

Navigation IML

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ENIB

11 septembre 2019

Goal

Navigation

- ▷ determine paths to go from one point to an other.



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Goal



Page 2 :

- 1 Classical approaches
 - Mesh
 - Graph
- 2 Video games
 - Quake 3 Arena bots
 - Counter-Strike bots
 - Unreal Tournament's series bots
 - Valve bots
- 3 GNG
- 4 SGNG

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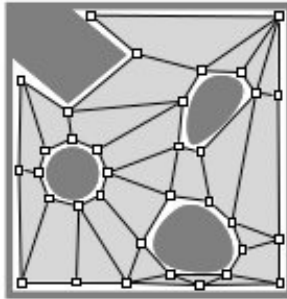


FIGURE – A simple environment (obstacles are in dark grey) represented by a mesh. The avatar can navigate in the zone defined by the mesh (in grey) because it knows there are no obstacles in this zone. Different algorithms can be used to find optimal paths.

Problems

- ▷ requires an algorithm to find the optimal path between 2 points
- ▷ a path which may not be natural or believable
- ▷ All the meshes used to render the environment are too complex for agents to handle.



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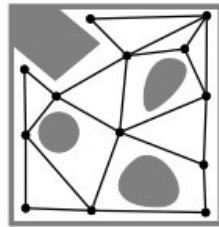


FIGURE – A simple environment (obstacles are in grey) represented by a graph. Nodes are represented by circles and edges by black lines. An avatar can move from one node to another only if the nodes are connected by an edge. Usually, an A* is used to find the path between two nodes.

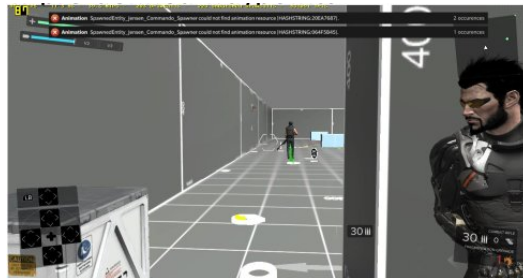


FIGURE – Classical bots are designed to follow pre-defined waypoints determined by the map designer.

Problems

- ▷ These bots need to have a waypoint file for each map, or a pathnode system embedded in the map.



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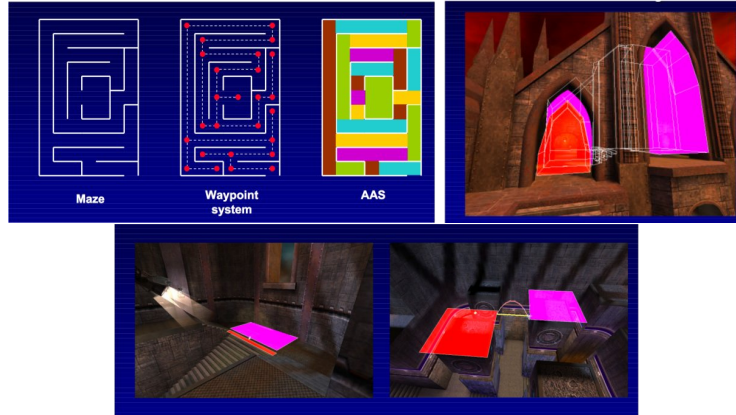


FIGURE – Quake 3 Arena bots use an area awareness system file to move around the map

- ▷ The structure of the levels is analyzed, which is used to extract volumes of space that are navigable (e.g. walkable surfaces, swimming areas).
- ▷ A process then analyzes these areas for connections by simulating potential movement from each of them, and then clusters the areas together to allow hierarchical path-finding
- ▷ Quake 3 uses a form of pathfinding within the AAS graph that relies on the clusters of areas.
- ▷ Within these clusters, the paths to common destinations are pre-calculated and stored for later use.

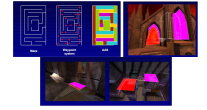


Figure – Quake 3 Arena bots use an area awareness system file to move around the map

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Counter-Strike bots use a waypoint file.



