

Parameter-free analysis of digital surfaces with plane-probing algorithms

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Outline of talk

1 Introduction

- Context
- Plane-probing algorithms

2 L-algorithm

- L-Neighborhood
- Complexity
- Delaunay Property

3 Normal vector estimation

- Estimation and evaluation
- Convergence on selected surfels
- Comparing plane-probing with other methods

4 Conclusion

1 Introduction

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2 L-algorithm

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- Delaunay Property

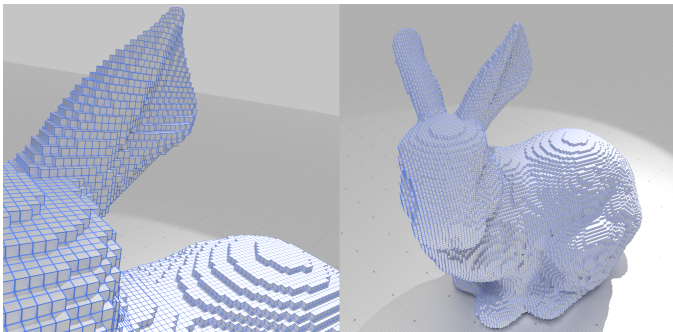
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Digital volume

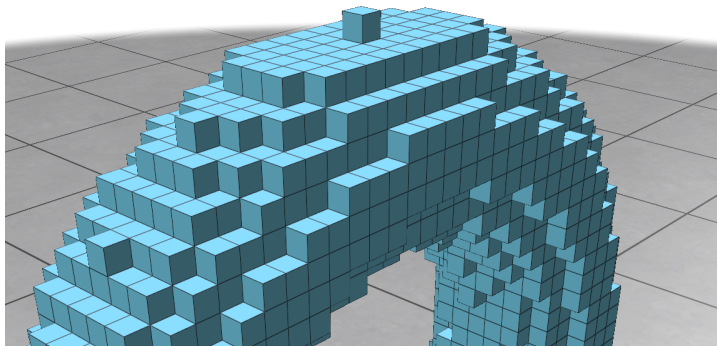
A *digital volume* can be defined as a collection of identical small cubes that share the same axes of direction



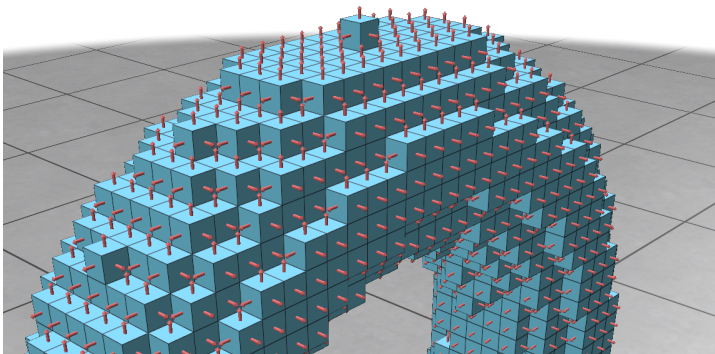
- ≡ Efficient spatial data structures.
- ≡ Calculation using integers.

Digital surface

We consider *digital surfaces* as boundary of digital volumes.

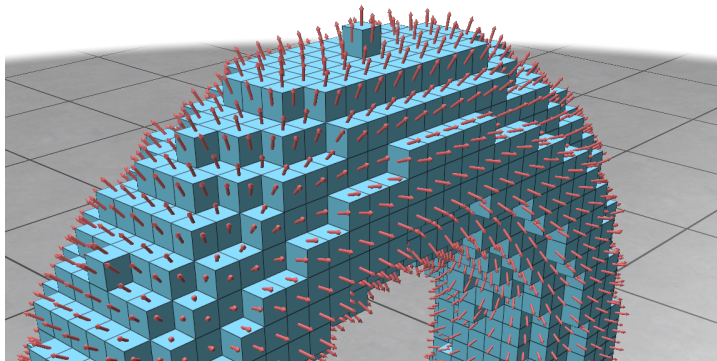


Characteristics of digital surfaces



The normal vector of a surfel always aligns with one of the axes.

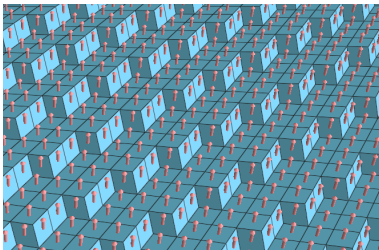
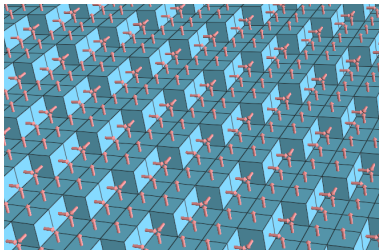
Geometry processing on digital surface



Objective: analyze digital surfaces ¹.
For example: estimate normal vectors.

¹ANR project: PARAmeter-free Analysis of Digital Surfaces

Special case: digital plane



Digital plane

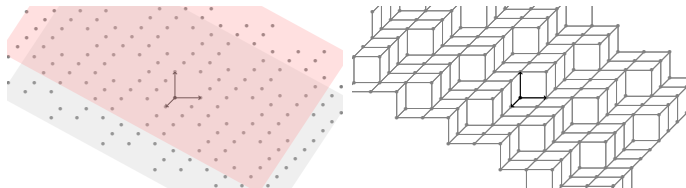
Definition

Given a normal vector $\mathbf{N} \in \mathbb{Z}^3 \setminus \{\mathbf{0}\}$ and a shift vector $\mu \in \mathbb{Z}$, a standard and rational *digital plane*² is an infinite digital set:

$$\mathbf{P}_{\mu, \mathbf{N}} := \{\mathbf{x} \in \mathbb{Z}^3 \mid \mu \leq \mathbf{x} \cdot \mathbf{N} < \mu + \|\mathbf{N}\|_1\}. \quad (1)$$

Here, we suppose that $\mu = 0$ and $\mathbf{N} \in \mathbb{N}^3 \setminus \{\mathbf{0}\}$.

$$\mathbf{P} := \{\mathbf{x} \in \mathbb{Z}^3 \mid 0 \leq \mathbf{x} \cdot \mathbf{N} < \|\mathbf{N}\|_1\}. \quad (2)$$



²J-P. Reveillès. “Géométrie Discrète, calculs en nombres entiers et algorithmique”. Thèse d’Etat. Université Louis Pasteur, 1991

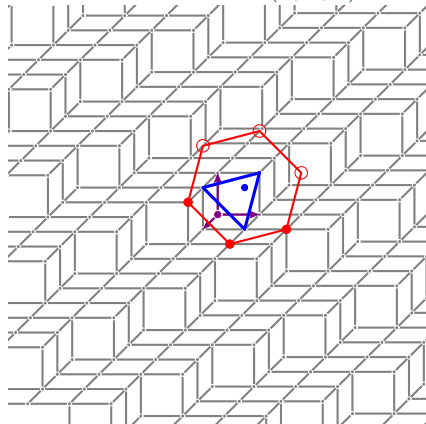
Plane-probing algorithm

Given a digital plane \mathbf{P} and a starting point $\mathbf{p} \in \mathbf{P}$, a plane-probing algorithm³ computes the normal vector of \mathbf{P} by sparsely probing it with the predicate “is $\mathbf{x} \in \mathbf{P}$ ” ?

³Jacques-Olivier Lachaud, Xavier Provençal, and Tristan Roussillon.
“Computation of the normal vector to a digital plane by sampling significant points”. In: *19th IAPR International Conference on Discrete Geometry for Computer Imagery*. Nantes, France, Apr. 2016.

An example of plane-probing algorithm on a plane

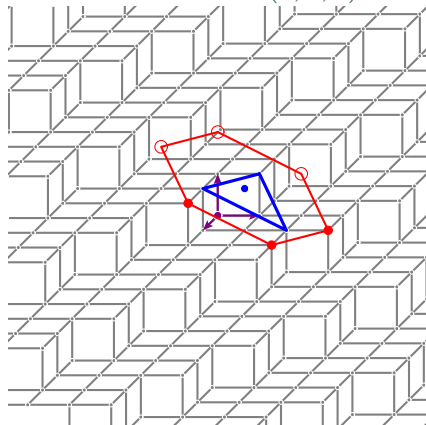
Normal vector: $(1, 2, 5)$



- ≡ A predicate **InPlane**: $x \in \mathbf{P}$?
- ≡ At each iteration:
 - Consider a **neighborhood** \mathcal{N} .
 - Choose a point from $\mathcal{N} \cap \mathbf{P}$.
 - Update one vertex of the base triangle.
- ≡ Termination: $\mathcal{N} \cap \mathbf{P} = \emptyset$, with $N(\mathbf{T}) = \mathbf{N}$.

