# **Geometric Structures**

#### 2. Quadtree, k-d stromy

Martin Samuelčík

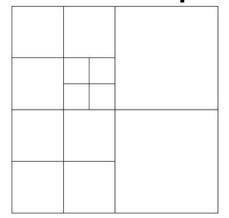
samuelcik@sccg.sk, www.sccg.sk/~samuelcik, I4

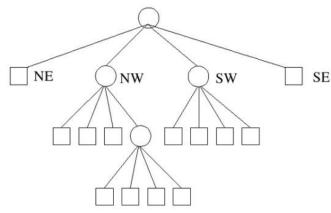
## Window and Point query

- From given set of points, find all that are inside of given d-dimensional interval
- Solution using multi-dimensional range trees
  - Higher memory complexity
  - General for all dimensions
  - Adaptive construction based on given points
- Other solution—split using hyperplanes in one dimesion—slower, but lower memory complexity

## Quadtree

- Each inner node of tree has exactly 4 siblings
- Each node represents area part of 2D space, usually square or rectangle, but other shapes are possible
- 4 children of node represents split of node area into 4 smaller equal areas
- 2D





## Quadtree construction

- *S* set of points in 2D
- Initial creation of bounding area for points in S
- Recursive

```
struct QuadTreeNode
{
    Point* point;
    float left, right, bottom, top;
    QuadTreeNode * parent;
    QuadTreeNode * NE;
    QuadTreeNode * NW;
    QuadTreeNode * SW;
    QuadTreeNode * SE;
}
```

```
struct QuadTree
{
   QuadTreeNode* root;
}
```

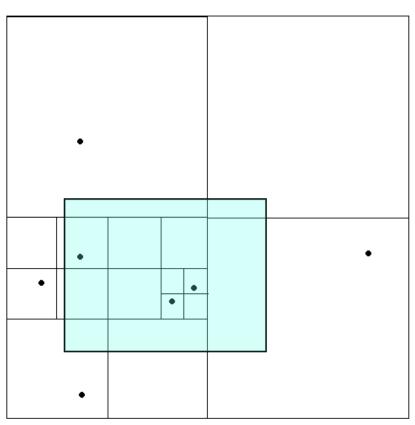
```
QuadTreeConstruct(S)
{
    (left, right, bottom, top) = BoundSquare(S);
    QuadTree* tree = new QuadTree;
    tree->root = QuadTreeNodeConstruct(S, left, right, bottom, top);
    return tree;
}
```

```
QuadTreeNodeConstruct(P, left, right, bottom, top)
 v = new QuadTreeNode;
 v->left = left; v->right = right; v->bottom = bottom; v->top = top;
 v-NE = v-NW = v-SW = v-SE = v-parent = v-point = NULL;
  if (|P| == 0) return v;
  if (|P| == 1)
    v->point = P.first;
    return v;
 xmid = (left + right)/2; ymid = (bottom + top)/2;
  (NE, NW, SW, SE) = P.Divide(midx, midy);
  v->NE = QuadTreeNodeConstruct(NE, xmid, right, ymid, top);
  v->NW = QuadTreeNodeConstruct(NW, left, xmid, ymid, top);
 v->SW = QuadTreeNodeConstruct(SW, left, xmid, bottom, ymid);
  v->SE = QuadTreeNodeConstruct(SE, xmid, right, bottom, ymid);
  v->NE->parent = v; v->NW->parent = v;
  v->SW->parent = v; v->SE->parent = v;
  return v;
```

## Quadtree search

Finding point inside rectangle

*B=[left,right,bottom,top]* 



```
QuadTreeQuery(tree, B)
{
    return QuadTreeNodeQuery(tree->root, B)
}
```

```
QuadTreeNodeQuery(node, B)
  List result:
  if (node == NULL)
    return result:
  if (B->left > node->right | | B->right < node->left | |
    B->bottom > node->top | B->top < node->bottom)
    return result;
  if (node->point)
    result.Add(point);
  result.Add(QuadTreeNodeQuery(v->NE, B));
  result.Add(QuadTreeNodeQuery(v->NW, B);
  result.Add(QuadTreeNodeQuery(v->SW, B);
  result.Add(QuadTreeNodeQuery(v->SE, B);
  return result;
```

## Quadtree properties

- Maximal depth of quadtree is log(s/c) + 3/2, where c is smallest distance between points in S and s is length of one side of initial bounding square
- Quadtree od depth d with |S|=n has O(n.(d+1)) nodes and can be constructed in time O(n.(d+1))
- Construction: O(n<sup>2</sup>)
- Memory: O(n<sup>2</sup>)
- Search: O(n)

## Finding neighbor node

- For given node and corresponding area, find node and its area adjacent to given node in given direction
- Time complexity O(d), d height of tree

```
NorthNeighbor(v, T)
{
    if (v == T->root) return NULL;
    if (v == v->parent->SW) return v->parent->NW;
    if (v == v->parent->SE) return v->parent->NE;
    u = NorthNeighbor(v->parent, T);
    if (u == NULL | | u->IsLeaf()) return u;
    if (v == v->parent->NW)
        return u->SW;
    else
        return u->SE;
}
```

```
SouthChilds(v)
{
    List result;
    if (v == NULL)
        return result;
    if (v->IsLeaf())
        result.Add(v);
    result.Add(SouthChilds(v->SE));
    result.Add(SouthChilds(v->SW));
    return result;
}
```