FIGURE – Unreal Tournament's series bots use a pathnode system embedded in the map to navigate

- ▷ To support the many community-created maps, some games include an automatic mesh generation system
- ▷ The first time users attempt to play a custom map with bots, the generation system will build a navigation file for that map. Starting at a player spawn point, walkable space is sampled by "flood-filling" outwards from that spot, searching for adjacent walkable points.

- ▷ Finally, dynamic bots are able to dynamically learn levels and maps as they play. RealBot, for Counter-Strike, is an example of this. However, this learning is not guided by human behavior.
- ▷ Navigation points obtained will therefore not produce believable behavior. The paths the bots use to go from one point in the environment to another do not resemble those human players would take. This problem comes not from the decision-making process itself, but from the representation of the environment it uses. Indeed, the bots use navigation points in the environment which may not accurately or naturally represent how players use the same environment.

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Graph model

- ▷ incremental learning
- ▷ node
 - ◇ position (x, y, z)
 - ◇ cumulated error (measures how well the node represents its surroundings)
- ▷ edge
 - ◇ links two nodes
 - ◇ an age informing us when it was last activated.
- ▷ Principle : modify its graph for each input of the teacher's position in order to alter the graph to match the teacher's position. The model can add or remove nodes and edges if they do not fit the behavior and change the position of the nodes to better represent the teacher's position.

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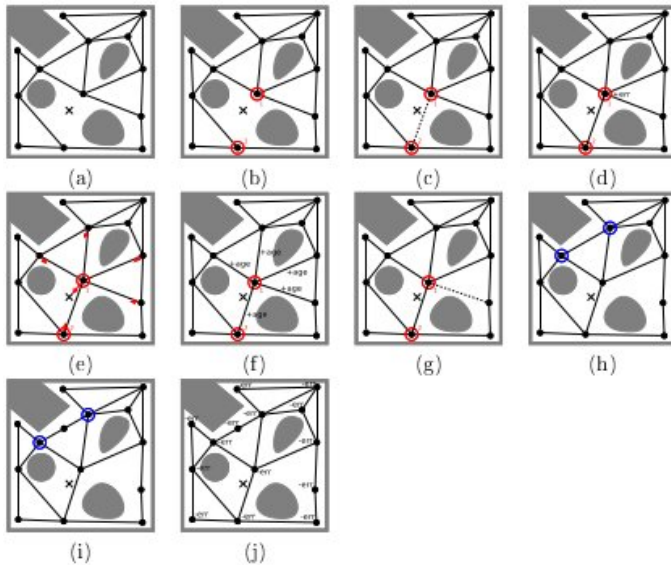
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Video : GNG.mp4
Video : moons.mov

GNG - algorithm

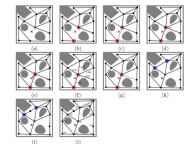
```

while Number of nodes  $\leq N_{max}$  do
  Get input position (a);
  Pick the closest ( $n_1$ ) and the second closest nodes ( $n_2$ ) (b);
  Create edge between  $n_1$  and  $n_2$  (c);
  If an edge already existed, reset its age to 0.;
  Increase the error of  $n_1$  (d);
  Move  $n_1$  and its neighbors toward the input (e);
  Increase the age of all the edges emanating from  $n_1$  by 1 (f);
  Delete edges exceeding a certain age (g);
  if Iteration number is a multiple of  $\eta$  then
    Find the maximum error node  $n_{max}$ ;
    Find the maximum error node  $n_{max2}$  among the neighbor of  $n_{max}$  (h);
    Insert node between  $n_{max}$  and  $n_{max2}$  (i);
    Decrease the error of  $n_{max}$  and  $n_{max2}$ ;
  end
  Decrease each node's error by a small amount (j);
end
  
```



```

GNG - algorithm
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  end
  Decrease each node's error by a small amount (j);
end
  
