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Virtual Reality & Physically-Based Simulation Collision Detection



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Examples of Applications



Virtual Prototyping







Physically-based simulation

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Virtual Reality

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Other Uses of Collision Detection

- Robotics: path planning (piano mover's problem)
- Medical training simulators
- Rendering of force feedback









Collision Detection Within Simulations



- Main loop:
 - Move objects
 - Check collisions
 - Handle collisions (e.g., compute penalty forces)
- Collisions pose two different problems:
 - 1. Collision detection
 - 2. Collision handling (e.g., physically-based simulation, or visualization)
- In this chapter: only collision detection





- Given *P*, $Q \subseteq \mathbb{R}^3$
- The detection problem: "P and Q collide" : $P \cap Q \neq \emptyset \Leftrightarrow$ $\exists x \in {}^3$: $x \in P \land x \in Q$
- The construction problem: compute $R := P \cap Q$



- For polygonal objects we define collisions as follows: P,Q collide $\Leftrightarrow \exists f \in F^P \exists f' \in F^Q : f \cap f' \neq \emptyset$
- The games community often has a different definition of "collision"



Classes of Objects

- Convex
- Closed and simple (no self-penetrations)
- Polygon soups
 - Not necessarily closed
 - Duplicate polygons
 - Coplanar polygons
 - Self-penetrations
 - Degenerate cardigans
 - Holes
- Deformable





Convex



Simple & closed



Polygon soup



Why is Collision Detection so Hard?



1. All-pairs weakness:



2. Discrete time steps:



 Efficient computation of proximity / penetration:











Importance of the Performance of Collision Detection





naïve algorithm (test all pairs of polygons) clever algorithm (use bbox hierarchy)

Conclusion: the performance of the algorithm for collision detection determines (often) the overall performance of the simulation!

In many simulations, the coll.det. part takes 60-90 % of the overall time

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Requirements on Collision Detection



- Handle a large class of objects
- Lots of moving objects (1000s in some cases)
- Very high performance, so that a physically-based simulation can do many iterations per frame (at least 2x 100,000 polygons in <1 millisec)
- Return a contact point ("witness") in case of collision
 - Optionally: return *all* intersection points
- Auxiliary data structures should not be too large (<2x memory usage of originial data)
 - Preprocessing for these auxiliary data structures should not take too long, so that it can be done at startup time (< 5sec / object)



The Collision Detection Pipeline







The Collision Interest Matrix



- Interest in collisions is specific to different applications/modules:
 - Not all modules in an application are interested in all possible collisions;
 - Some pairs of objects collide all the time, some can never collide;
- Goal: prevent unnecessary collision tests
 - \Rightarrow Collision Interest Matrix
- The elements in this matrix comprise:
 - Flag for collision detection
 - Additional info that needs to be stored from frame to frame for each pair for certain algorithms (e.g., the separating plane)
 - Callbacks in die Module





Methods for the Broad Phase



- Broad phase = one or more filtering step
 - Goal: quickly filter pairs of objects that cannot intersect because they are too far away from each other
- Standard approach:
 - Enclose each object within a bounding box (bbox)
 - Compare the 2 bboxes for a given pair of objects
- Assumption: n objects are moving
- > Brute-force method needs to compare $O(n^2)$ bboxes
- Goal: determine neighbors more efficiently
- 3D grid, sweep plane techniques ("sweep and prune"), feature tracking on convex hulls, etc.





The 3D Grid

- 1. Partition the "universe" by a 3D grid
- 2. Objects are considered neighbors, if they occupy the same cell
- 3. Determine cell occupancy by bbox
- 4. When objects move \rightarrow update grid
- Neighbor-finding = find all cells that contain more than one obj
 - Data structure here: hash table (!)
 - Collision in hash table \rightarrow probably neighbor

The trade-off:

- Fewer cells = larger cells
 - Distant objects are still "neighbors"
- More cells = smaller cells
 - Objects occupy more cells
 - Effort for updating increases
- Rule of thumb: cell size ≈ avg obj diameter