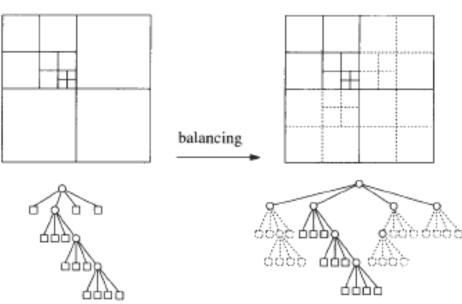
```
NorthNeighbors(v, T)
{
    List result;
    North = NorthNeighbor(v, T);
    if (North == NULL)
        return result;
    return SouthChilds(North);
}
```

## **Balancing quadtree**

- Balanced quadtree each two adjacent areas has almost same size
- Balancing simple adding empty subtrees

 If T has m nodes, then balanced version has O(m) nodes and can be created in time

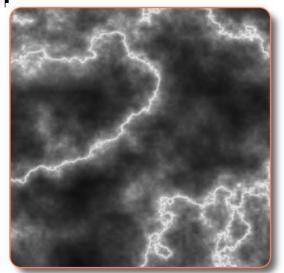
O(m(d+1))



## **Balancing quadtree**

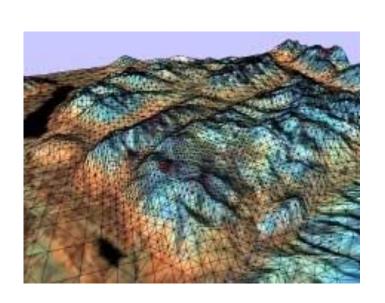
- CheckDivide checking, if node v has to be divided, finding if neighbor siblings are leaves or not
- Divide dividing node of tree into four siblings, adding point from node to one sibling
- CheckNeighbours if there unbalanced neighbours, then add neighbors to list L

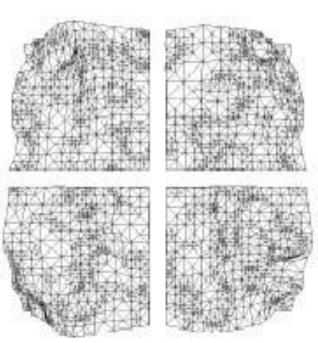
- View above terrain surface some parts are close, some away – using LOD (Level Of Detail), each part of terrain is rendered in some detail based on distance from camera
- Needed structure for storing all levels of detail for each part of terrain
- Terrain
  - Height field





- Creating complete quadtree over height filed
- Traversing tree during rendering based on distance of camera and node area, the traverse is stopped or contiinued

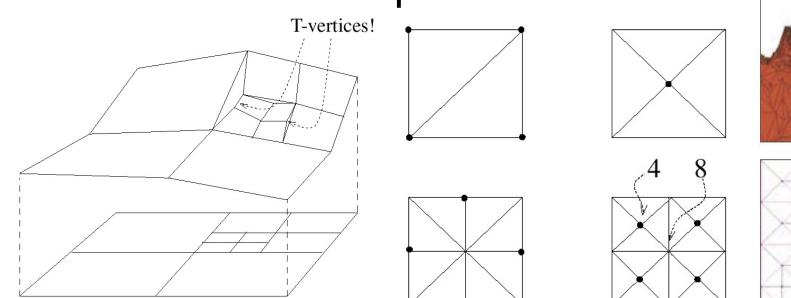


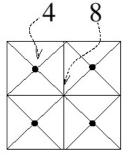


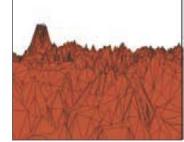
 Problems with the edge between areas on different levels in quadtree

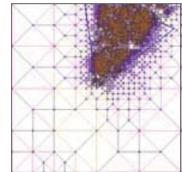
Solution using triangulation = connection of