An example of plane-probing algorithm on a plane

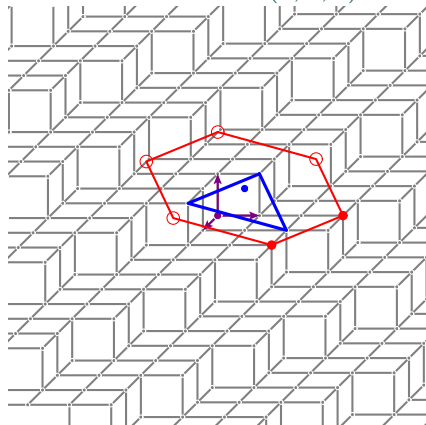
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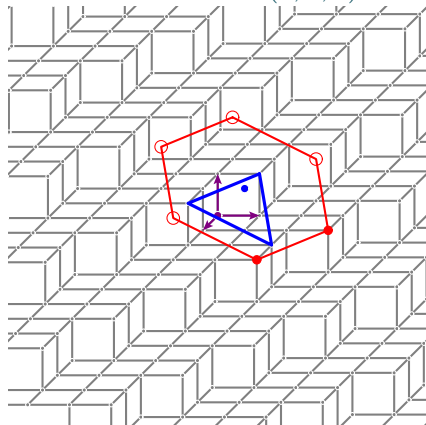
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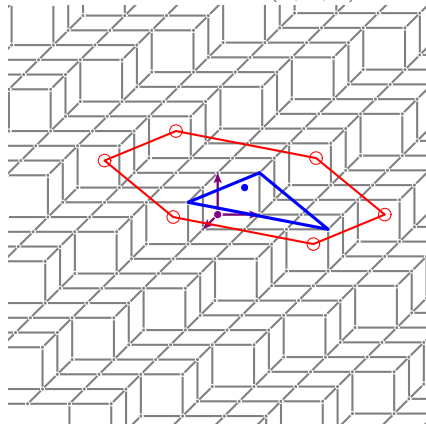
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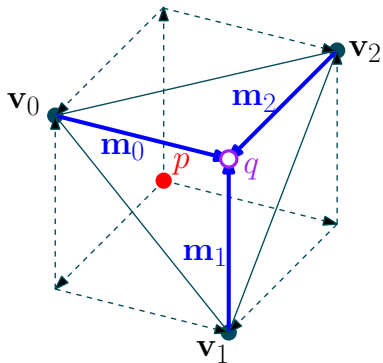
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- ≡ A predicate **InPlane**: $x \in \mathbf{P}$?
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Initialization

- ≡ Given $\mathbf{p} \in \mathbf{P}$
- ≡ Define $\mathbf{T}^{(0)} := (\mathbf{v}_k^{(0)})_{k\{0,1,2\}}$ such that $(\forall k)$
 $\mathbf{v}_k^{(0)} := \mathbf{p} + \mathbf{e}_k + \mathbf{e}_{k+1} \in \mathbf{P}$,
 where $(\mathbf{e}_0, \mathbf{e}_1, \mathbf{e}_2)$ is the canonical basis.
- ≡ $\mathbf{q} := \mathbf{p} + \mathbf{e}_0 + \mathbf{e}_1 + \mathbf{e}_2 \notin \mathbf{P}$.
- ≡ $\forall k, \mathbf{m}_k^{(i)} = \mathbf{q} - \mathbf{v}_k^{(i)}$.



Neighborhood of existing plane-probing algorithms

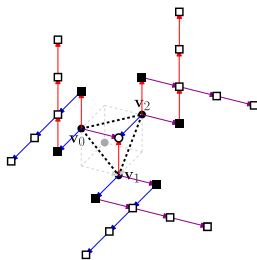
Let Σ be the set of all possible permutation of $\{0, 1, 2\}$.

- ≡ The H-algorithm explores a hexagonal neighborhood,

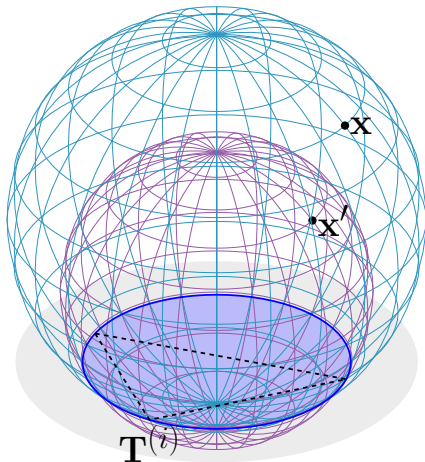
$$\mathcal{N}_H = \left\{ \mathbf{v}_{\sigma(0)}^{(i)} + \mathbf{m}_{\sigma(1)}^{(i)} \mid \sigma \in \Sigma \right\} \quad (3)$$

- ≡ The R-algorithm explores a neighborhood that includes 6 rays,

$$\mathcal{N}_R = \left\{ \mathbf{v}_{\sigma(0)}^{(i)} + \mathbf{m}_{\sigma(1)}^{(i)} + \lambda \mathbf{m}_{\sigma(2)}^{(i)} \mid \lambda \in \mathbb{N}; \sigma \in \Sigma \right\} \quad (4)$$



We favor a point that, with the three vertices of the triangle, defines a sphere that occupies the smallest area above the triangle.



We say x' is closer than x and we note $x' \leq_T x$.

Plane-probing algorithms on digital planes

Input : The predicate $\text{InPlane} := \text{“Is a point } \mathbf{x} \in \mathbf{P}\text{?”}$, a point $\mathbf{p} \in \mathbf{P}$ and the type of neighborhood $\mathcal{N} \in \{\mathcal{N}_H, \mathcal{N}_R\}$

Output : A normal vector $\hat{\mathbf{N}}$

1 **Function** *normalEstimation()*:

2 $\mathbf{q} \leftarrow \mathbf{p} + (1, 1, 1)$; $\mathbf{T}^{(0)} \equiv (\mathbf{v}_k^{(0)})_{k \in \{0,1,2\}} \leftarrow (\mathbf{q} - \mathbf{e}_k)_{k \in \{0,1,2\}}$; $i \leftarrow 0$;

3 **while** $\mathcal{N}^{(i)} \cap \{\mathbf{x} \mid \text{InPlane}(\mathbf{x})\} \neq \emptyset$ **do**

4 Let (k, α, β) be such that, for all $\mathbf{y} \in \mathcal{N}^{(i)} \cap \{\mathbf{x} \mid \text{InPlane}(\mathbf{x})\}$,

$$\mathbf{v}_k^{(i)} + \alpha \mathbf{m}_{k+1}^{(i)} + \beta \mathbf{m}_{k+2}^{(i)} \leq_{\mathbf{T}^{(i)}} \mathbf{y},$$

5 $\mathbf{v}_k^{(i+1)} \leftarrow \mathbf{v}_k^{(i)} + \alpha \mathbf{m}_{k+1}^{(i)} + \beta \mathbf{m}_{k+2}^{(i)}$,

6 $\forall l \in \{0, 1, 2\} \setminus k, \mathbf{v}_l^{(i+1)} \leftarrow \mathbf{v}_l^{(i)}$ // $\mathbf{T}^{(i)}$ updated to $\mathbf{T}^{(i+1)}$

7 $i \leftarrow i + 1$;

8 $B \leftarrow \{\mathbf{v}_0^{(i)} - \mathbf{v}_1^{(i)}, \mathbf{v}_1^{(i)} - \mathbf{v}_2^{(i)}, \mathbf{v}_2^{(i)} - \mathbf{v}_0^{(i)}\}$;

9 Let \mathbf{b}_1 and \mathbf{b}_2 be the shortest and second shortest vectors of B ;

10 **return** $\mathbf{b}_1 \times \mathbf{b}_2$

Termination ⁴

Invariants

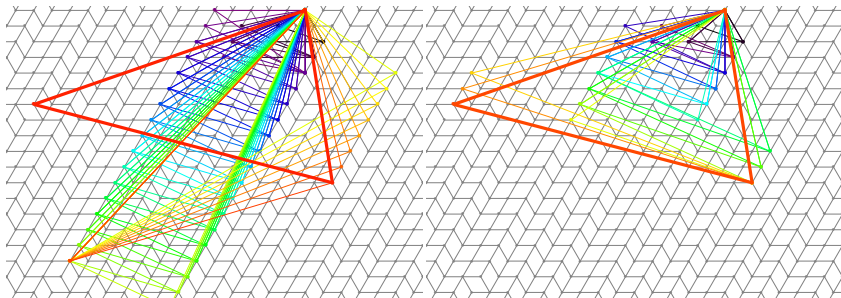
- ≡ Height of \mathbf{m}_k : For all $i \in \{0, \dots, n\}$, $\forall k \in \mathbb{Z}/3\mathbb{Z}$, $\mathbf{m}_k^{(i)} \cdot \mathbf{N} > 0$.
- ≡ Unimodularity: For all $i \in \{0, \dots, n\}$, $\det(\mathbf{m}_0^{(i)}, \mathbf{m}_1^{(i)}, \mathbf{m}_2^{(i)}) = 1$.