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The Plane Sweep Technique (aka Sweep and Prune)

- The idea: sweep plane through space perpendicular to the X axis
- The algorithm:

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```
sort the X coordinates of all boxes
```

start with the leftmost box

keep a list of active boxes

loop over x-coords (= left/right box borders):

if current box border is the left side (= "opening"):

check this box against all boxes in the active list

```
add this box to the list of active boxes
```

else (= "closing"):

remove this box from the list of active boxes



Collision Detection

18





Temporal Coherence



Observation:

Two consecutive images in a sequence differ only by very little (usually).

- Terminology: temporal coherence (a.k.a. frame-to-frame coherence)
- Examples:
 - Motion of a camera
 - Motion of objects in a film / animation
- Applications:
 - Computer Vision (e.g. tracking of markers)
 - MPEG
 - Collision detection
 - Ray-tracing of animations (e.g. using kinetic data structures)
- Algorithms based on frame-to-frame coherence are called "incremental", sometimes "dynamic" or "online" (albeit the latter is the wrong term)



Convex Objects



Definition of "convex polyhedron":

$$P \subset \mathbb{R}^3$$
 convex \Leftrightarrow
 $\forall x, y \in P : \overline{xy} \subset P \Leftrightarrow$
 $P = \bigcap_{i=1...n} H_i$, $H_i = \text{half-spaces}$



A condition for "non-collision":
 P and *Q* are "linearly separable" :⇔
 ∃ half-space *H* : *P* ⊆ *H* ∧ *Q* ⊆ *H^c*

("P is completely on one side of H, Q completely on the other side")







The idea: utilize temporal coherence →
 if E_t was a separating plane between P and Q at time t, then the
 new separating plane E_{t+1} is probably not very "far" from E_t
 (perhaps it is even the same)







load E_t = separating plane between P & Q at time tE := E_t

repeat max n times

if exists $v \in vertices(P)$ on the back side of E: rot./transl. E such that v is now on the front side of E if exists $v \in vertices(Q)$ on the front side of E: rot./transl. E such that v is now on the back side of E if there are no vertices on the "wrong" side of E, resp.: return "no collision"

if there are still vertices on the "wrong" side of E:

return "collision" {could be wrong}

save $E_{t+1} := E$ for the next frame



E+

For details on the "rot./transl. E" step \rightarrow see perceptron learning algorithm

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- The brute-force method: test all **v** whether $f(\mathbf{v}) = (\mathbf{v} - \mathbf{p}) \cdot \mathbf{n} > 0$
- Observation:
 - 1. f is linear,
 - 2. P is convex $\Rightarrow f(x)$ has (usually) exactly one minimum over all points x on the surface of P
 - **3.** $\exists^1 v^* : f(v^*) = \min$
- The algorithm (steepest descent on the surface w.r.t. f):
 - Start with an arbitrary vertex v
 - Walk to the neighbor v' of v for which $f(v') = \min$. (among all neighbors)