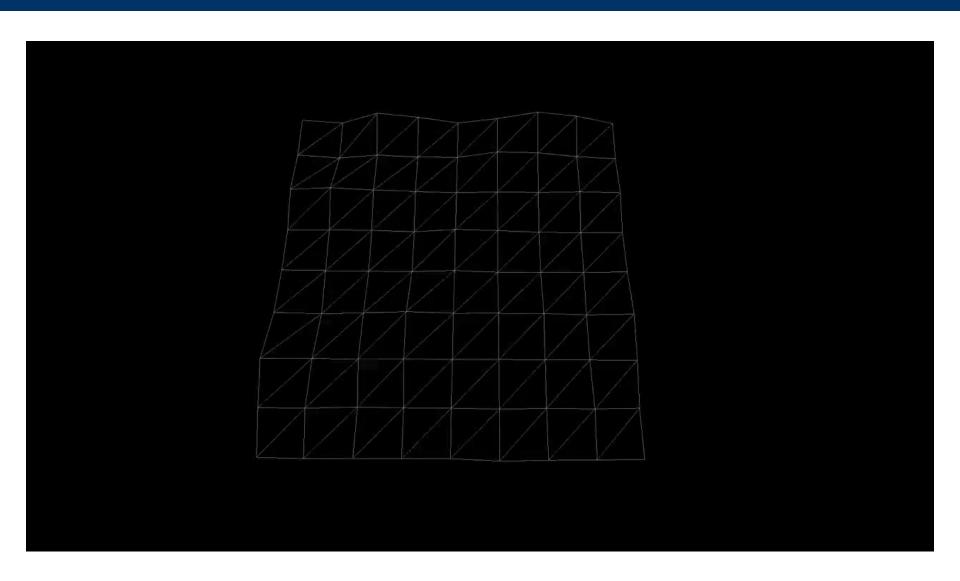
two consecutive quadtrees







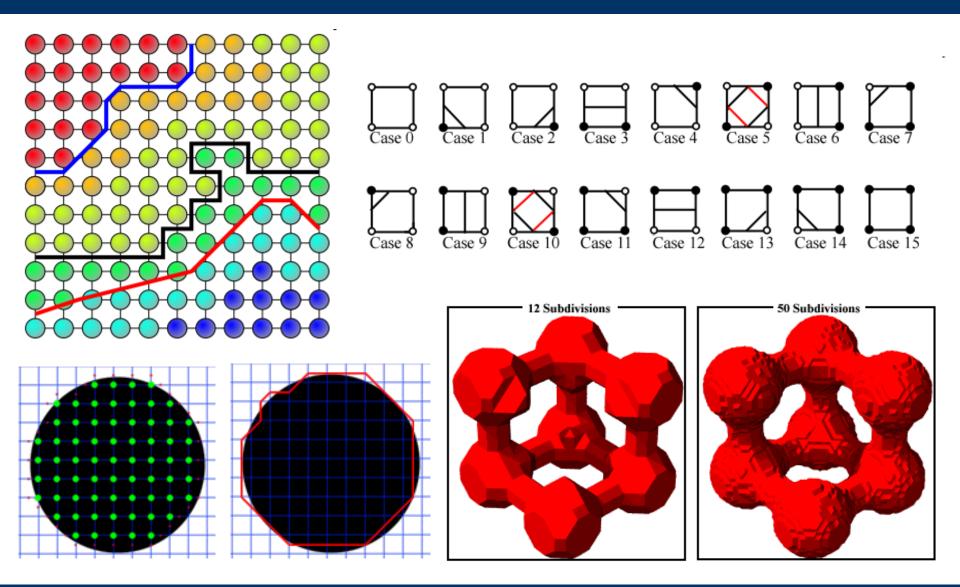




## Isosurface generation

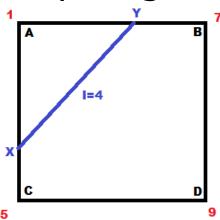
- Input are intensities given in uniform grid, output is curve or surface approximating one level of intensity
- Constructing complete quadtree, each node storing minimal and maximal intensity in subtree of node
- For homogenous intensity areas, no need for dividing
- "Marching Cubes" algoritmus constructing triangles or segments for each cell

## Isocurve, isosurface generation



## Bilinear interpolation in cell

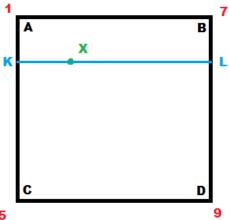
Computing end points of segments



$$X = \frac{|5-4|}{|5-1|}A + \frac{|4-1|}{|5-1|}C = \frac{1}{4}A + \frac{3}{4}C$$

$$Y = \frac{|7-4|}{|7-1|}A + \frac{|4-1|}{|7-1|}B = \frac{1}{2}A + \frac{1}{2}B$$

Computing intensity for point inside cell



$$I_{K} = \frac{\left| Xy - Ay \right|}{\left| Cy - Ay \right|} 5 + \frac{\left| Cy - Xy \right|}{\left| Cy - Ay \right|} 1 \qquad I_{L} = \frac{\left| Xy - By \right|}{\left| Dy - By \right|} 9 + \frac{\left| Dy - Xy \right|}{\left| Dy - By \right|} 7$$

$$I_{X} = \frac{\left| Xx - Ax \right|}{\left| Bx - Ax \right|} I_{L} + \frac{\left| Bx - Xx \right|}{\left| Bx - Ax \right|} I_{K}$$

## Quadtree for Marching Squares

Input is 2D array of intesities

```
-P[i,j]; i = 0,...,2^n; j = 0,...,2^m
```

```
struct MCQuadTree
{
    MCQuadTreeNode* root;
}
```

