions of constant complexity. We also obtained an output-sensitive bound on the size of the vertical decomposition of the full arrangement of a family of semi-algebraic sets in \mathbb{R}^3 of constant complexity. We also obtained an output-sensitive bound on the size of the vertical decomposition of the full arrangement of a family of semi-algebraic sets in \mathbb{R}^3 of constant complexity. These results lead to efficient algorithms for constructing the vertical decompositions themselves, for constructing (1/r)-cuttings of the above substructures of arrangements, and for answering point-enclosure queries. Finally, we applied these results to obtain faster data structures for various basic proximity problems involving lines and points in \mathbb{R}^3 .

We conclude by mentioning a few open problems:

The major open question is, of course, to improve the complexity of the vertical decomposition
of the arrangement of a family of semi-algebraic sets in ℝ^d for d ≥ 5. But an immediate

open question is whether the techniques developed in this paper can be extended to obtain improved bounds on the vertical decomposition of various substructures of arrangements (besides lower or upper envelopes) in \mathbb{R}^4 .

 No non-trivial lower bounds are known for nearest-neighbor data structures involving lines in R³. This raises the question whether the data structures presented in Sections 7 and 8 are (almost) best possible, or whether one can obtain significantly faster data structures. For example, can the nearest neighbor of a line amid a set of points in R³ be returned in O(log *n*) time using an O^{*}(n³) size data structure?

References

- P. K. Agarwal, Simplex range searching and its variants: A review, in *Journey through Discrete Mathematics: A Tribute to Jiří Matoušek*, M. Loebl, J. Nešetřil, and R. Thomas (editors), Springer Verlag, Berlin-Heidelberg, 2017, pp. 1–30.
- [2] P. K. Agarwal, B. Aronov, E. Ezra, M. J. Katz, and M. Sharir, Intersection queries for flat semi-algebraic objects in three dimensions and related problems. https://doi.org/10.48550/arXiv.2203.10241. (A preliminary version appeared in *Proc. 38th Intl. Sympos. Comput. Geom.*, pages 4:1–4:14, 2022.)
- [3] P. K. Agarwal, B. Aronov, E. Ezra, and J. Zahl, An efficient algorithm for generalized polynomial partitioning and its applications, *SIAM J. Comput.* 50 (2021), 760–787.
- [4] P. K. Agarwal, B. Aronov, and M. Sharir, Computing envelopes in four dimensions with applications, SIAM J. Comput. 26(6) (1997), 1714–1732.
- [5] P. K. Agarwal, A. Efrat, and M. Sharir, Vertical decomposition of shallow levels in 3-dimensional arrangements and its applications, *SIAM J. Comput.* 29(3) (1999), 912–953.
- [6] P. K. Agarwal and J. Erickson, Geometric range searching and its relatives, in *Advances in Discrete and Computational Geometry*, volume 223 of *Contemp. Math.*, pages 1–56, AMS Press, Providence, RI, 1999.
- [7] P. K. Agarwal and E. Ezra, Line intersection searching amid unit balls in 3-Space, Proc. 39th Intl. Sympos. Comput. Geom., pages 5:1–5:14, 2023.
- [8] P. K. Agarwal and J. Matoušek, Ray shooting and parametric search, SIAM J. Comput. 22 (1993), 794–806.
- [9] P. K. Agarwal and J. Matousek, On range searching with semialgebraic sets, *Discrete Comput. Geom.* 11 (1994), 393–418.
- [10] P. K. Agarwal, J. Matousek, O. Schwarzkopf, Computing many faces in arrangements of lines and segments, SIAM J. Comput. 27(2) (1998), 491–505.
- [11] P. K. Agarwal, J. Matoušek, and M. Sharir, On range searching with semialgebraic sets II, SIAM J. Comput. 42 (2013), 2039–2062.
- [12] P. K. Agarwal and M. Sharir, Efficient randomized algorithms for some geometric optimization problems, *Discrete Comput. Geom.* 16 (1996), 317–337.