 - Stop if there is no neighbor \mathbf{v}' of \mathbf{v} for which $f(\mathbf{v}') < f(\mathbf{v})$





Properties of this Algorithm



- + Expected running time is in O(1)! The algo exploits *frame-to-frame coherence*: if the objects move only very little, then the algo just checks whether the old separating plane is still a separating plane; if the separating plane has to be moved, then the algo is often finished after a few iterations.
- + Works even for deformable objects, so long as they stay convex
- Works only for convex objects
- Could return the wrong answer if P and Q are extremely close but not intersecting (bias)
- Research question: can you find an un-biased (deterministic) variant?



Visualization







Closest Feature Tracking



- Idea:
 - Maintain the minimal distance between a pair of objects
 - Which is realized by one point on the surface of each object
 - If the objects move continuously, then those points move continuously on the surface of their objects
- The algorithm is based on the following methods:
 - Voronoi diagrams
 - The "closest features" lemma



Voronoi Diagrams for Point Sets



- Given a set of points $S = {\mathbf{p}_i}$, called sites (or generators)
- Definition of a Voronoi region/cell :

 $V(p_i) := \{\mathbf{p} \in \mathbb{R}^2 \mid \forall j \neq i : ||\mathbf{p} - \mathbf{p}_i|| < ||\mathbf{p} - \mathbf{p}_j||\}$

- Definition of Voronoi diagrams: The Voronoi diagram VD(S) over a set of points S is the union of all Voronoi regions over the points in S.
- VD(S) induces a partition of the plane into Voronoi edges, Voronoi nodes, and Voronoi regions



Interaktive Demo: <u>http://web.cs.uni-bonn.de/I/GeomLab/VoroGlide/</u>



Voronoi Diagrams over Sets of Points, Edges, Optional



- Voronoi diagrams can be defined analogously in 3D (and higher dimensions)
- What if the generators are not points but edges / polygons?
- Definition of a Voronoi cell is still the same: The Voronoi region of an edge/polygon := all points in space that are closer to "their" generator than to any other
- Example in 2D:





Outer Voronoi Regions Generated by a Polyhoptional







The external Voronoi regions of ...

(a) faces

(b) edges

- (c) a single edge
- (d) vertices





Outer Voronoi regions for convex polyhedra can be constructed very easily! (We won't need inner Voronoi regions.)

(c)



Closest Features



- Definition *Feature* $f^P := a$ vertex, edge, polygon of polyhedron *P*.
- Definition "Closest Feature": Let f^P and f^Q be two features on polyhedra P and Q, resp., and let p, q be points on f^P and f^Q, resp., that realize the minimal distance between P and Q, i.e.

$$d(P,Q) = d(f^P, f^Q) = ||p-q||$$

Then f^{P} and f^{Q} are called "closest features".

 The "closest feature" lemma: Let V(f) denote the Voronoi region generated by feature f; let p and q be points on the surface of P and Q realizing the minimal distance. Then



 f^{P} , f^{Q} are closest features $\Leftrightarrow p$ is in $V(f^{Q})$, q is in $V(f^{P})$.









The Algorithm (Another Kind of a Steepest Degetional