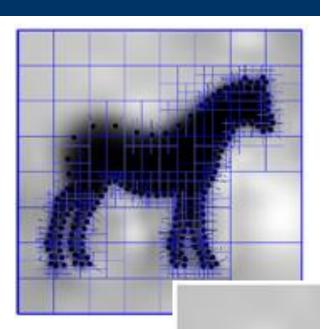
```
struct MCQuadTreeNode
{
    float MinIntensity;
    float MaxIntensity;
    float Corner1, Corner2;
    float Corner3, Corner4;
    QuadTreeNode * parent;
    QuadTreeNode * NE;
    QuadTreeNode * NW;
    QuadTreeNode * SW;
    QuadTreeNode * SE;
}
```

```
MCQuadTreeNodeConstruct(P, MinXIndex, MaxXIndex, MinYIndex, MaxYIndex)
 v = new MCQuadTreeNode;
 v->Corner1 = P[MinXIndex, MinYIndex]; v->Corner2 = P[MaxXIndex, MinYIndex];
 v->Corner3 = P[MaxXIndex, MaxYIndex]; v->Corner4 = P[MinXIndex, MaxYIndex];
 v->NE = v->NW = v->SW = v->SE = v->parent = NULL;
  (Min, Max) = GetMinMaxIntensities(P, MinXIndex, MaxXIndex,
                                      MinYIndex, MaxYIndex);
 v->MinIntensity = Min;
 v->MaxIntensity = Max;
 if (Min == Max)
    return v:
  MidXIndex = (MinXIndex + MaxXIndex) / 2;
  MidYIndex = (MinYIndex + MaxYIndex) / 2;
 v->NE = MCQuadTreeNodeConstruct(P, MidXIndex, MaxXIndex, MidYIndex, MaxYIndex);
 v->NW = MCQuadTreeNodeConstruct(P, MinXIndex, MidXIndex, MidYIndex, MaxYIndex);
 v->SW = MCQuadTreeNodeConstruct(P, MinXIndex, MidXIndex, MinYIndex, MidYIndex);
 v->SE = MCQuadTreeNodeConstruct(P, MidXIndex, MaxXIndex, MinYIndex, MidYIndex);
 v->NE->parent = v; v->NW->parent = v;
 v->SW->parent = v; v->SE->parent = v;
 return v;
```

## **Marching Squares**

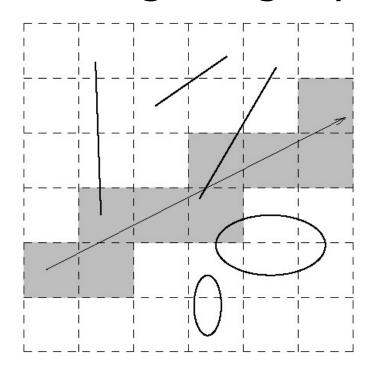
```
MarchCubes(T, intensity, left, right, bottom, top)
{
    MarchCubesNode(T->root, intensity, left, right, bottom, top);
}
```

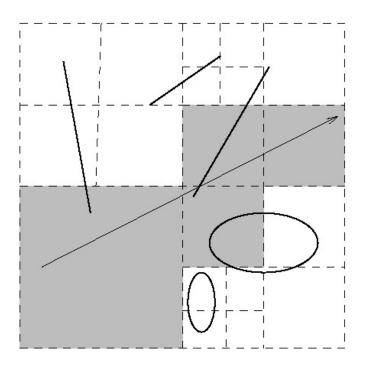
```
MarchCubesNode(v, intensity, left, right, bottom, top)
  if (intensity < MinIntensity | | intensity > MaxIntensity)
    return;
  if (MinIntensity == MaxIntensity)
    return;
  if (v->IsLeaf())
    CreateLinesInRextangle(left, right, bottom, top,
       v->Corner1, v->Corner2, v->Corner3, v->Corner4);
    return;
  float midx = (left+right) / 2;
  float midy = (bottom+top) / 2;
  MarchCubesNode(v->SW, intensity, left, midx, bottom, midy);
  MarchCubesNode(v->SE, intensity, midx, right, bottom, midy);
  MarchCubesNode(v->NE, intensity, midx, right, midy, top);
  MarchCubesNode(v->NE, intensity, left, midx, midy, top);
```



## Raytracing

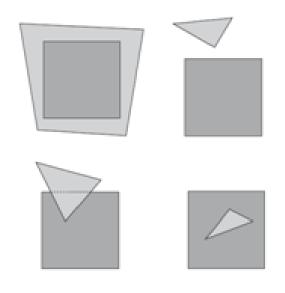
- Storing pointers to objects inside quadtree
- Finding neighbor cells in quadtree when traversing along ray

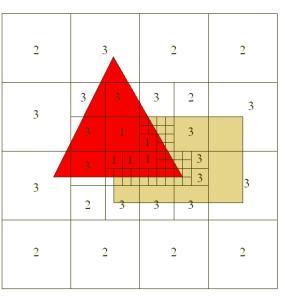




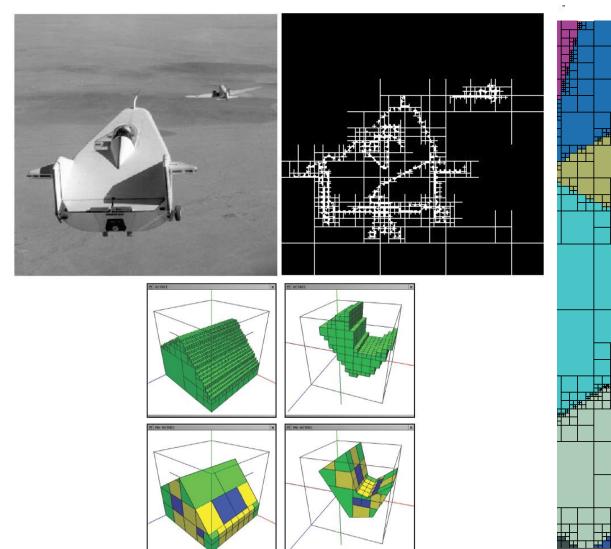
## Visibility computation (Warnock)