Termination

- ≡ The number of iterations is $O(\|\mathbf{N}\|_1)$.
- ≡ If $\mathbf{p} \cdot \mathbf{N} = 0$, the normal vector of the last triangle $\mathbf{T}^{(n)}$ is equal to \mathbf{N} .

⁴Jacques-Olivier Lachaud, X. Provençal, and Tristan Roussillon. “Two Plane-Probing Algorithms for the Computation of the Normal Vector to a Digital Plane”. In: *J. Math. Imaging Vis.* 59.1 (2017), pp. 23–39

Locality



(a) *H*-algorithm

(b) *R*-algorithm

Existing plane-probing algorithms

We note R1 an optimized version of R.

Comparison among H, R and R1

	H	R	R1
Neighborhood size	$ \mathcal{N}_H = 6$	$ \mathcal{N}_R > 6$	$ \mathcal{N}_{R1} = \mathcal{N}_R $
Complexity	$O(\ \mathbf{N}\ _1)$	$O(\ \mathbf{N}\ _1 \log \ \mathbf{N}\ _1)$	$O(\ \mathbf{N}\ _1)$
The last triangle is always not obtuse	\times	$\checkmark_{exp.}$	$\checkmark_{exp.}$

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2 L-algorithm

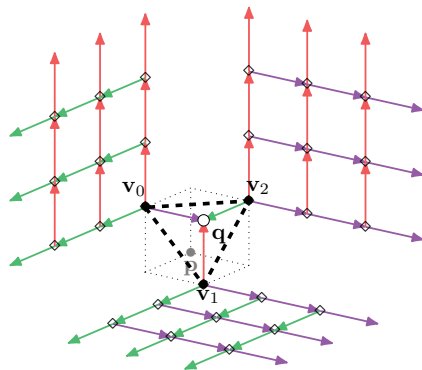
- L-Neighborhood
- Complexity
- Delaunay Property

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Neighborhood

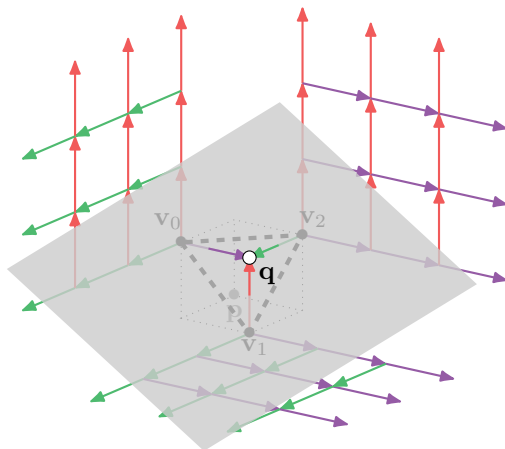


$$\mathcal{N}_L = \left\{ \mathbf{v}_{\sigma(0)}^{(i)} + \alpha \mathbf{m}_{\sigma(1)}^{(i)} + \beta \mathbf{m}_{\sigma(2)}^{(i)} \mid \alpha, \beta \in \mathbb{N}; \sigma \in \Sigma \right\} \quad (5)$$

Lemma

The set $\mathcal{N}_L \cap \mathbf{P}$ is finite.

Idea: For all $i \in \{0, \dots, n\}$, $\forall k \in \mathbb{Z}/3\mathbb{Z}$, $\mathbf{m}_k^{(i)} \cdot \mathbf{N} > 0$.



Plane-probing algorithms on digital planes

Input : The predicate $\text{InPlane} := \text{"Is a point } \mathbf{x} \in \mathbf{P}?\text{"}$, a point $\mathbf{p} \in \mathbf{P}$ and the type of neighborhood $\mathcal{N} \in \{\mathcal{N}_H, \mathcal{N}_R, \mathcal{N}_L\}$

Output : A normal vector $\hat{\mathbf{N}}$

1 **Function** *normalEstimation()*:

2 $\mathbf{q} \leftarrow \mathbf{p} + (1, 1, 1)$; $\mathbf{T}^{(0)} \equiv (\mathbf{v}_k^{(0)})_{k \in \{0,1,2\}} \leftarrow (\mathbf{q} - \mathbf{e}_k)_{k \in \{0,1,2\}}$; $i \leftarrow 0$;

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9 Let \mathbf{b}_1 and \mathbf{b}_2 be the shortest and second shortest vectors of B ;

10 **return** $\mathbf{b}_1 \times \mathbf{b}_2$

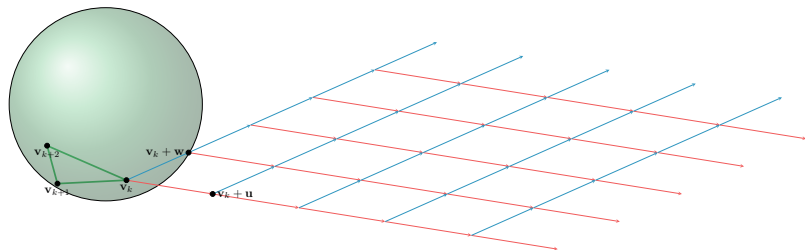
Comparison among H, R1 and L

	H	R1	L
Neighborhood size	$ \mathcal{N}_H = 6$	$ \mathcal{N}_R > 6$	$ \mathcal{N}_L > \mathcal{N}_R $
Complexity	$O(\ \mathbf{N}\ _1)$	$O(\ \mathbf{N}\ _1)$?
The last triangle is always not obtuse	\times	$\checkmark_{exp.}$?

Reduction of candidate set

Lemma

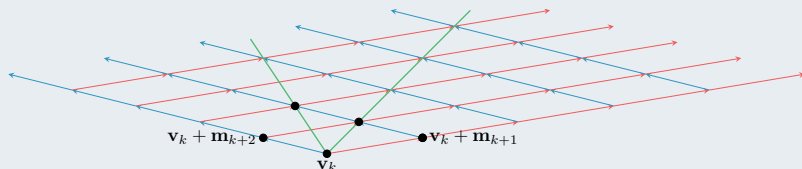
For all $k \in \mathbb{Z}/3\mathbb{Z}$, let Λ_k be the set $\{\mathbf{v}_k + \alpha\mathbf{u} + \beta\mathbf{w} \mid (\alpha, \beta) \in \mathbb{N}^2 \setminus \{0\}\}$, where \mathbf{u}, \mathbf{w} are any two non-zero vectors of \mathbb{Z}^3 such that $\mathbf{v}_k + \mathbf{u}, \mathbf{v}_k + \mathbf{w} \in \mathcal{H}_+$. If $\mathbf{u} \cdot \mathbf{w} \geq 0$, we have either $\mathbf{v}_k + \mathbf{u} \leq_{\mathbf{T}} \mathbf{x}$ for all $\mathbf{x} \in \Lambda_k$ or $\mathbf{v}_k + \mathbf{w} \leq_{\mathbf{T}} \mathbf{x}$ for all $\mathbf{x} \in \Lambda_k$.



Reduction of candidate set

Smaller candidate set

We partition the neighborhood into sectors with acute angle. Instead of exploring an infinite lattice, the L-algorithm only needs to look into a finite set of representative points (●) of these sections.



Complexity

Complexity for the search of updated point

The number of calls to predicate `InPlane` at each iteration is in $O(\log(\|\mathbf{N}\|_1))$.⁵

⁵Jui-Ting Lu, Tristan Roussillon, and David Coeurjolly. “A New Lattice-based Plane-probing Algorithm”. en. In: *Second International Conference on Discrete Geometry and Mathematical Morphology (DGMM 2022)*. Ed. by Etienne Baudrier et al. Lecture Notes in Computer Science. Springer Verlag, 2022

Complexity

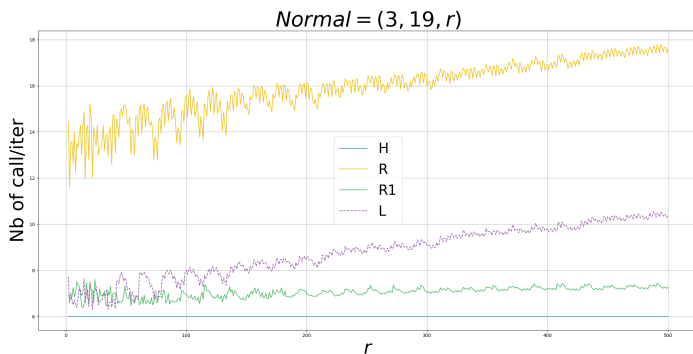


Figure: Number of calls to predicate **per iteration** for normal vectors of form $\{(3, 19, r), 1 \leq r \leq 500\}$.