- [13] P. K. Agarwal and M. Sharir, Arrangements of surfaces in higher dimensions, in *Handbook of Computational Geometry* (eds. J.R. Sack and J. Urrutia), pp. 49–119, North-Holland, Amsterdam, 2000.
- [14] P. K. Agarwal and M. Sharir, Pipes, cigars, and kreplach: The union of Minkowski sums in three dimensions, *Discrete Comput. Geom.* 24 (2000), 645–685.
- [15] P. K. Agarwal, M. Sharir and A. Steiger, Decomposing the complement of the union of cubes in three dimensions, *Proc. 32nd Annu. ACM-SIAM Sympos. Discrete Algorithms*, 2021, 1425–1444.
- [16] N. Alon, and J. H. Spencer, *The Probabilistic Method*, Third Edition. Wiley-Interscience series in discrete mathematics and optimization, Wiley, New York, 2008.
- [17] B. Aronov, A. Efrat, V. Koltun, and M. Sharir, On the union of κ-round objects in three and four dimensions, *Discrete Comput. Geom.* 36(4) (2006), 511–526.
- [18] B. Aronov and M. Sharir, Triangles in space or building (and analyzing) castles in the air, *Combinatorica* 10(2) (1990), 137–173.
- [19] S. Basu, R. Pollack, and M.-F. Roy, Algorithms in Real Algebraic Geometry, 2nd Edition, Springer Verlag, Berlin, 2006.
- [20] M. de Berg, O. Cheong, M. van Kreveld, and M. Overmars, Computational Geometry: Algorithms and Applications, 3rd Ed., Springer Verlag, Berlin-Heidelberg, 2008.
- [21] M. de Berg, L. J. Guibas and D. Halperin, Vertical decomposition for triangles in 3-space, Discrete Comput. Geom. 15 (1996), 35–61.
- [22] M. de Berg and O. Schwarzkopf, Cuttings and applications, Int. J. Comput. Geom. Appl. 5(4) (1995), 343–355.
- [23] B. Chazelle, H. Edelsbrunner, L. Guibas and M. Sharir, A singly exponential stratification scheme for real semi-algebraic varieties and its applications, *Theoret. Comput. Sci.* 84 (1991), 77–105. Also in *Proc. 16th Int. Colloq. on Automata, Languages and Programming*, 1989, pp. 179–193.
- [24] B. Chazelle and J. Friedman, A deterministic view of random sampling and its use in geometry, *Combinatorica*, 10 (1990), 229–249.
- [25] B. Chazelle and J. Incerpi, Triangulation and shape-complexity, *ACM Trans. Graphics* 3 (1984), 135–152.
- [26] K. L. Clarkson, New applications of random sampling in computational geometry, Discrete Comput. Geom., 2 (1987), 195–222.
- [27] K. L. Clarkson, H. Edelsbrunner, L. J. Guibas, M. Sharir, and E. Welzl, Combinatorial complexity bounds for arrangement of curves and spheres, *Discrete Comput. Geom.* 5 (1990), 99–160.
- [28] G. E. Collins, Quantifier elimination for the elementary theory of real closed fields by cylindrical algebraic decomposition, *Proc. 2nd GI Conf. Automata Theory and Formal Languages*, volume 33. Springer LNCS, 1975.
- [29] E. Ezra, On the union of cylinders in three dimensions, *Discrete Comput. Geom.* 45(1) (2011), 45–64.

- [30] E. Ezra and M. Sharir, On the union of fat tetrahedra in three dimensions, *J. ACM* 57(1) (2009), 2:1–2:23.
- [31] L. J. Guibas, D. Halperin, J. Matousek, and M. Sharir, Vertical decomposition of arrangements of hyperplanes in four dimensions, *Discrete Comput. Geom.*, 14(2) (1995), 113–122.
- [32] D. Halperin and M. Sharir, A near-quadratic algorithm for planning the motion of a polygon in a polygonal environment, *Discret. Comput. Geom.* 16(2) (1996), 121–134.
- [33] S. Har-Peled, Multicolor combination lemma, Comput. Geom. 12 (1999), 155–176.
- [34] D. Haussler and E. Welzl, Epsilon-nets and simplex range queries, *Discrete Comput. Geom.*, 2 (1987), 127–151.
- [35] V. Koltun, Almost tight upper bounds for vertical decompositions in four dimensions, *J. ACM* 51(5) (2004), 699–730.
- [36] V. Koltun, Sharp bounds for vertical decompositions of linear arrangements in four dimensions, *Discrete Comput. Geom.* 31(3) (2004), 435–460.
- [37] V. Koltun and M. Sharir, The partition technique for the overlay of envelopes. *SIAM J. Comput.* 32 (2003), 841–863.
- [38] J. Matoušek, Efficient partition trees, Discrete Comput. Geom., 8 (1992), 315–334.
- [39] J. Matoušek, Reporting points in halfspaces, Comput. Geom. Theory Appl. 2 (1992), 169–186.
- [40] J. Matoušek and Z. Patáková, Multilevel polynomial partitioning and simplified range searching, Discrete Comput. Geom. 54 (2015), 22–41.
- [41] S. Mohaban and M. Sharir, Ray shooting amidst spheres in 3 dimensions and related problems. *SIAM J. Comput.* 26 (1997), 654–674.
- [42] J. T. Schwartz and M. Sharir, On the Piano Movers' problem: II. General techniques for computing topological properties of real algebraic manifolds, *Advances in Appl. Math.*, 4 (1983), 298–351.
- [43] O. Schwarzkopf and M. Sharir, Vertical decomposition of a single cell in a three-dimensional arrangement of surfaces, *Discrete Comput. Geom.*, 18(3) (1997), 269–288.
- [44] M. Sharir and P.K. Agarwal, Davenport-Schinzel Sequences and Their Geometric Applications, Cambridge University Press, Cambridge-New York-Melbourne, 1995.
- [45] M. Sharir and H. Shaul, Semialgebraic range reporting and emptiness searching with applications, SIAM J. Comput. 40(4) (2011), 1045–1074.
- [46] B. Tagansky, A new technique for analyzing substructures in arrangements of piecewise linear surfaces, *Discret. Comput. Geom.* 16(4) (1996), 455–479.