```
Start with two arbitrary features f<sup>P</sup>, f<sup>Q</sup> on P and Q, resp.
while (f^{P}, f^{Q}) are not (yet) closest features and dist(f^{P}, f^{Q}) > 0:
     if (f<sup>P</sup>, f<sup>Q</sup>) has been considered already:
                    return "collision" (b/c we've hit a cycle)
     compute p and q that realize the distance between f^{P} and f^{Q}
     if p \in V(q) und q \in V(p):
                    return "no collision", (f<sup>P</sup>, f<sup>Q</sup>) are the closest features
     if p lies on the "wrong" side of V(q):
                    f^{P} := the feature on that "other side" of V(q)
     do the same for q, if q \notin V(p)
if dist(f^{P}, f^{Q}) > 0:
                                                 Notice: in case of collision, some features
```

return "no collision"

else

```
return "collision"
```

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44

are inside the other object, but we did not

compute Voronoi regions inside objects!

 \rightarrow hence the chance for cycles



Animation of the Algorithm









Some Remarks



- A little question to make you think: Actually, we don't really need the Voronoi diagram! (but with a Voronoi diagram, the algorithm is faster)
- The running time (in each frame) depends on the "degree" of temporal coherence
- Better initialization by using a lookup table:
 - Partition a surrounding sphere by a grid
 - Put each feature in each grid cell that it covers when propjected onto the sphere
 - Connect the two centers of a pair of objets by a line segment



Initialize the algorithm by the features hit by that line

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The Minkowski Sum

Optional



- Hermann Minkowski (1864 1909),
 German mathematician and physicist
- Definition (Minkowski Sum):

Let *A* and *B* be subsets of a vector space; the Minkowski sum of *A* and *B* is defined as

 $A \oplus B = \{\mathbf{a} + \mathbf{b} \,|\, \mathbf{a} \in A, \, \mathbf{b} \in B\}$



Analogously, we define the Minkowski difference:

 $A \ominus B = \{\mathbf{a} - \mathbf{b} \mid \mathbf{a} \in A, \mathbf{b} \in B\}$

Clearly, the connection between Minkowski sum and difference:

$$A \ominus B = A \oplus (-B)$$

 Applications: computer graphics, computer vision, linear optimization, path planning in robotics, ...

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Some Simple Properties





- Commutative: $A \oplus B = B \oplus A$
- Associative: $A \oplus (B \oplus C) = (A \oplus B) \oplus C$
- Distributive w.r.t. set union: $A \oplus (B \cup C) = (A \oplus B) \cup (A \oplus C)$
- Invariant against translation: $T(A) \oplus B = T(A \oplus B)$







Intuitive "computation" of the Minkowski sum/difference:



Warning: the yellow polygon in the animation shows the Minkowsi sum **modulo**(!) possible translations!

Analogous construction of Minkowski difference:





Visualizations of Simple Examples







Minkowski sum of a ball and a cube

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Minkowski sum of cube and cone, only the cone is rotating



Minkowski sum of cube and cone, both are translating







Optional The Complexity of the Minkowski Sum (in 2D, without proofs)



- Let A and B be polygons with n and m vertices, resp.:
 - If both A and B are convex, then $A \oplus B$ is convex, too, and has complexity O(m + n)
 - If only *B* is convex, then $A \oplus B$ has complexity O(mn)
 - If neither is convex, then $A \oplus B$ has complexity $O(m^2n^2)$
- Algorithmic complexity of the computation of $A \oplus B$:
 - If A and B are convex, then $A \oplus B$ can be computed in time O(m+n)
 - If only *B* is convex, then $A \oplus B$ can be computed in randomized time $O(mn \log^2(mn))$
 - If neither is convex, then $A \oplus B$ can be computed in time $O(mn^2 log(mn))$



Optional An Intersection Test for Two Convex Objects using Minkowski Sums



- Translate both objects so that the coordinate system's origin 0 is inside B
- Compute the Minkowski difference
- A and B intersect \Leftrightarrow $0 \in A \ominus B$
- Example where an intersection occurs:





 $A \ominus B = A \oplus -B = C$





Hierarchical Collision Detection



- The standard approach for "polygon soups"