```



```
import numpy as np
from scipy import spatial
import networkx as nx
import matplotlib.pyplot as plt
from sklearn import decomposition
```

```
class GrowingNeuralGas:
```

```
def __init__(self, input_data):
    self.network = None
    self.data = input_data
    self.units_created = 0
```

```
def find_nearest_units(self, observation):
    distance = []
    for u, attributes in self.network.nodes(data=True):
        vector = attributes['vector']
        dist = spatial.distance.euclidean(vector, observation)
        distance.append((u, dist))
    distance.sort(key=lambda x: x[1])
    ranking = [u for u, dist in distance]
    return ranking
```

```
def prune_connections(self, a_max):
    for u, v, attributes in self.network.edges(data=True):
        if attributes['age'] > a_max:
            self.network.remove_edge(u, v)
    for u in self.network.nodes():
        if self.network.degree(u) == 0:
            self.network.remove_node(u)
```

```
def fit_network(self, e_b, e_n, a_max, l, a, d, passes=1, plot_evolution=
    False):
    # logging variables
    accumulated_local_error = []
    global_error = []
    network_order = []
    network_size = []
    total_units = []
    self.units_created = 0
    # 0. start with two units a and b at random position w_a and w_b
    w_a = [np.random.uniform(-2, 2) for _ in range(np.shape(self.data)[1])]
    w_b = [np.random.uniform(-2, 2) for _ in range(np.shape(self.data)[1])]
    self.network = nx.Graph()
    self.network.add_node(self.units_created, vector=w_a, error=0)
    self.units_created += 1
    self.network.add_node(self.units_created, vector=w_b, error=0)
    self.units_created += 1
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```
def fit_network(self, e_b, e_n, a_max, l, a, d, passes=1, plot_evolution=
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    w_a = [np.random.uniform(-2, 2) for _ in range(np.shape(self.data)[1])]
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    self.network = nx.Graph()
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    self.network = nx.Graph()
    self.network.add_node(self.units_created, vector=w_a, error=0)
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    self.units_created += 1
```

```
def fit_network(self, e_b, e_n, a_max, l, a, d, passes=1, plot_evolution=
    False):
    ...
    # 1. iterate through the data
    sequence = 0
    for p in range(passes):
        print('###Pass_#d' % (p + 1))
        np.random.shuffle(self.data)
        steps = 0
        for observation in self.data:
            # 2. find the nearest unit s_1 and the second nearest unit s_2
            nearest_units = self.find_nearest_units(observation)
            s_1 = nearest_units[0]
            s_2 = nearest_units[1]
            # 3. increment the age of all edges emanating from s_1
            for u, v, attributes in self.network.edges_iter(data=True,
                nbunch=[s_1]):
                self.network.add_edge(u, v, age=attributes['age']+1)
            # 4. add the squared distance between the observation and the
            nearest unit in input space
            self.network.node[s_1]['error'] += spatial.distance.euclidean(
                observation, self.network.node[s_1]['vector'])**2
```

```
def fit_network(self, e_b, e_n, a_max, l, a, d, passes=1, plot_evolution=
    False):
    ...
    # 5 .move s_1 and its direct topological neighbors towards the
    observation by the fractions
    # e_b and e_n, respectively, of the total distance
    update_w_s_1 = e_b * (np.subtract(observation, self.network.node
        [s_1]['vector']))
    self.network.node[s_1]['vector'] = np.add(self.network.node[s_1]
        ['vector'], update_w_s_1)
    update_w_s_n = e_n * (np.subtract(observation, self.network.node
        [s_1]['vector']))
    for neighbor in self.network.neighbors(s_1):
        self.network.node[neighbor]['vector'] = np.add(self.network.
            node[neighbor]['vector'], update_w_s_n)

    # 6. if s_1 and s_2 are connected by an edge, set the age of
    this edge to zero
    # if such an edge does not exist create it
    self.network.add_edge(s_1, s_2, age=0)
    # 7. remove edges with an age larger than a_max
    # if this results in units having no emanating edges, remove
    them as well
    self.prune_connections(a_max)
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def fit_network(self, e_b, e_n, a_max, l, a, d, passes=1, plot_evolution=
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            for u, v, attributes in self.network.edges_iter(data=True,
                nbunch=[s_1]):
                self.network.add_edge(u, v, age=attributes['age']+1)
            # 4. add the squared distance between the observation and the
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            self.network.node[s_1]['error'] += spatial.distance.euclidean(
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def fit_network(self, e_b, e_n, a_max, l, a, d, passes=1, plot_evolution=False):  
    ...  
  