Complexity

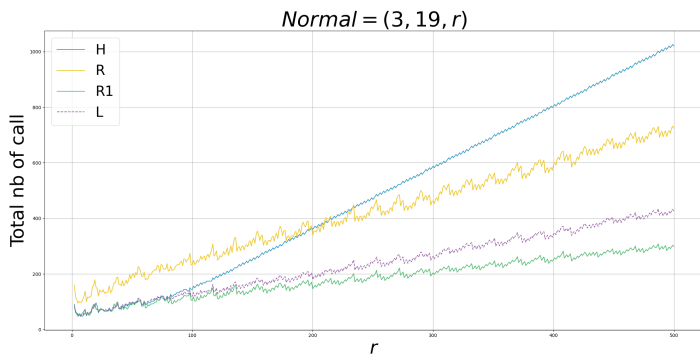
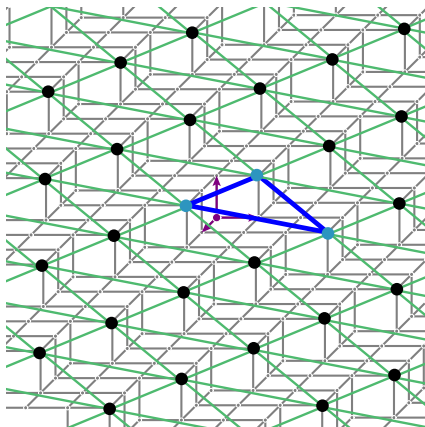


Figure: Number of calls to predicate **in total** for normal vectors of form $\{(3, 19, r), 1 \leq r \leq 500\}$.

Comparison among H, R1 and L

	H	R1	L
Neighborhood size	$ \mathcal{N}_H = 6$	$ \mathcal{N}_R > 6$	$ \mathcal{N}_L > \mathcal{N}_R $
Complexity	$O(\ \mathbf{N}\ _1)$	$O(\ \mathbf{N}\ _1)$	$O(\ \mathbf{N}\ _1 \log \ \mathbf{N}\ _1)$
The last triangle is always not obtuse	\times	$\checkmark_{exp.}$?

Delaunay triangulation



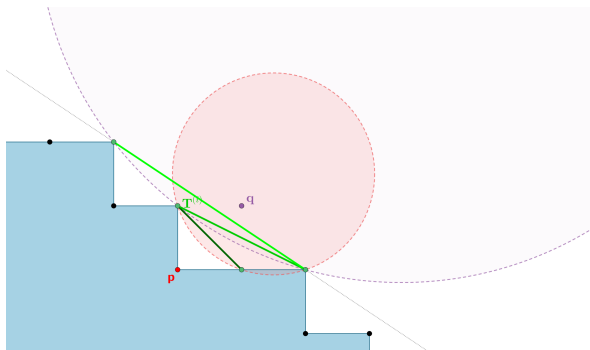
When the last triangle is non-obtuse, it belongs to the Delaunay triangulation of the lattice $\{\mathbf{x} \in \mathbb{Z}^3 \mid \mathbf{x} \cdot \mathbf{N} = \|\mathbf{N}\|_1 - 1\}$.

The Delaunay Property

For all $i \in \{0, \dots, n\}$, let $\mathcal{B}^{(i)}$ be the ball uniquely determined by the four distinct points of two consecutive triangles.

Theorem: Delaunay property for L-algorithm

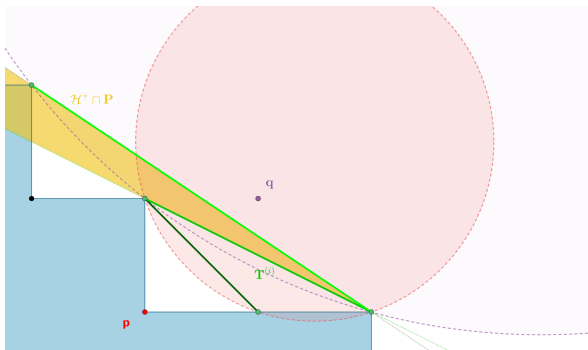
For all $i \in \{0, \dots, n\}$, the ball $\mathcal{B}^{(i)}$ does not contain any point of \mathbf{P} in its interior.



Let $\mathcal{H}_+^{(i)}$ be the half-space delimited by $\mathbf{T}^{(i)}$ that includes \mathbf{q} .

Lemma

For all $i \in \{0, \dots, n-1\}$, if the interior of $\mathcal{B}^{(i)}$ contains no point of \mathbf{P} , then the interior of $\mathcal{B}^{(i+1)}$ contains no point of $\mathbf{P} \cap \mathcal{H}_+^{(i)}$.



Outline of the proof

Since $(\mathbf{m}_0, \mathbf{m}_1, \mathbf{m}_2)$ is unimodular, we can represent all point of \mathbb{Z}^3 as

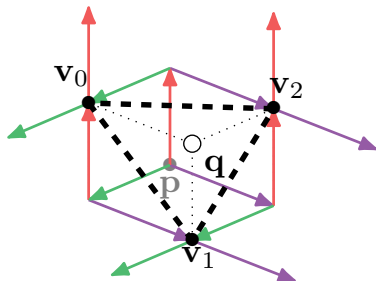
$$\mathbf{x} = \mathbf{p} + \sum_k c_k \mathbf{m}_k.$$

Points that lie in the plane that passes $\mathbf{T}^{(i)}$ satisfy:

$$\sum_k c_k = 2.$$

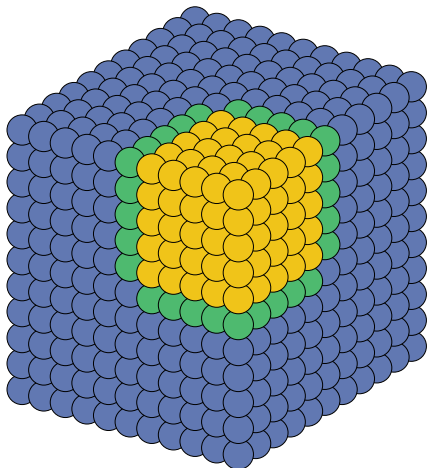
Then, points that lies in $\mathcal{H}_+^{(i)}$ satisfy:

$$\sum_k c_k \geq 2.$$



$$\{\mathbf{p} + \sum_k c_k \mathbf{m}_k\} \sim \mathbb{Z}^3$$

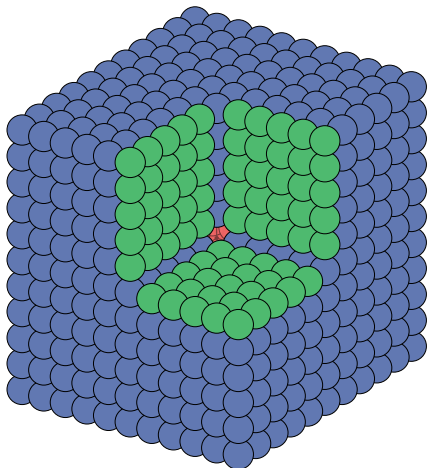
can be divided into:



1. the points are not in the plane so not considered by the lemma.
2. these points are exactly the ones probed in the L-algorithm
3. these points are farther than specific green points.
4. the red one is discarded because none of its points lie in $\mathcal{H}_+^{(i)}$

$$\{\mathbf{p} + \sum_k c_k \mathbf{m}_k\} \sim \mathbb{Z}^3$$

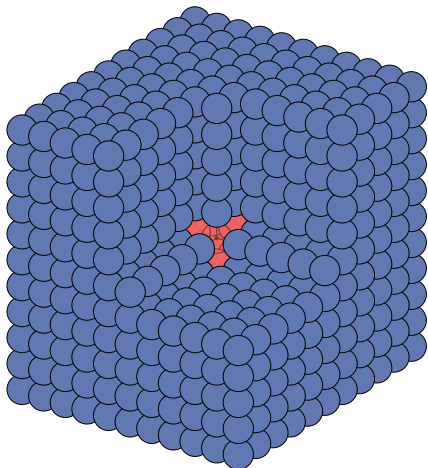
can be divided into:



1. the points are not in the plane so not considered by the lemma.
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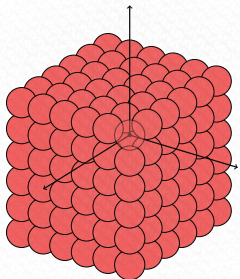
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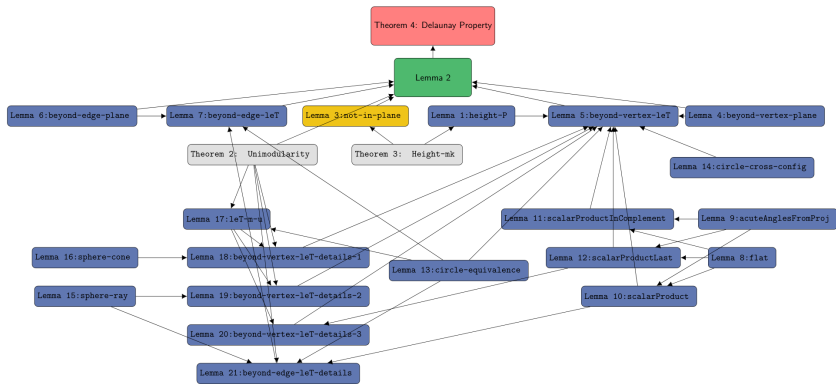


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$\{\mathbf{p} + \sum_k c_k \mathbf{m}_k\} \sim \mathbb{Z}^3$
can be divided into:

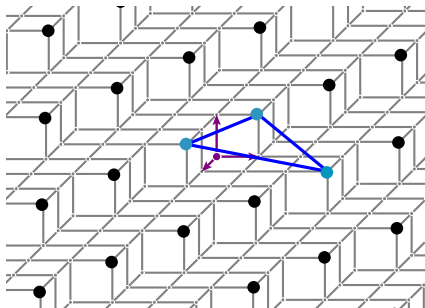


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4. the red one is discarded because none of its points lie in $\mathcal{H}_+^{(i)}$



Consequence 1: Last triangle

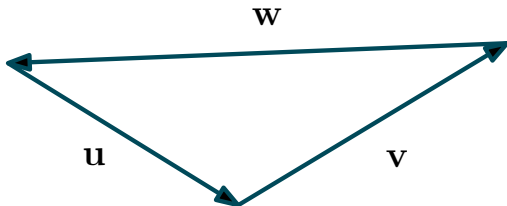
The last triangle returned by the L-algorithm is always acute or straight.



Consequence 2: Minimal basis

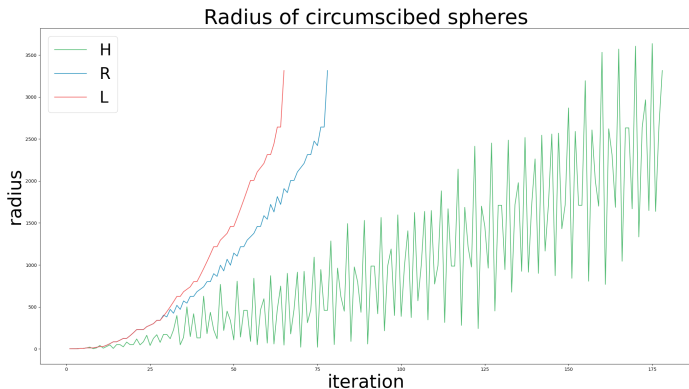
Let L be a rank-two integral lattice. A basis (\mathbf{x}, \mathbf{y}) of L is minimal if and only if $\|\mathbf{x}\|_2, \|\mathbf{y}\|_2 \leq \|\mathbf{x} - \mathbf{y}\|_2 \leq \|\mathbf{x} + \mathbf{y}\|_2$, where $\|\cdot\|_2$ denotes the Euclidean norm.

The two shortest edges of the final triangle form a minimal basis of the lattice $\{\mathbf{x} \in \mathbb{Z}^3 \mid \mathbf{x} \cdot \mathbf{N} = \|\mathbf{N}\|_1 - 1\}$.



Consequence 3: Increasing ball radius

$N = (198, 195, 193)$



Evolution of basis of the tetrahedron ($\mathbf{N} = (2, 5, 156)$)

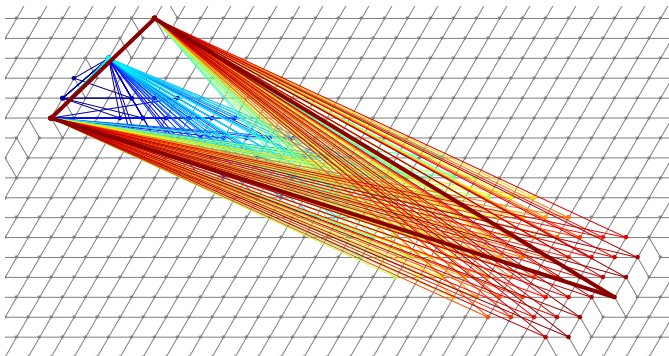


Figure: *H*-algorithm

Evolution of basis of the tetrahedron ($\mathbf{N} = (2, 5, 156)$)

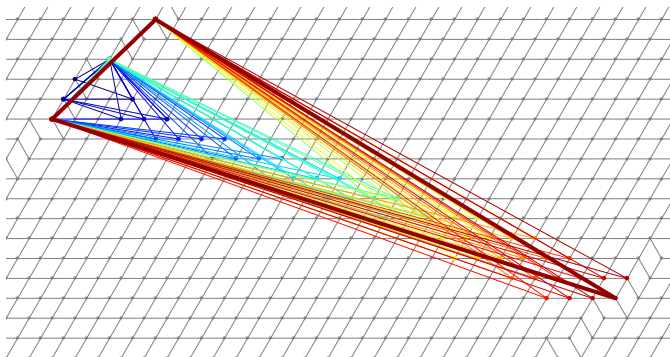


Figure: *R*-algorithm

Evolution of basis of the tetrahedron ($\mathbf{N} = (2, 5, 156)$)

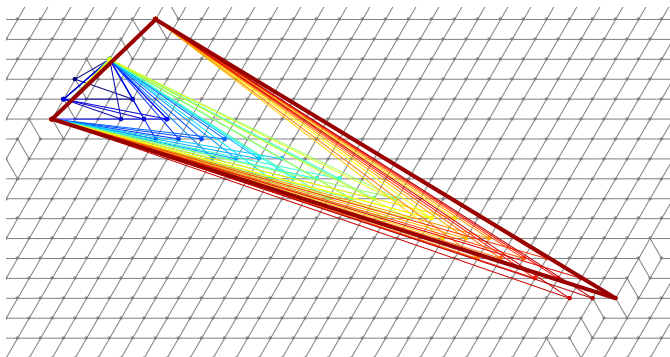


Figure: *L*-algorithm

Summary

Comparison among H, R1 and L

	H	R1	L
Neighborhood size	$ \mathcal{N}_H = 6$	$ \mathcal{N}_R > 6$	$ \mathcal{N}_L > \mathcal{N}_R $
Complexity	$O(\ \mathbf{N}\ _1)$	$O(\ \mathbf{N}\ _1)$	$O(\ \mathbf{N}\ _1 \log \ \mathbf{N}\ _1)$
The Delaunay property	✗	✗	✓
The last triangle is always not obtuse	✗	✓ _{exp.}	✓

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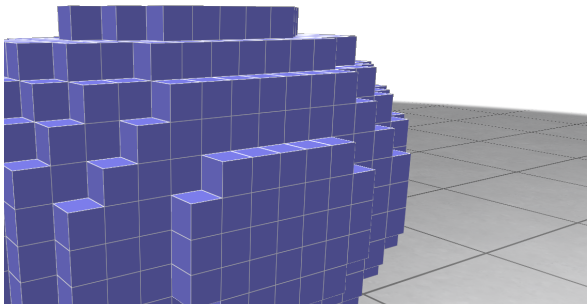
3 Normal vector estimation

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- Comparing plane-probing with other methods

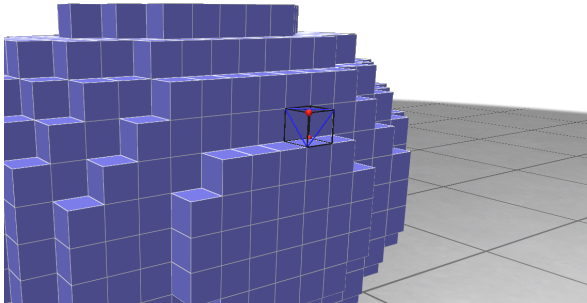
4 Conclusion

What happens when launching a plane-probing algorithm on a digital surface ?