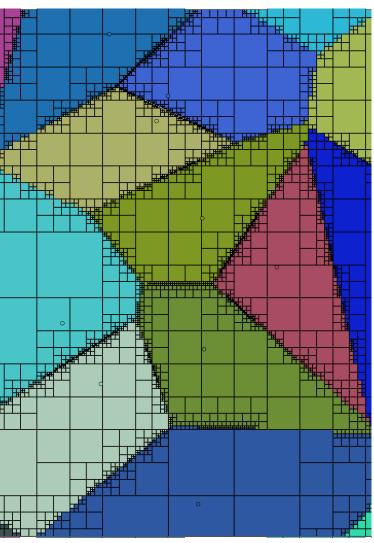
- Computation in screen space
- Divide parts of screen using quadtree until simple cases occur
- In each leaf of quadtree, compute color of all pixels in node ares from nearest polygon





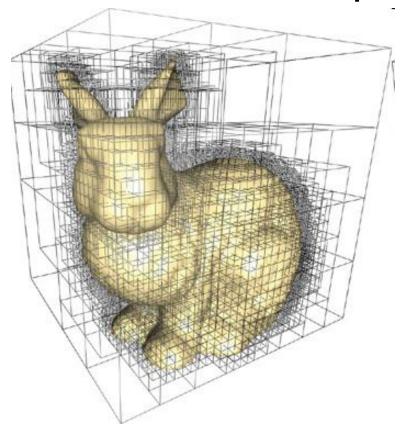
## Representations

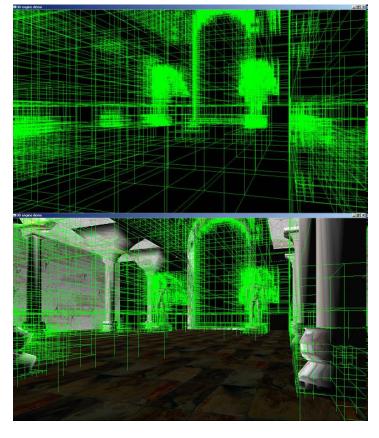




#### Octree

 Extension of quadtree in 3D space, solution of same or similar problems

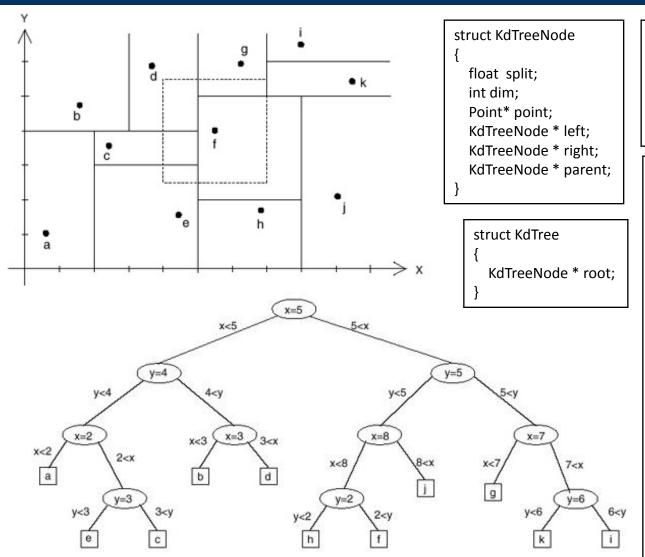




#### K-d tree

- Input: set of points *S* from *R*<sup>d</sup>
- Query: *d*-dimensional interval *B*
- Output: set of points from S, that are inside set B
- Recursive construction:  $D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \}, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \}, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_{\langle s_i \rangle} = \{(x_1, \dots, x_i, \dots, x_n) \in D | x_i \langle s \rangle, \\ D_$ 
  - Given set of points D from R<sup>d</sup> and split coordinate i
  - If D is empty, return empty node
  - If D contains 1 point, current node becomes leaf
  - Else compute split value s in i-th coordinate and based on this value divide D into two sets  $D_{< s_f}$   $D_{> s_i}$  and for these two sets recursively construct two sibling nodes with increase coordinate i by 1

#### K-d tree construction



```
KdTreeConstruct(S, d)
{
    T = new KdTree;
    T->root = KdTreeNodeConstruct(S, 0, d);
    return T;
}
```

```
KdTreeNodeConstruct(D, dim, d)
  if (|D| = 0) return NULL;
  v = new KdTreeNode;
  v->dim = dim;
  if (|D| = 1)
    v->point = D.Element;
    v->left = NULL;
    v->right = NULL;
    return v;
  v->point = NULL;
  v->split = D.ComputeSplitValue(dim);
  D<sub><s</sub> = D.Left(dim, v->split);
  D<sub>>s</sub> = D.Right(dim, v->split);
  j = (dim + 1) \mod d;
  v->left = KdTreeNodeConstruct(D<sub><s</sub>, j);
  v->right = KdTreeNodeConstruct(D_s, j);
  return v;
```

## Query

 When searching for points inside given d-dimensional interval B, we are working with areas representing each node of k-d tree (Q)

```
KdTreeQuery(T, B)
{
   Q = WholeSpace();
   return KdTreeNodeQuery(T->root, Q, B);
}
```

```
Report(v)
{
    List L;
    if (v->IsLeaf() && (v->point))
    {
        L.add(v->point);
        return L;
    }
    L.add(Report(v->left));
    L.add(Report(v->right));
    return L;
}
```