    # 8. if the number of steps so far is an integer multiple of  
    parameter l, insert a new unit  
    steps += 1  
    if steps % l == 0:  
        if plot_evolution:  
            self.plot_network('visualization/sequence/' + str(  
                sequence) + '.png')  
            sequence += 1  
        # 8.a determine the unit q with the maximum accumulated  
        error  
        q = 0  
        error_max = 0  
        for u in self.network.nodes_iter():  
            if self.network.node[u]['error'] > error_max:  
                error_max = self.network.node[u]['error']  
                q = u  
        # 8.b insert a new unit r halfway between q and its neighbor  
        f with the largest error variable  
        f = -1  
        largest_error = -1  
        for u in self.network.neighbors(q):  
            if self.network.node[u]['error'] > largest_error:  
                largest_error = self.network.node[u]['error']  
                f = u  
        w_r = 0.5 * (np.add(self.network.node[q]['vector'], self.  
            network.node[f]['vector']))
```

```
def fit_network(self, e_b, e_n, a_max, l, a, d, passes=1, plot_evolution=False):  
    ...  
  
    # 8.c insert edges connecting the new unit r with q and f  
    # remove the original edge between q and f  
    self.network.add_node(r, vector=w_r, error=0)  
    self.network.add_edge(r, q, age=0)  
    self.network.add_edge(r, f, age=0)  
    self.network.remove_edge(q, f)  
    # 8.d decrease the error variables of q and f by multiplying  
    them with a  
    # initialize the error variable of r with the new value  
    of the error variable of q  
    self.network.node[q]['error'] *= a  
    self.network.node[f]['error'] *= a  
    self.network.node[r]['error'] = self.network.node[q]['error']  
    ]  
    # 9. decrease all error variables by multiplying them with a  
    constant d  
    error = 0  
    for u in self.network.nodes_iter():  
        error += self.network.node[u]['error']  
    accumulated_local_error.append(error)  
    network_order.append(self.network.order())  
    network_size.append(self.network.size())  
    total_units.append(self.units_created)  
    for u in self.network.nodes_iter():  
        self.network.node[u]['error'] *= d  
        if self.network.degree(nbunch=[u]) == 0:  
            print(u)
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                error_max = self.network.node[u]['error']  
                q = u  
        # 8.b insert a new unit r halfway between q and its neighbor  
        f with the largest error variable  
        f = -1  
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        for u in self.network.neighbors(q):  
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    for u in self.network.nodes_iter():  
        self.network.node[u]['error'] *= d  
        if self.network.degree(nbunch=[u]) == 0:  
            print(u)
```

```
def fit_network(self, e_b, e_n, a_max, l, a, d, passes=1, plot_evolution=False):  
    ...  
    plt.clf()  
    plt.title('Accumulated local error')  
    plt.xlabel('iterations')  
    plt.plot(range(len(accumulated_local_error)), accumulated_local_error)  
    plt.savefig('visualization/accumulated_local_error.png')  
    plt.clf()  
    plt.title('Global error')  
    plt.xlabel('passes')  
    plt.plot(range(len(global_error)), global_error)  
    plt.savefig('visualization/global_error.png')  
    plt.clf()  
    plt.title('Neural network properties')  
    plt.plot(range(len(network_order)), network_order, label='Network order')  
    )  
    plt.plot(range(len(network_size)), network_size, label='Network size')  
    plt.legend()  
    plt.savefig('visualization/network_properties.png')
```

```
def plot_network(self, file_path):  
    plt.clf()  
    plt.scatter(self.data[:, 0], self.data[:, 1])  
    node_pos = {}  
    for u in self.network.nodes_iter():  
        vector = self.network.node[u]['vector']  
        node_pos[u] = (vector[0], vector[1])  
    nx.draw(self.network, pos=node_pos)  
    plt.draw()  
    plt.savefig(file_path)  
  
def number_of_clusters(self):  
    return nx.number_connected_components(self.network)
```

```
def fit_network(self, e_b, e_n, a_max, l, a, d, passes=1, plot_evolution=False):  
    ...  
    plt.clf()  
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    plt.plot(range(len(accumulated_local_error)), accumulated_local_error)  
    plt.savefig('visualization/accumulated_local_error.png')  
    plt.clf()  
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def plot_network(self, file_path):  
    plt.clf()  
    plt.scatter(self.data[:, 0], self.data[:, 1])  
    node_pos = {}  
    for u in self.network.nodes_iter():  
        vector = self.network.node[u]['vector']  
        node_pos[u] = (vector[0], vector[1])  
    nx.draw(self.network, pos=node_pos)  
    plt.draw()  
    plt.savefig(file_path)  
  
def number_of_clusters(self):  
    return nx.number_connected_components(self.network)
```