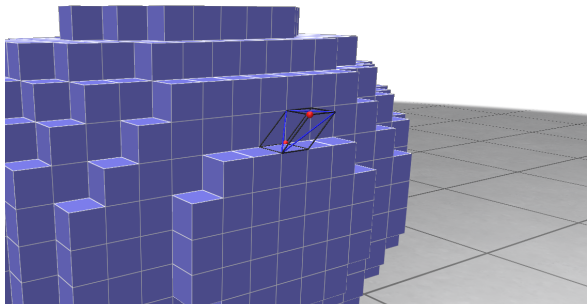
Parallelepiped-based plane-probing algorithm



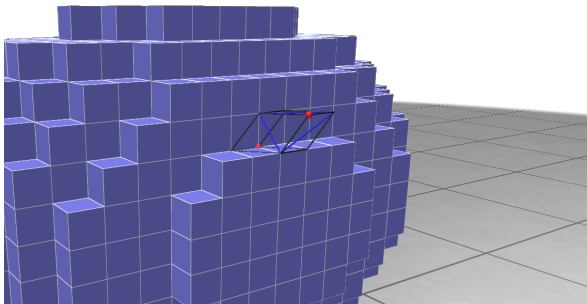
Parallelepiped-based plane-probing algorithm



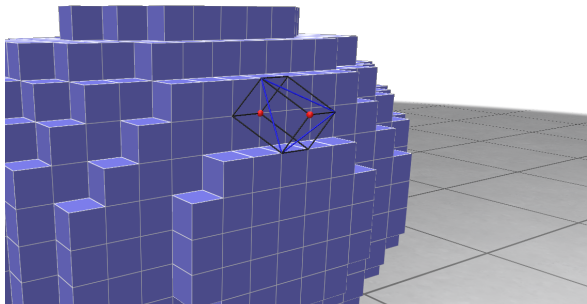
Parallelepiped-based plane-probing algorithm



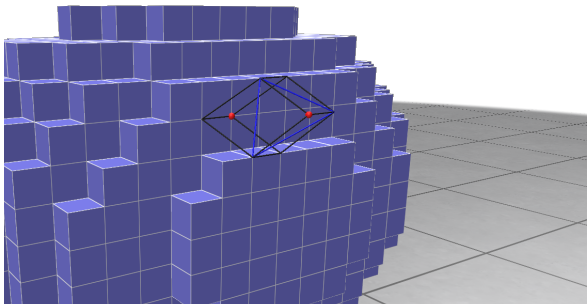
Parallelepiped-based plane-probing algorithm



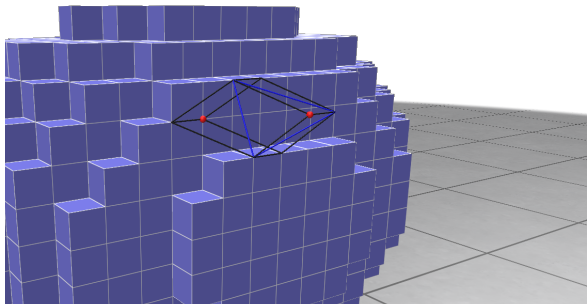
Parallelepiped-based plane-probing algorithm



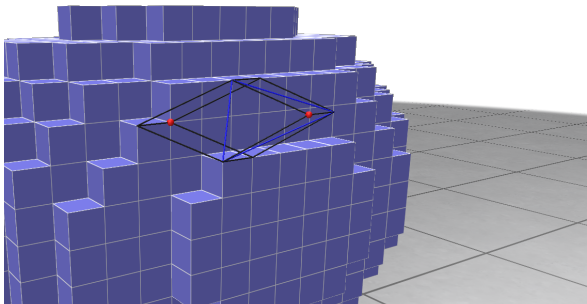
Parallelepiped-based plane-probing algorithm



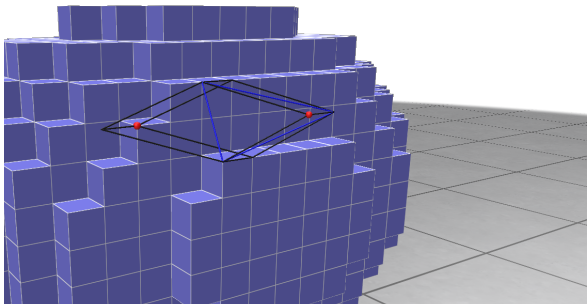
Parallelepiped-based plane-probing algorithm



Parallelepiped-based plane-probing algorithm



Parallelepiped-based plane-probing algorithm



Plane-probing algorithms on digital surfaces

Input : The predicate $\text{InSurface} := \text{"Is a point } \mathbf{x} \in \mathbf{S} \text{"}$, an octant $\mathbf{s} \in \{\pm 1, \pm 1, \pm 1\}$, a point $\mathbf{p} \in \mathbf{S}$ and the type of neighborhood $\mathcal{N} \in \{\mathcal{N}_H, \mathcal{N}_R, \mathcal{N}_L\}$

Output : A normal vector $\hat{\mathbf{N}}$.

1 **Function** *normalEstimation*():

2 $\mathbf{q} \leftarrow \mathbf{p} + \mathbf{s}$; $\mathbf{T}^{(0)} \equiv (\mathbf{v}_k^{(0)})_{k \in \mathbb{Z}/3\mathbb{Z}} \leftarrow (\mathbf{q} - \mathbf{e}_k)_{k \in \mathbb{Z}/3\mathbb{Z}}$;
 3 $i \leftarrow 0$;

4 **while** $\mathcal{N}^{(i)} \cap \{\mathbf{x} \mid \text{InSurface}(\mathbf{x})\} \neq \emptyset$ **do**
 5 compute $\mathbf{T}^{(i+1)}$, updated copy of $\mathbf{T}^{(i)}$;
 6 $i \leftarrow i + 1$;

7 $B \leftarrow \{\mathbf{v}_0^{(i)} - \mathbf{v}_1^{(i)}, \mathbf{v}_1^{(i)} - \mathbf{v}_2^{(i)}, \mathbf{v}_2^{(i)} - \mathbf{v}_0^{(i)}\}$;

8 Let \mathbf{b}_1 and \mathbf{b}_2 be the shortest and second shortest vectors of B ;

9 **return** $\mathbf{b}_1 \times \mathbf{b}_2$

Plane-probing algorithms on digital surfaces

Input : The predicate **NotAbove**, an octant $\mathbf{s} \in \{\pm 1, \pm 1, \pm 1\}$, a point $\mathbf{p} \in \mathbf{S}$ and the type of neighborhood $\mathcal{N} \in \{\mathcal{N}_H, \mathcal{N}_R, \mathcal{N}_L\}$

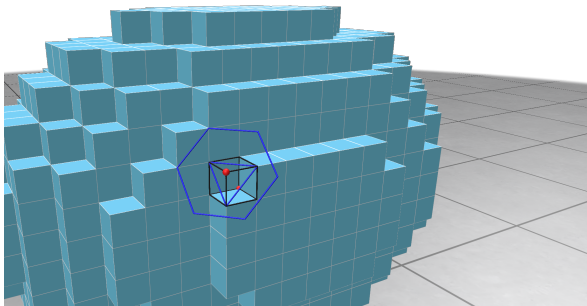
Output : A normal vector $\hat{\mathbf{N}}$.

```

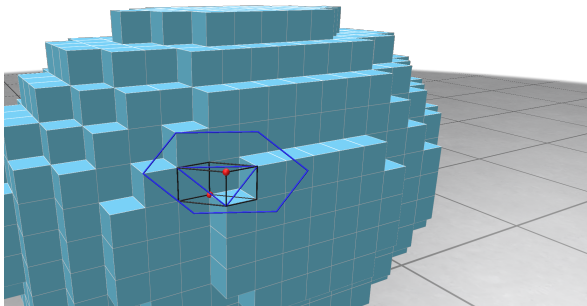
1 Function normalEstimation():
2    $\mathbf{q} \leftarrow \mathbf{p} + \mathbf{s}$  ;  $\mathbf{T}^{(0)} \equiv (\mathbf{v}_k^{(0)})_{k \in \mathbb{Z}/3\mathbb{Z}} \leftarrow (\mathbf{q} - \mathbf{e}_k)_{k \in \mathbb{Z}/3\mathbb{Z}}$  ;
3    $i \leftarrow 0$  ;
4   while  $\mathcal{N}^{(i)} \cap \{\mathbf{x} \mid \text{NotAbove}(\mathbf{x})\} \neq \emptyset$  do
5     compute  $\mathbf{T}^{(i+1)}$ , updated copy of  $\mathbf{T}^{(i)}$  ;
6     if  $\text{Card}(\{\mathbf{x} \in \Pi^{(i)} \mid \text{NotAbove}(\mathbf{x})\}) < 4$  then
7        $\lfloor$  compute  $\mathbf{q}^{(i+1)}$ , translated copy of  $\mathbf{q}^{(i)}$  ;
8      $i \leftarrow i + 1$  ;
9    $B \leftarrow \{\mathbf{v}_0^{(i)} - \mathbf{v}_1^{(i)}, \mathbf{v}_1^{(i)} - \mathbf{v}_2^{(i)}, \mathbf{v}_2^{(i)} - \mathbf{v}_0^{(i)}\}$  ;
10  Let  $\mathbf{b}_1$  and  $\mathbf{b}_2$  be the shortest and second shortest vectors of  $B$  ;
11  return  $\mathbf{b}_1 \times \mathbf{b}_2$ 

