A comparative study of $k$-nearest neighbour techniques in crowd simulation

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We want efficient crowd simulations.
Large amount of computation spent on collision avoidance. Needs several nearest neighbours.

Which method for finding nearest neighbours is most efficient?

Efficient:

- Construction
- Querying
- Variance
The $k$-nearest neighbour ($k$NN) problem is well-known.

- Robotics
- Machine learning
- Databases
- Computer vision
- ...

Usually: high dimensionality, separation between offline construction and online querying, disk storage.

Our case: two or three dimensions, changing data, main memory.
Data structures

Data structures selected on prevalence and availability of good implementations.

We tested:

<table>
<thead>
<tr>
<th>Data structure</th>
<th>Construction time</th>
<th>kNN query time</th>
</tr>
</thead>
<tbody>
<tr>
<td>k-d tree</td>
<td>$O(n \log n)$</td>
<td>$O(k \log n)$</td>
</tr>
<tr>
<td>BD-tree</td>
<td>$O(n \log n)$</td>
<td>$O(k \log n)$</td>
</tr>
<tr>
<td>R-tree</td>
<td>$O(n \log n)$</td>
<td>$O(k \log n)$</td>
</tr>
<tr>
<td>Voronoi diagram</td>
<td>$O(n \log n)$</td>
<td>$O(k \log n)$</td>
</tr>
<tr>
<td>k-means</td>
<td>$O(n^2)$</td>
<td>$O(n)$</td>
</tr>
<tr>
<td>Linear search</td>
<td>$O(1)$</td>
<td>$O(n)$</td>
</tr>
<tr>
<td>Grid</td>
<td>$O(n)$</td>
<td>$O(n)$</td>
</tr>
</tbody>
</table>
Split alternatingly along axes.

Try to split remaining data in half.

https://www.cs.umd.edu/~mount/ANN/Files/1.1.2/ANNmanual_1.1.pdf
Box-decomposition tree

**k-d tree with extra split rule.**

Split into inner and outer box.

Point or volumetric data.

Partitions may overlap.

Insertion and deletion of data possible.

https://en.wikipedia.org/wiki/R-tree
Hierarchical $k$-means clustering

Assign points to centroid.

Calculate new centroid and iterate.

Apply hierarchically.

http://rossfarrelly.blogspot.com/2012/12/k-means-clustering.html
Voronoi diagrams

Cells of points closest to site.

Find nearest neighbours by examining neighbouring cells.

http://merganser.math.gvsu.edu/david/voronoi.08.06/
Implementations

**k-d tree implementations** provided by FLANN [1] and nanoflann [2].

- FLANN: general-purpose implementation
- nanoflann: highly optimised for 2D and 3D data

FLANN also provides $k$-means implementation.

BD-tree is provided by ANN [3].

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Implementations

R-tree and Voronoi diagrams are provided by Boost [1].

R-tree has good update performance, test two versions:

1. Rebuild entire tree each time step
2. Update tree incrementally

Linear search and grid are own implementations.

Scenarios

Test on artificial and real-world scenarios.

Artificial: test specific properties.

- Density: uniform vs clustered
- Stationary agents: test with 25, 50 or 75% of agents not moving
- Scaling: add more agents each time step

Real-world:

- Simulations of evacuation of building
- Simulations for Tour de France [1]
- Jülich trajectory data of real crowds [2]

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Scenarios - density
Scenarios - evacuation
Scenarios - Tour de France
### Scenarios - Jülich bottleneck

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</table>
Experimental setup

Jülich data only available as trajectories (tuples of id, time, x- and y-coordinate).

For fair comparison, converted all data to trajectories.

C++ testing program reads data per time step, and:

1. Builds the structure for agent positions at current time step
2. Performs $k$NN query for each agent

For realism, queries are performed in parallel.

We fix $k$ at 10; collision avoidance does not need more.
Total of 62 different scenarios: multiple instances of similar settings.

Tested on machine running Ubuntu 15.10, with two Xeon 12-core processors and 32 GB of DDR4 RAM.
## Results

### Overall results per agent per time step:

<table>
<thead>
<tr>
<th>Data Structure</th>
<th>Update Time (μs)</th>
<th>Query Time (μs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BD-tree</td>
<td></td>
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<tr>
<td>Grid</td>
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<tr>
<td>k-d tree (FLANN)</td>
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<td>k-d tree (nanoflann)</td>
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<td>R-tree (rebuild)</td>
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<tr>
<td>R-tree (update)</td>
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<tr>
<td>Voronoi</td>
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</table>

![Graph showing overall results per agent per time step](image-url)
Linear search quickly infeasible: 16 seconds per time step for 100,000 agents
R-tree and FLANN k-d tree have similar query performance, but R-tree over 3x more expensive to update
Results - scaling

R-tree update 20% faster than rebuild
nanoflann 2x faster than FLANN: 100,000 agents in ~35 ms
Conclusion

nanoflann implementation of k-d tree clearly best option.
▶ Fastest except when number of agents very small
▶ Lowest variance
▶ 100,000 agents in 35 ms per time step

Grid competitive for small number of agents (< 1000) due to low update cost. Linear search efficient up to a few hundred agents.

Updating R-tree more efficient than rebuilding.
Future work

Currently working on extending \( k\)NN algorithm to *multi-layered environments*, e.g. buildings with multiple floors.

- Euclidean nearest neighbours not enough: close \( x\)- and \( y\)-coordinates may be on different floor
- Need to consider visibility
Future work

Local neighbourhood does not change much between time steps: could update only once every few steps.

- How often should we update?

Compare performance of GPU methods, looking for people with expertise.