- Algorithmic technique: divide & conquer





The Bounding Volume Hierarchy (BVH)



- Constructive definition of a bounding volume hierarchy:
 - 1. Enclose all polygons, *P*, in a bounding volume BV(*P*)
 - **2.** Partition *P* into subsets $P_1, ..., P_n$
 - 3. Rekursively construct a BVH for each P_i and put them as children of P in the tree
- Typical arity = 2 or 4













 Visualizations of different levels of some BVHs:







The General Hierarchical Collision Detection Algo



Resulting, conceptual(!) Bounding Volume Test Tree (BVTT)

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else



A Simple Running Time Estimation

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Best-case: O (log n)



Path through the Bounding Volume Test Tree (BVTT)

Optional

- Extremely simple average-case estimation:
 - Let P[k] = probability that *exactly* k children pairs overlap, $k \in [0,...,4]$

$$P[k] = {4 \choose k}/16$$
, $P[0] = rac{1}{16}$

- Assumption: all events are equally likely, each subtree has ½ of the polygons
- Expected running time:

$$T(n) = \frac{1}{16} \cdot 0 + \frac{4}{16} \cdot T(\frac{n}{2}) + \frac{6}{16} \cdot 2T(\frac{n}{2}) + \frac{4}{16} \cdot 3T(\frac{n}{2}) + \frac{1}{16} \cdot 4T(\frac{n}{2})$$
$$T(n) = 2T(\frac{n}{2}) \in O(n)$$

In praxi: running time is better/worse depending on degree of overlap



Different Kinds of Bounding Volumes



Requirements (for collision detection):

- *Very* fast overlap test \rightarrow "simple" BVs
 - Even if BVs have been translated/rotated
- Little overlap among BVs on the same level in a BVH (i.e., if you want to cover the whole space with the BVs, there should be as little overlap as possible) → "*tight BVs*"



Different Kinds of Bounding Volumes







The Wheel of Re-Invention



 OBB-Trees: have been proposed already in 1981 by Dana Ballard for bounding 2D curves, except they called it "strip trees"



 AABB hierarchies: have been invented(?) in the 80-ies in the spatial data bases community, except they call them "R-tree", or "R*-tree", or "X-tree", etc.



Digression: the Wheel of Fortune (Rad der Fortuna)





Boccaccio De Casibus Virorum Illustrium Paris: 1467



Codex Buranus

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In case of rigid collision detection (BVH construction can be neglected):

 $T = N_V C_V + N_P C_P$

 N_V = number of BV overlap tests

 $C_V = \text{cost of one BV overlap test}$

 N_P = number of intersection tests of primitives (e.g., triangles)

 $C_P = \text{cost of one intersection test of two primitives}$

In case of deformable objects (BVH must be updated):

$$T = N_V C_V + N_P C_P + N_U C_U$$

 N_U / C_U = number/cost of a BV update

 As the kind of BV gets tighter, N_V (and, to some degree, N_P) decreases, but C_V and (usually) C_U increases

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The "separating plane" lemma

(just a different wording of the "separating axis" lemma): Two convex polyhedra *A* and *B* do *not* overlap \Leftrightarrow there is an axis (line) in space so that the projections of *A* and *B* onto that axis do not overlap. This axis is called the separating axis.

- This axis is called the separating axis.
- Lemma "Separating Axis Test" (SAT):

Let *A* and *B* be two convex 3D polyhedra.

If there is a separating plane, then there is also a separting plane that is either parallel to one side of *A*, or parallel to one side of *B*, or parallel to one edge of *A* and one edge of *B* simultaneously. [Gottschalk, Lin, Manocha; 1996]



Proof of the SAT Lemma

- 1. Assumption: *A* and *B* are disjoint
- **2.** Consider the Minkowski sum $C = A \ominus B$
- 3. All faces of *C* are either parallel to one face of *A*, or to one face of *B*, or to one edge of *A* and one of *B* (the latter cannot be seen in 2D)
- 4. C is convex
- 5. Therefore: $C = \bigcap_{i=1}^{m} H_i$
- $6. \quad A \cap B = \varnothing \Leftrightarrow 0 \notin C$
- 7. $\exists i : 0 \notin H_i$ (i.e., 0 is outside some H_i)
- 8. That H_i defines the separating plane; the line perpendicular to H_i is the separating axis



Optional







Actually Computing the SAT for OBBs



- W.I.o.g.: compute everything in the coordinate frame of OBB A