```

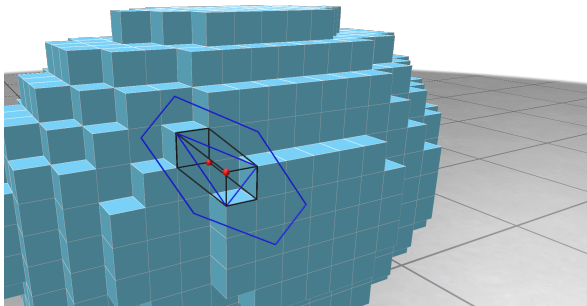
Example with fixed q



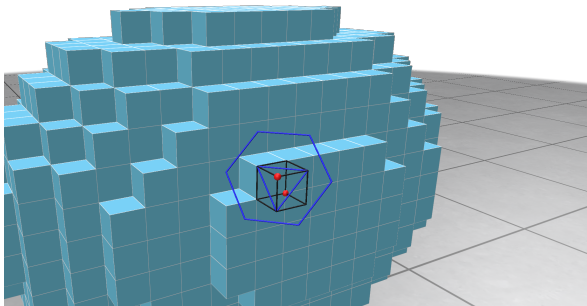
Example with fixed q



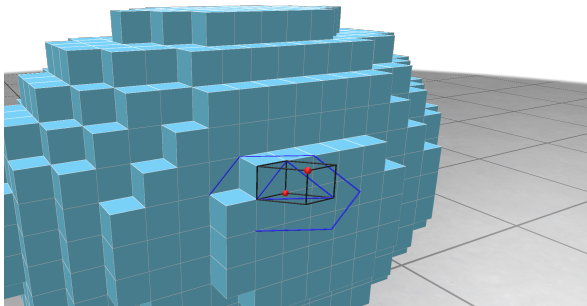
Example with fixed q



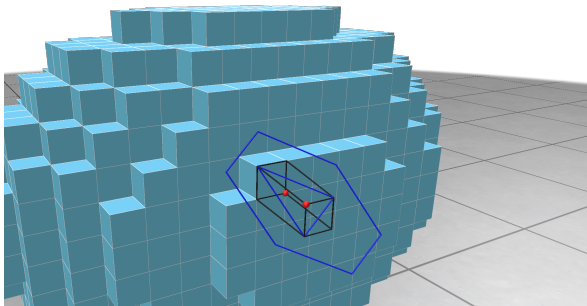
Example with moving q



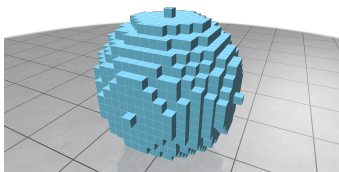
Example with moving q



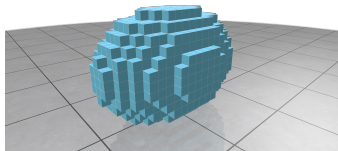
Example with moving q



Equations of Euclidean shapes for experimental evaluation



(a) sphere9



(b) ellipsoid

Figure: Visualization when $h = 1$

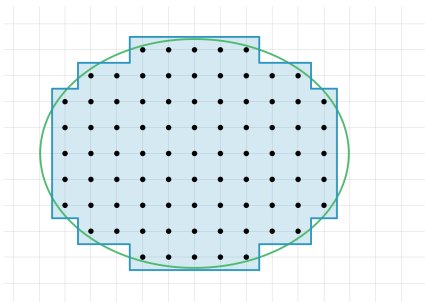
Shape	DGtal name	Equation
Sphere	sphere9	$x^2 + y^2 + z^2 - 9^2 = 0$
Ellipse	ellipse	$90 - 3x^2 - 2y^2 - z^2 = 0$

Gauss digitization

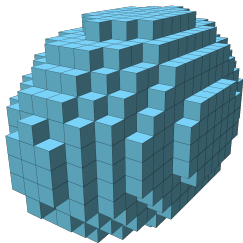
Definition

Let $X \subset \mathbb{R}^3$ be a compact simply connected volume. The *Gauss digitization* of X with grid step $h > 0$, denoted by $\mathbf{DS}(X)_h$, is the set of all discrete points $p \in h(\mathbb{Z}^3)$ lying in X . In other words,

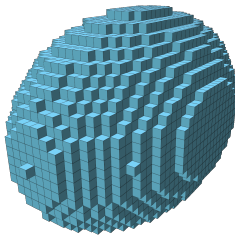
$$\mathbf{DS}(X)_h = X \cap h(\mathbb{Z}^3). \quad (6)$$



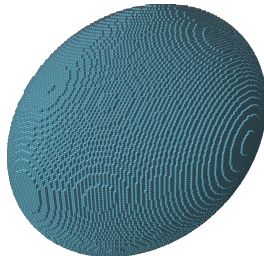
Multigrid convergence



(a) $h = 1$

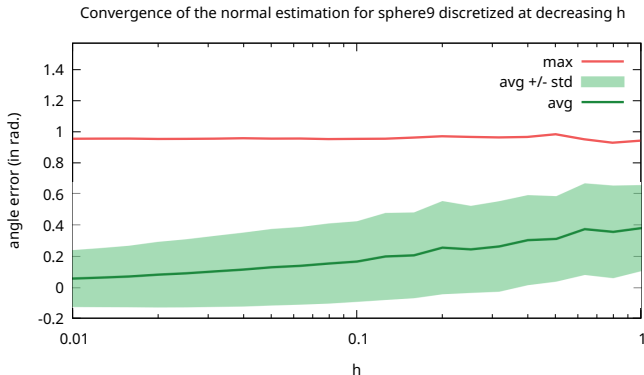


(b) $h = 0.5$



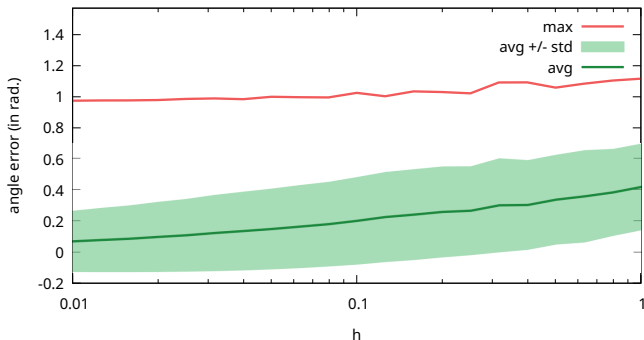
(c) $h = 0.1$

Plane-probing algorithm



Plane-probing algorithm

Convergence of the normal estimation for ellipsoid discretized at decreasing h



Selection of starting surfels

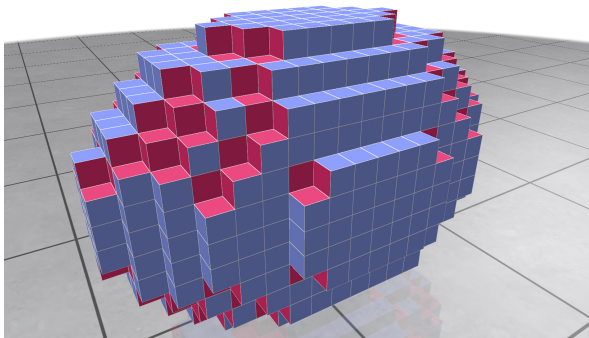
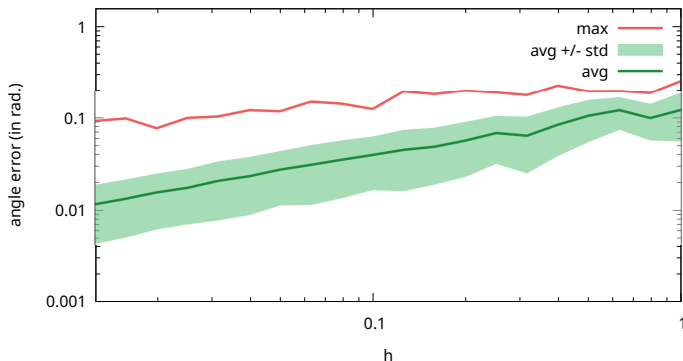


Figure: Illustration of the reentrant corners (red) on a digital ellipsoid.

1. A reentrant corner exists in the initial parallelepiped (unique octant).
2. The point $\mathbf{q}^{(i)}$ does not translate throughout iterations.