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```
def cluster_data(self):
    unit_to_cluster = np.zeros(self.units_created)
    cluster = 0
    for c in nx.connected_components(self.network):
        for unit in c:
            unit_to_cluster[unit] = cluster
        cluster += 1
    clustered_data = []
    for observation in self.data:
        nearest_units = self.find_nearest_units(observation)
        s = nearest_units[0]
        clustered_data.append((observation, unit_to_cluster[s]))
    return clustered_data

def reduce_dimension(self, clustered_data):
    transformed_clustered_data = []
    svd = decomposition.PCA(n_components=2)
    transformed_observations = svd.fit_transform(self.data)
    for i in range(len(clustered_data)):
        transformed_clustered_data.append((transformed_observations[i],
            clustered_data[i][1]))
    return transformed_clustered_data
```

```
def plot_clusters(self, clustered_data):
    number_of_clusters = nx.number_connected_components(self.network)
    plt.clf()
    plt.title('Cluster affectation')
    color = ['r', 'b', 'g', 'k', 'm', 'r', 'b', 'g', 'k', 'm']
    for i in range(number_of_clusters):
        observations = [observation for observation, s in clustered_data if
            s == i]
        if len(observations) > 0:
            observations = np.array(observations)
            plt.scatter(observations[:, 0], observations[:, 1], color=color[
                i], label='cluster_#'+str(i))
    plt.legend()
    plt.savefig('visualization/clusters.png')

def compute_global_error(self):
    global_error = 0
    for observation in self.data:
        nearest_units = self.find_nearest_units(observation)
        s_1 = nearest_units[0]
        global_error += spatial.distance.euclidean(observation, self.network
            .node[s_1]['vector'])**2
    return global_error
```

```
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    cluster = 0
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            .node[s_1]['vector'])**2
    return global_error
```

example

```
from gng import GrowingNeuralGas
from sklearn import datasets
from sklearn.preprocessing import StandardScaler

print('Generating data...')
data = datasets.make_moons(n_samples=2000, noise=.05)
data = StandardScaler().fit_transform(data[0])
print('Done.')
print('Fitting neural network...')
gng = GrowingNeuralGas(data)
gng.fit_network(e_b=0.1, e_n=0.006, a_max=10, l=200, a=0.5, d=0.995, passes=8,
               plot_evolution=True)
print('Found %d clusters.' % gng.number_of_clusters())
gng.plot_clusters(gng.cluster_data())
```

example