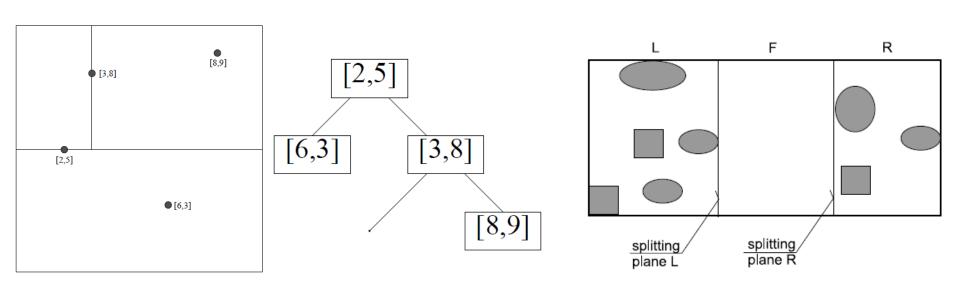
```
KdTreeNodeQuery(v, Q, B)
  List L:
  if (v->IsLeaf() && (v->point in B))
    L.add(v->point);
    return L;
  v_i := v - | eft;
  v<sub>r</sub> := v->right;
  Q := Q.LeftPart(v->dim, v->split);
  Q_:= Q.RightPart(v->dim, v->split);
  if (Q<sub>i</sub> in B)
    L.add(Report(v->left));
  else if (Q_i \cap B != 0)
    L.add(KdTreeQuery(v->left,Q,,B));
  if (Q_in B)
    L.add(Report(v->right));
  else if (Q_r \cap B! = 0)
    L.add(KdTreeQuery(v->right, Q,, B));
  return L;
```

## K-d tree properties

- If split sets  $D_{\langle s_i \rangle}$ ,  $D_{\langle s_i \rangle}$  are almost equal (using for example median), then tree is balanced
- Balanced k-d tree in R<sup>d</sup> can be constructed in time O(n.log(n)) with memory complexity O(n)
- Query for searching using k-d tree in R<sup>d</sup> hjas time complexity O(n<sup>(1-1/d)</sup> + k), where k is cardinality of output
- High time complexity in worst cases (bad divide), expected complexity is O(log(n) + k)
- Point insertion: O(log(n))
- Point removal: O(log(n))

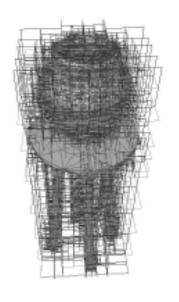
#### K-d trees

 Trees variations: points stored not only in leafs, non-periodic change od split hyperplane, different ways for split and termination, two split hyperplanes

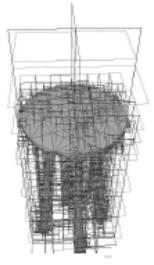


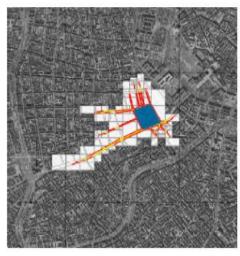
## K-d trees





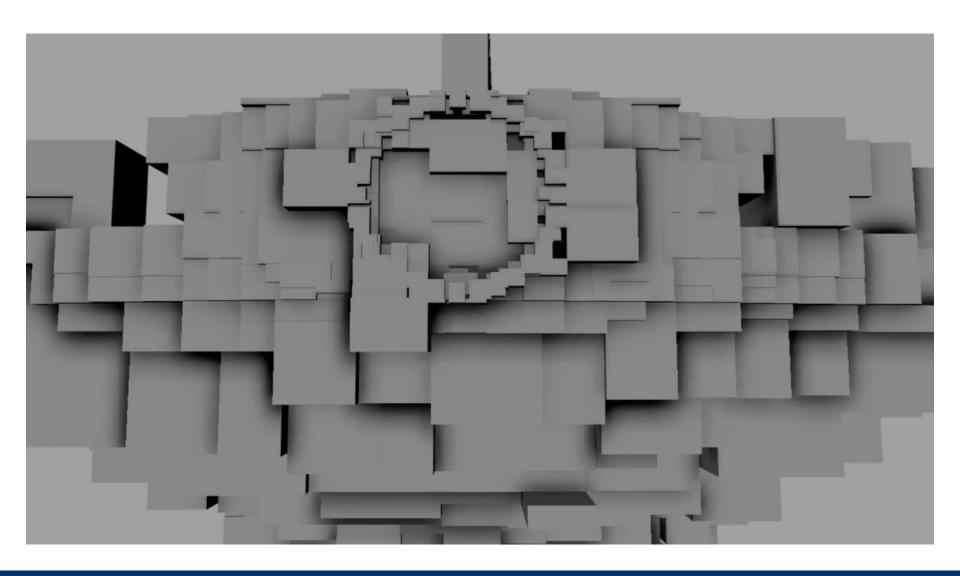




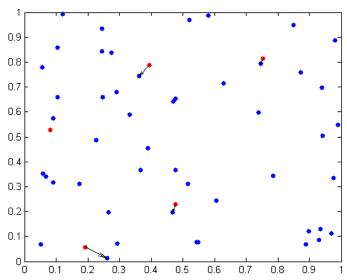


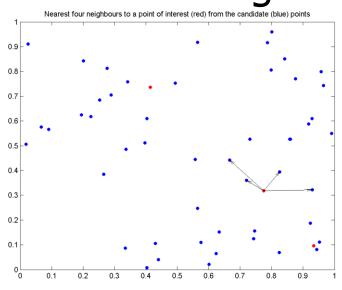


## K-d trees



- For set of points S from R<sup>d</sup> and one other point P from R<sup>d</sup>, find one point Q from S such that distance |PQ| is minimal
- Extension find k nearest neighbors, or alternatively k approximate nearest neighbors