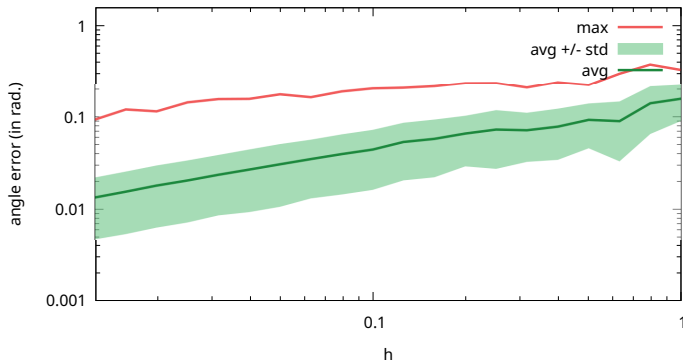
Multigrid convergence on selected surfels

Convergence of the normal estimation for sphere9 discretized at decreasing h



Multigrid convergence on selected surfels

Convergence of the normal estimation for ellipsoid discretized at decreasing h



Digital methods for normal estimations

There are three methods that are multigrid convergent:

- ≡ *Slice method*⁶ computes the cross product of two 2D tangent vectors of two perpendicular slices.
- ≡ *Voronoi covariance measure*⁷ is a covariance tensor that requires two parameters: offset radius and kernel radius.
- ≡ *Integral invariant*⁸ compute integrals on the intersection between the shape and the convolution kernel, that has a specific radius.

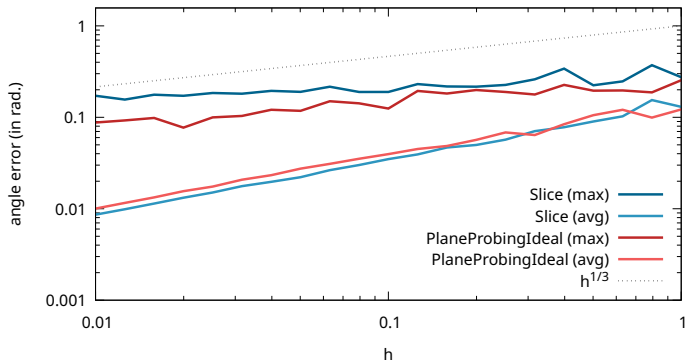
⁶Lachaud and Vialard, “Geometric Measures on Arbitrary Dimensional Digital Surfaces”.

⁷Cuel et al., “Robust Geometry Estimation Using the Generalized Voronoi Covariance Measure”.

⁸Levallois, Coeurjolly, and Lachaud, “Parameter-free and Multigrid Convergent Digital Curvature Estimators”.

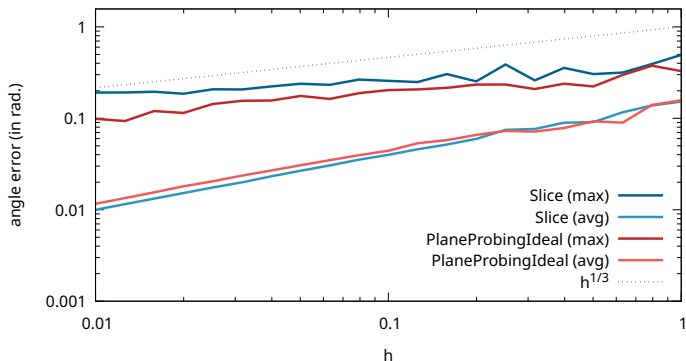
Slice method

Convergence of the normal estimation for sphere9 discretized at decreasing h



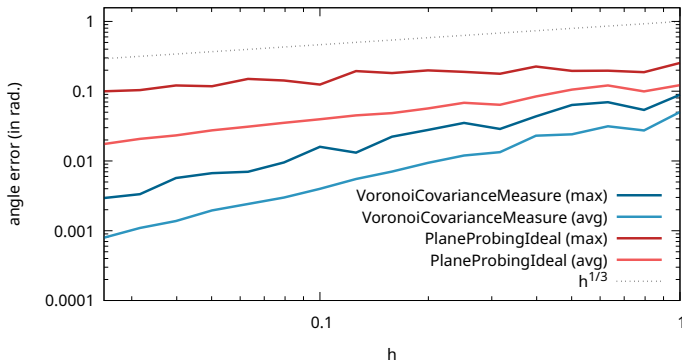
Slice method

Convergence of the normal estimation for ellipsoid discretized at decreasing h



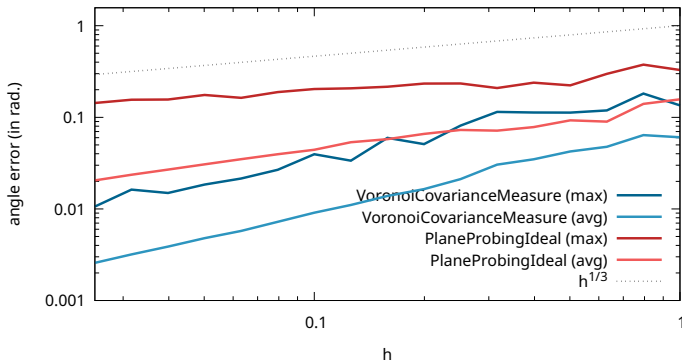
Voronoi Covariance Measure (VCM)

Convergence of the normal estimation for sphere9 discretized at decreasing h



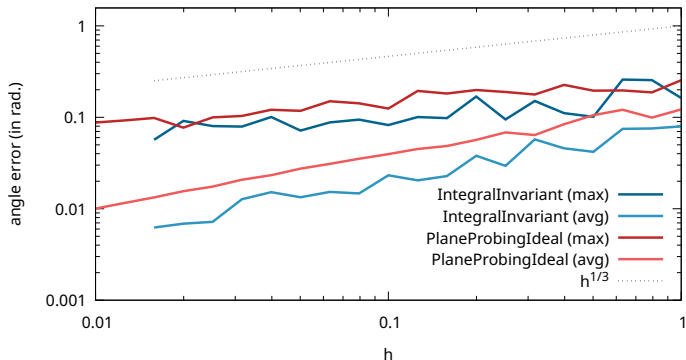
Voronoi Covariance Measure (VCM)

Convergence of the normal estimation for ellipsoid discretized at decreasing h



Integral Invariant

Convergence of the normal estimation for sphere9 discretized at decreasing h



Integral Invariant

Convergence of the normal estimation for ellipsoid discretized at decreasing h

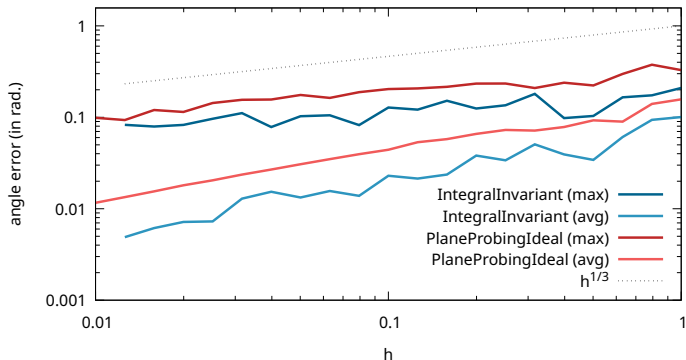


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- Delaunay Property

3 Normal vector estimation

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- Convergence on selected surfels
- Comparing plane-probing with other methods

4 Conclusion

A new plane-probing algorithm

We introduce a new plane-probing algorithm, the L-algorithm.

- ≡ If $\mathbf{p} \cdot \mathbf{N} = 0$, it return the exact normal vector and stops in $O(\|\mathbf{N}\|_1)$ steps.
- ≡ It requires theoretically $O(\|\mathbf{N}\|_1 \log \|\mathbf{N}\|_1)$ calls to predicate in total.

Geometrical properties:

- ≡ The Delaunay property: the interior of $\mathcal{B}^{(i)}$ does not include any point of \mathbf{P} .
- ≡ The sequence of radius of the balls $\mathcal{B}^{(i)}$ is non decreasing.
- ≡ Always returns a non obtuse triangle (experimentally verified for R-algorithm).

Perspectives for plane-probing algorithms

- ≡ Understand why R-algorithm also returns a non obtuse triangle.
- ≡ Improve the complexity of the L-algorithm.
- ≡ Other approaches, such as: select multiple points to update at each iteration.

Normal vector estimation

A parallelepipedic version of the L-algorithm can be applied for normal vector estimation on digital surfaces:

- ≡ The current method does not converge on all surfels
- ≡ On some selected surfels, there is convergence.

Future work:

- ≡ Provide a proof for the multigrid convergence on selected surfels:
- ≡ Identify the surfels where there is no convergence.
- ≡ Study the estimation of normal vectors on other shapes (for example, non convex).