```
Preparing data...
Done.
Fitting neural network...
Pass #1
Pass #2
Pass #3
Pass #4
Pass #5
Pass #6
Pass #7
Pass #8
Found 2 clusters.
```

```
from gng import GrowingNeuralGas
from sklearn import datasets
from sklearn.preprocessing import StandardScaler

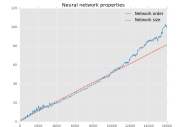
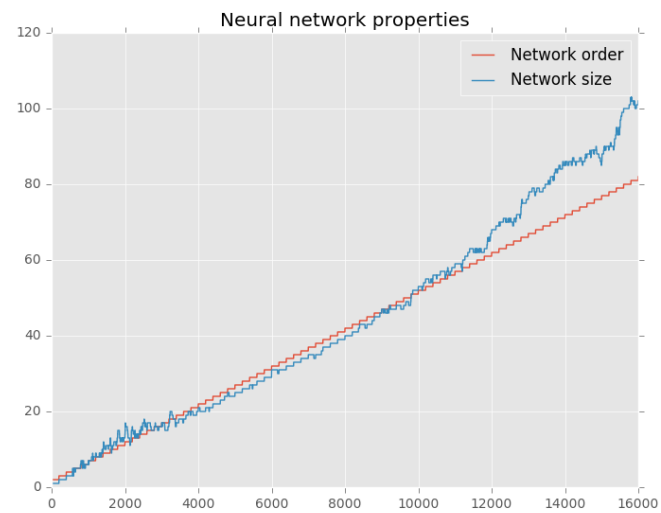
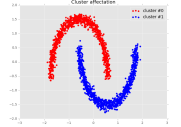
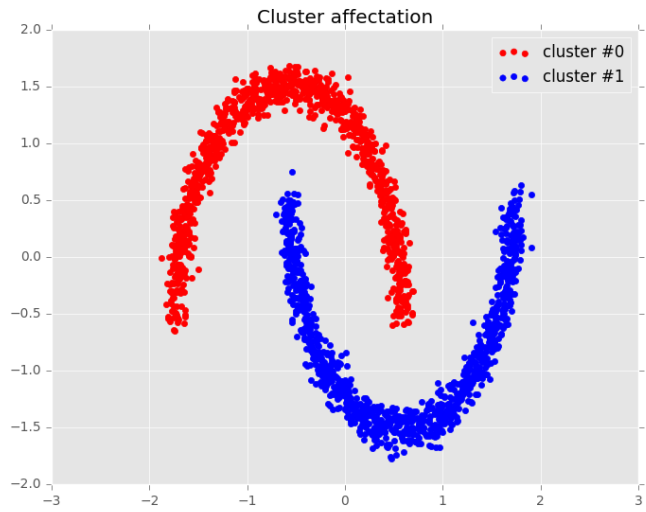
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```

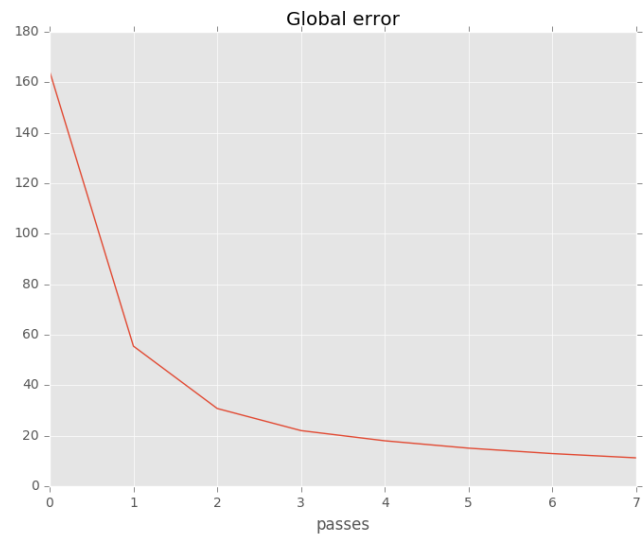
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Demo : generateDataGNG.py
Demo : exampleGNG.py (use gng.py)

```
Preparing data...
Done.
Fitting neural network...
Pass #1
Pass #2
Pass #3
Pass #4
Pass #5
Pass #6
Pass #7
Pass #8
Found 2 clusters.
```