- A is defined by: center c, axes A¹, A², A³, and extents a¹, a², a³, resp.
- B's position relative to A is defined by rot. R and transl. T
- In the coord. frame of A:
 Bⁱ are the columns of R
- Let L be a line in space; then A and B overlap, if $|T \cdot L| < r_A + r_B$



Optional

- Remark: L = normal to the separating plane
- According to the lemma, we need to check only a few special lines
- With boxes, that number of special lines = 15



Optional



- Example: $L = A^1 \times B^2$
- We need to compute: $r_A = \sum_i a_i |A^i \cdot L|$ (and similarly r_B)
- For instance, the 2nd term of the sum is:



In general, we have one test of the following form for each of the 15 axes: $T = \frac{T}{16} = \frac{1}{16} = \frac{1}{$

$$T \cdot L | < a_2 |R_{32}| + a_3 |R_{22}| + b_1 |R_{13}| + b_3 |R_{11}|$$



Discretely Oriented Polytopes (k-DOPs)



Definition of k-DOPs:

Choose k fixed vectors $\mathbf{b}_i \in \mathbb{R}^3$, with k even, and $\mathbf{b}_i = -\mathbf{b}_{i+k/2}$. We call these vectors generating vectors

(or just generators).

A *k*-DOP is a volume defined by the intersection of *k* half-spaces:

$$b_3$$

 b_4
 b_5
 b_6
 b_6
 b_7
 b_8

Optional

$$D = \bigcap_{i=1..k} H_i$$
 , $H_i : \mathbf{b}_i \cdot x - d_i \leq 0$

• A *k*-DOP is completely described by $D = (d_1...d_k) \in \mathbb{R}^k$







b₁

Optional







- Computation of a *k*-DOP, given a polygon soup with vertices V :
 - $\mathcal{V} = \{\mathbf{v}_0, \ldots, \mathbf{v}_n\}$
 - $D = (d_1...d_k) \in \mathbb{R}^k$
 - For each *i* = 1, .., *k*, compute

$$d_i = \max_{j=0,\ldots,n} \{\mathbf{v}_j \cdot \mathbf{b}_i\}$$





Some Properties of k-DOPs



Optional

- AABBs are special DOPs
- The overlap test takes time $\in O(k)$, k = number of orientations
- With growing *k*, the convex hull can be approximated arbitrarily precise:





The Overlap Test for Rotated *k*-DOPs





- The object's orientation is given by rotation R & translation T
- The axis-aligned DOP D' = (d'₁, ..., d'_k) can be computed as follows (without proof):



- The correspondence jⁱ₁ is identical for all DOPs in the same hierarchy (thus, it can be precomputed)
- Complexity: O(k)
 - Compare this to a SAT-based overlap test



Optional Restricted Boxtrees (a Variant of kd-Trees)

- Restricted Boxtrees are a combination of kd-trees and AABB trees:
 - For defining the children of a node B: for the left child, split off a portion of the "right" part of the box B; for the right child of B, split off a portion of the left part of B
- Memory usage: 1 float, 1 axis ID, 1 pointer (= 9 bytes)
- Other names for the same DS:
 - Bounding Interval Hierarchy (BIH)
 - Spatial kd-tree (SKD-Tree)













 Overlap tests by "re-alignment" (i.e., enclosing the non-axisaligned box in an axis-aligned one, exploiting the special structure of restricted boxtrees):



12 FLOPs (8.5 with a little trick)

- Compare this to
 - SAT: 82 FLOPs
 - SAT lite: 24 FLOPs
 - Sphere test: 29 FLOPs

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Optional







The Construction of BV Hierarchies



Optional

• Obviously:

if the BVH is bad \rightarrow collision detection has a bad performance

- The general algorithm for BVH construction: top-down
 - 1. Compute the BV enclosing the set of polygons
 - 2. Partition the set of polygons
 - 3. Recursively compute a BVH for each subset
- The essential question: the splitting criterion?
- Guiding principle: the expected cost of collision detection incured by a particular split

$$egin{aligned} \mathcal{C}\left(X,\,Y
ight) &= 4 + \sum_{i,j=1,2} P\left(X_i,\,Y_j
ight) \mathcal{C}\left(X_i,\,Y_j
ight) \ &pprox 4\left(1 + P\left(X_1,\,Y_1
ight) + \dots + P\left(X_2,\,Y_2
ight)
ight) \end{aligned}$$



 X_1

Х



Υ

 Y_1

 $X_1 \ominus Y_1$

 $X \ominus Y$

0

- Goal: estimation of P(X_i,Y_i)
- Our tool: the Minkowski sum
- Reminder:

$$X_i \cap Y_j = \varnothing \Leftrightarrow 0 \notin X_i \ominus Y_j$$

Therefore, the probability is:

 $P(X_i, Y_j) = \frac{\# \text{``good'' cases}}{\# \text{ all possible cases}}$ $= \frac{\operatorname{vol}(X_i \ominus Y_j)}{\operatorname{vol}(X \ominus Y)} = \frac{\operatorname{vol}(X_i \oplus Y_j)}{\operatorname{vol}(X \oplus Y)} \approx \frac{\operatorname{vol}(X_i) + \operatorname{vol}(Y_j)}{\operatorname{vol}(X) + \operatorname{vol}(Y)}$