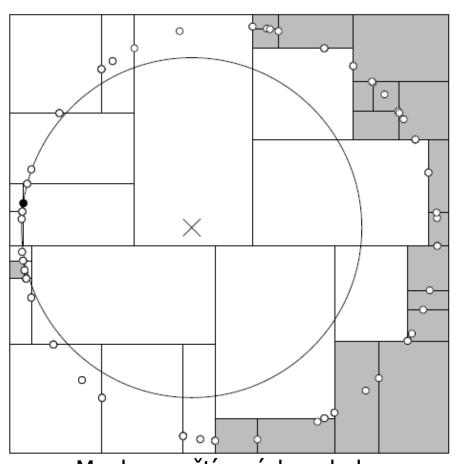


```
SearchSubtree(v, nearest node, P)
  List nodes:
  nodes.Add(v);
  current nearest = nearest node;
  while (nodes.size() > 0)
    current node = nodes.PopFirst();
                                                                         }; return nearest node;
    if (current node->IsLeaf() && (current node->point))
      if (Distance(current_node->point, P) < Distance(current_nearest->point, P))
         current nearest = current node;
       continue;
   hyperplane distance = Distance(P, current node->dim, current node->split);
    if (hyperplane distance > Distance(current nearest->point, P))
       if (InLeftPart(P, current node->dim, current node->split)) nodes.Add(current node->left);
       else nodes.Add(current node->right);
    else
       nodes.Add(current node->left);
      nodes.Add(current node->right);
  return current nearest;
```

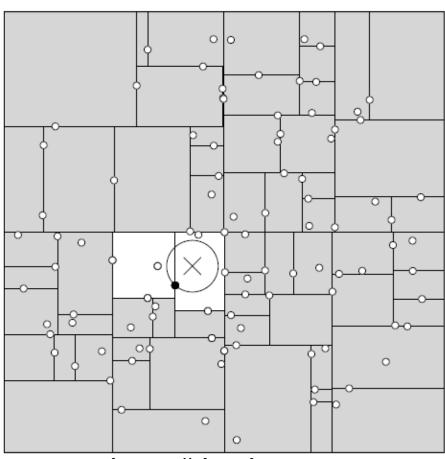
```
FindNearPoint(v, P)
{
    if (v->lsLeaf() && (v->point))
        return v;
    if (InLeftPart(P, v->dim, v->split))
        return FindNearPoint(v->left, P);
    else
        return FindNearPoint(v->right, P);
}
```

```
KdTreeNearestNeighbor(T, P)
{
  near = FindNearPoint(T->root, P);
  return FindNearestPoint(T, near, P);
}
```

- First step: find node (leaf of k-d tree) containing point that is near to point P
- Second step: From this leaf, traverse tree back to root and search for nearer points stored in opposite subtrees
- Time complexity: O(d. n<sup>(1-1/d)</sup>)
- For random distribution of points, expected time complexity is O(log(n))
- http://dl.acm.org/citation.cfm?id=355745
- http://dimacs.rutgers.edu/Workshops/MiningTutori al/pindyk-slides.ppt
- http://www.ri.cmu.edu/pub\_files/pub1/moore\_andr ew\_1991\_1/moore\_andrew\_1991\_1.pdf



Mnoho navštívených vrcholov



Málo navštívených vrcholov

## k nearest neighbors

- Extension of previous algorithm
- Instead of sphere with 1 actually nearest point, we have sphere containing k actually nearest points
- If the sphere in one moment contains less than k points, its radius is infinite
- In first step, we find k potentially nearest points instead of 1

```
Struct SearchRecord
{
  vector<KdTreeNode> points;
  float radius;
}
```

```
KdTreeNearestNeighbors(T, P, k)
{
    SearchRecord result;
    FindNearPoints(T->root, P, k, &result);
    FindNearestPoints(T, P, k, &result);
    return result;
}
```

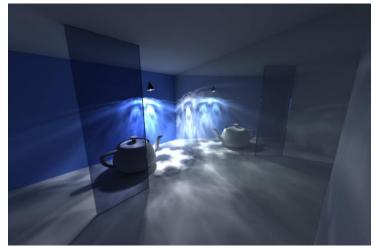
```
FindNearPoints(v, P, k, result)
  if (v->IsLeaf() && (v->point))
    result->points.Add(v);
    result->UpdateRadius(P);
    return;
  if (InLeftPart(P, v->dim, v->split))
    FindNearPoints(v->left, P, k, result);
    if (result->points.size < k)
       FindNearPoints(v->right, P, k, result);
  else
    FindNearPoints(v->right, P, k, result);
    if (result->points.size < k)
       FindNearPoints(v->left, P, k, result);
```

```
SearchSubtree(v, P, k, result)
  List nodes;
  nodes.Add(v);
  while (nodes.size() > 0)
    current node = nodes.PopFirst();
    if (current node->IsLeaf() && (current node->point))
      if (Distance(current node->point, P) < result->radius)
         result->points.AddNewAndRemove(current node, P, k);
         result->UpdateRadius(P);
       continue;
    hyperplane distance = Distance(P, current node->dim, current node->split);
    if (hyperplane distance > result->radius)
       if (InLeftPart(P, current node->dim, current node->split))
          nodes.Add(current node->left);
       else
          nodes.Add(current node->right);
    else
       nodes.Add(current node->left);
      nodes.Add(current node->right);
  return;
```