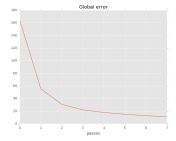
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Problems

- ▷ Fails to handle temporal series
- ▷ Grow up over the time (constant iteration insertion policy)



Page 33 :

- Problems
 - ▷ Fails to handle temporal series
 - ▷ Grow up over the time (constant iteration insertion policy)

Page 34 :

- 1 Classical approaches
 - Mesh
 - Graph
- 2 Video games
 - Quake 3 Arena bots
 - Counter-Strike bots
 - Unreal Tournament's series bots
 - Valve bots
- 3 GNG
- 4 SGNG

SGNG : Pro

- ▷ Grow up over the time : a node should be inserted when the error of a node is superior to a parameter \overline{Err} (add nodes only in the area just visited and add nodes only when the network fails to fit the data suitably).

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SGNG : Pro
▷ Grow up over the time : a node should be inserted when the error of a node is superior to a parameter \overline{Err} (add nodes only in the area just visited and add nodes only when the network fails to fit the data suitably).

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SGNG - algorithm

```

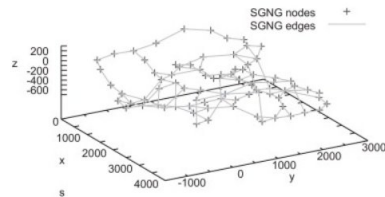
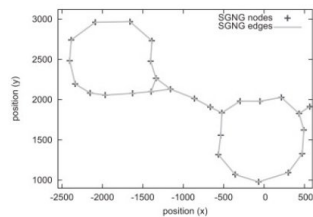
nodes ← {}
edges ← {}
while teacher plays do
  (x,y,z) ← teacher's position
  if |nodes| = 0 or 1 then
    nodes ← nodes ∪ {(x,y,z,error=0)}
  end if
  if |nodes| = 2 then
    edges ← {(nodes,age=0)}
  end if
  n1 ← closest((x,y,z),nodes)
  n2 ← secondClosest((x,y,z),nodes)
  edge ← edges ∪ {(n1,n2},age=0)}

  n1.error += |(x,y,z)-n1|
  Attract n1 toward (x,y,z)
  ∀ edge ∈ edgesFrom(n1), edge.age++
  Delete edges older than Age
  Attract neighbors(n1) toward (x,y,z)
  ∀ node ∈ nodes, node.error -= Err

  if n1.error > Err then
    maxErrNei ← maxErrorNeighbour(n1)
    newNode ← between(n1,maxErrNei)
    n1.error /= 2
    maxErrNei.error /= 2
    newError ← n1.error + maxErrNei.error
    nodes ← nodes ∪ {(newNode,newError)}
  end if

```

SGNG : Application to video games



<https://www.youtube.com/watch?v=HSKkr4CQYr8>

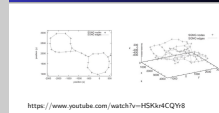
```

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  ∀ node ∈ nodes, node.error -= Err

  if n1.error > Err then
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    n1.error /= 2
    maxErrNei.error /= 2
    newError ← n1.error + maxErrNei.error
    nodes ← nodes ∪ {(newNode,newError)}
  end if

```



<https://www.youtube.com/watch?v=HSKkr4CQYr8>

SGNG : Application to video games

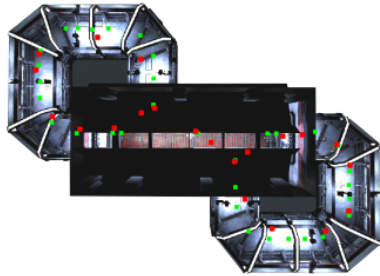


FIGURE – Comparison of nodes learned by the SGNG (in red) with the navigation points placed manually by the game developers (in green). The environment viewed from above is visible in the background.