 Conclusion: for a good BVH (for coll.det.) minimize the total volume of the children of each node



Usual Algorithm for Constructing a BVH

 Find good orientation for a "good" splitting plane using PCA

2. Find the minimum of the total volume by a sweep of the splitting plane along that axis



Complexity of that *plane-sweep* algorithm:

 $T(n) = n \log n + T(\alpha n) + T((1 - \alpha)n) \in O(n \log^2 n)$

 Assumption: splits are not too uneven, i.e., a fraction of α / (1-α) polygons goes into the left/right subtree, α not "too small"

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Optional



Optional Coll.Det. Algorithm Depends on Object Representation



- Example: Voxmap-Pointshell
 - Objects are represented by point shell and by a voxel grid
- The fundamental operation: does a point hit a black voxel?
- Problems:
 - What to do in case of non-closed objects?
 - Memory consumption for all the voxels!
 - Hierarchy might help, but also slows coll.det. down
 - Collision detection is not exact (b/c of discretization)





Inner Sphere Trees: the Basic Idea



- Challenge: compute proximity, i.e., distance or measure of penetration
- Don't approximate an object from the outside; instead, approximate it
 - from the *inside*,
 - with non-overlapping spheres, and
 - with as little empty volume as possible
- Sphere packing
- Build sphere hierarchy on top of inner spheres





Computation of Sphere Packings



Have a long history ...



Johannes Kepler (1571 - 1630)

Has many applications, besides collision detection:



Radio surgery



Discrete element method



Architecture

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- Our requirements / variety of sphere packings:
 - Non-overlapping
 - Arbitrary radii
 - Must work for any kind of container (not just boxes)
- Optimization according to some criteria, e.g. number of spheres
- No algorithm yet for that \rightarrow our approach:
 - Find inner Voronoi nodes of container object
 - (See course "Computational Geometry for CG")
 - In our case, use approximation by iterative algorithm
 - Place spheres
 - Compute new Voronoi nodes of object *plus* spheres



Visualization of Our Algorithm













Our Algorithm can be Parallelized for the GPU







Performance of Construction of Sphere Packing






Optional Construction of Hierarchy Over Sphere Packing



- Based on clustering method known in machine learning (batch neural gas clustering)
 - Bears some resemblance to k-means
- We can assign "importance" to spheres
- Easily parallelizable on the GPU
- Naturally generalizes to higher tree degrees (out-degree of 4-8 seems optimal)







- BNG hierarchy construction on CPU has complexity of $O(n \log n)$
- Parallelization of BNG reduces complexity to O(log² n)











 Works by the standard simultaneous traversal of BVHs



- First algo that can compute both minimal distance or intersection volume with one unified algorithm
- Can compute forces and torques
 - Which can be proven to be continuous







Optional Computation Timings for the Intersection Volume







Parallel Computation Times for Intersection on GPU







- Optional Penalty Forces for Simulation/Force-Feedback
 - Accumulate sphere-sphere interaction forces:
 - Linear force:

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$$\mathbf{f}_{ij}^{\mathsf{blue}} = \mathsf{Vol}(s_j^{\mathsf{red}} \cap s_i^{\mathsf{blue}}) \cdot \mathbf{n}_i^{\mathsf{blue}}$$

 $\mathbf{f}^{\mathsf{blue}} = \sum \mathbf{f}^{\mathsf{blue}}_{ij}$

Torque:

$$au_{ij}^{ ext{blue}} = (P_{ ext{ij}} - C_m) imes \mathbf{f}_{ ext{ij}}$$
 $au^{ ext{blue}} = \sum au_{ij}^{ ext{blue}}$

Forces/torques an be proven to be continuous







Application: Multi-User Haptic Workspace





12 moving objects ; 3.5M triangles ; 1 kHz simulation rate ; intersection volume ≈ 1-3 msec

G. Zachmann

Master / Bachelor Thesis Topics



- Perform collision detection using machine learning
 - Use deep learning, or GLVQ (ask Barbara)
 - For riigid objects first, then deformable, or continuous collision detection