## **Photon mapping**

- 1. pass:
  - Shooting photons from light source in random directions
  - Computing intersections and bounces of photons in scene
  - Storing intersection points in map
- 2. pass:
  - Rendering from camera
  - Using light data from map (searching for k closest photons in map from surface point) for global illumination computation
- Photon map structure = k-d tree

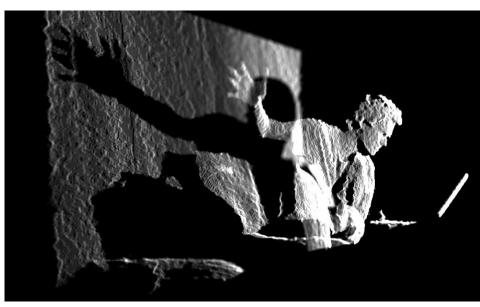




#### **Point clouds**

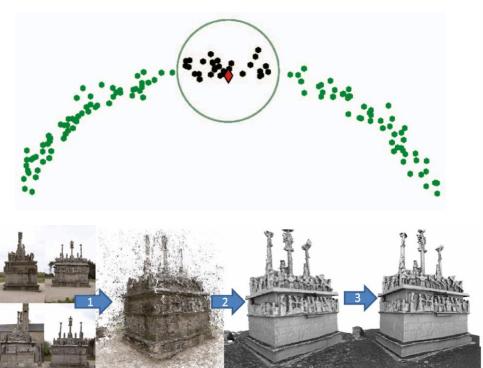
- Many construction possibilities: laser scanning, Kinect, structured light, ...
- Surface reconstruction find continuous surface based on points





#### **Surface reconstruction**

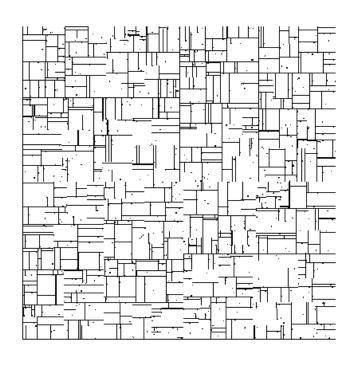
- Searching for points inside given sphere
- Small modification of nearest neighbor search

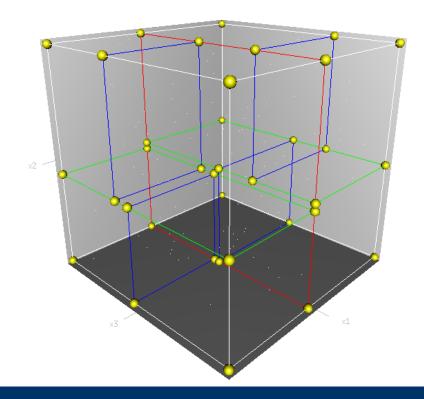




#### **Database**

- Record in database = d-dimensional vector
- For input record, find most similar record in database = nearest neighbor search





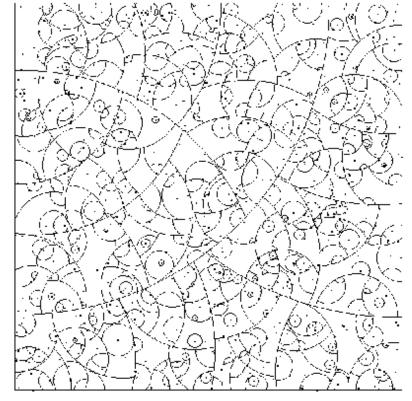
## vp (Vantage-point) tree

Binary tree, each node contains center point
 P and radius r, in left subtree are points with distance P less than r, in right subtree are all

other points

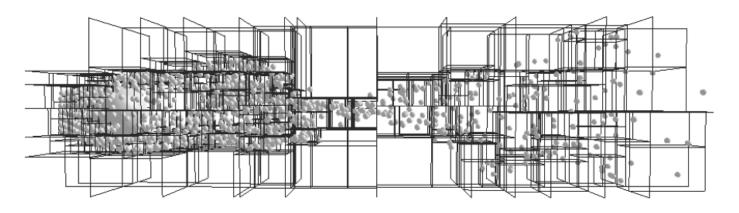
Pick P – random point

 Pick r – median of distances of **P** and all other points



## Raytracing

- K-d tree is best space partition for raytracing (minimalizing ray-object intersection count)
- http://dcgi.felk.cvut.cz/home/havran/phdthe sis.html
- Adaptively divide based on surface
- Traversing structure along ray



## Raytracing

- Divide in node
  - Spatial median
  - Object median
  - Direction largest variation
  - In center in direction of "longest" dimension
  - Cost techniques
    - Computing split cost based on ray-area hit probability (ordinary surface area heuristic)

$$C_{\mathbf{v}^G} = \frac{1}{SA(\mathcal{AB}(\mathbf{v}^G))}[SA(\mathcal{AB}(lchild(\mathbf{v}^G))).(N_L + N_{SP}) + SA(\mathcal{AB}(rchild(\mathbf{v}^G))).(N_R + N_{SP})],$$



## Questions?