SGNG : Evaluation

Sensitivity

Sensitivity measures how successfully the SGNG represents the part of the environment the teacher used, which can be seen as true positives. $mindist(a, B)$ is the minimum distance between point a and the points in set B . We computed this measure using the following formula :

$$Sensitivity \propto \frac{1}{\sum_i mindist(NP_i, nodes)} \quad (1)$$

Where NP_i is the i^{th} navigation point. The higher the value, the more sensitive the SGNG.

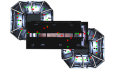


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SGNG : Evaluation

Specificity

Specificity measures how much the SGNG did not represent the part of the environment the teacher did not use, which can be seen as true negatives. We computed this measure using the following formula :

$$Specificity \propto \frac{Number\ of\ Nodes}{\sum_i mindist(Node_i, NPs)} \quad (2)$$

The higher the value, the more specific the SGNG.

SGNG : Evaluation

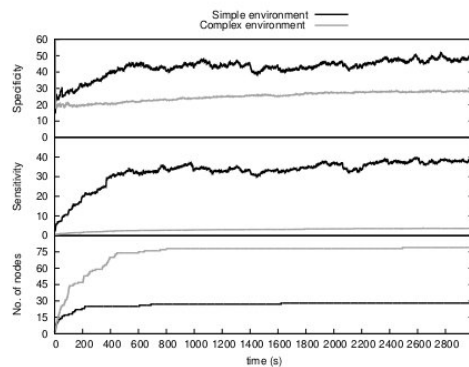


FIGURE – Time evolution of the SGNG number of nodes and the cumulated distance between the SGNG nodes and the navigation points.

SGNG : Evaluation

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SGNG : Evaluation

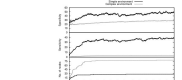


FIGURE – Time evolution of the SGNG number of nodes and the cumulated distance between the SGNG nodes and the navigation points.

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SGNG : Evaluation

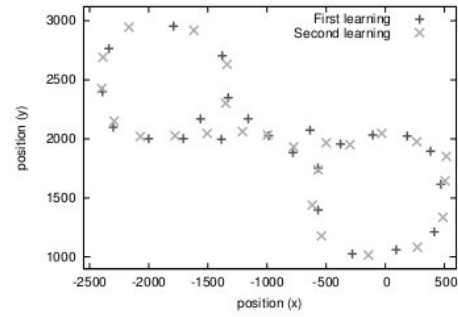


FIGURE – Comparison of two SGNG learned on the same environment after a very long training period of 10 hours.

SGNG : Evaluation

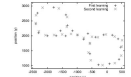
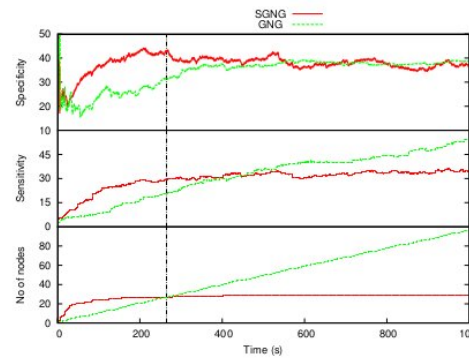
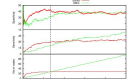


FIGURE – Comparison of two SGNG learned on the same environment after a very long training period of 10 hours.



F. Tence, L. Gaubert, J. Soler, P. De Loor, and C. Buche.
Stable Growing Neural Gas : a Topology Learning Algorithm based on Player
Tracking in Video Games.
Applied Soft Computing (ASC),
13(10) :4174-4184, 2013.

https://www.enib.fr/~buche/article/ASC_13.pdf

Navigation
IML

Cédric Buche

ENIB

11 septembre 2019

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