META-COGNITVE MAPPINGS: GROWING NEURAL NETWORKS FOR GENERATIVE URBANISM

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Abstract

This paper examines the use of dynamic learning systems and adaptive topologies within neural networks models, and their implications as a tool for architectural mappings. The principal investigation is the ability of such systems to identify/ map/ model/ represent flows within dynamic data sets and identify topological relationships between these flows.
A growing neural network [GNN] model is proposed, able to map dynamic data inputs over time. It is based on Kohonen's early self-organising feature maps [SOM] and takes as its starting point previous work by CECA with neural networks in an architectural context, as well as other examples of neural gases, and GNNs, in order to develop a model capable of 'autopoietic' behaviour and 'meta – learning'.
The principal investigation is the ability of such a system to identify/ map/ model/ represent flows within dynamic data sets and identify topological relationships between these flows.

As a case study, the proposed neural network model has been used to map 'urban territory', as part of an on going architectural research project, based in North London. The project takes the notion of 'urban territories' rather than 'urban space' as the field for interrogation, as a description of temporal spatial occupation space, rather than spatial physical permanence.
Furthermore, the GNN may be used to identify the relationships between unused and vacant sites along the street. In this way, the GNN may become a means of proposing architectural interventions for these spaces, so that the territories of those that occupy it and the negotiations between them are not lost.

1. Precedents – Design and Application of Neural Network Models

1.1 Kohonen - Self-Organising Feature Maps

Kohonen[1] proposed the self-organising feature map as a neural model, simulating organizational modes within brain. It substitutes the neurons and synapses of the brain, with artificial processing nodes and connections.
Kohonen demonstrated the ability of brain map simulations, based on 2D grid topologies, to create self-organising maps of such inputs as acoustic frequencies, speech, and colour hue/ saturation.

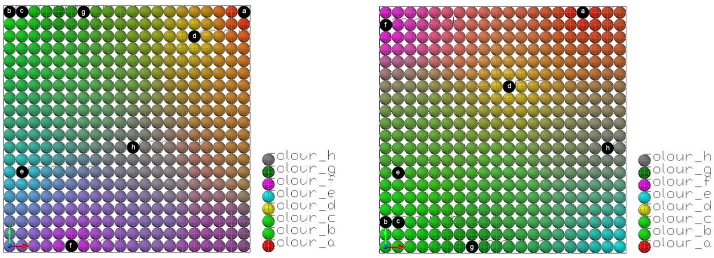


fig 1. Self Organising Feature Map – Inputs of RGB colour references [authors example]

The basic SOM algorithm consists of 2 stages - training and calibration. Firstly the map is trained using a range of inputs across the signal space. The second stage, calibration, can be seen as a king of 'testing' of the output map – further inputs are used and their position in the map, relative to initial inputs is used to evaluate the accuracy of the classification.

The learning system proposed by Kohonen can be summarised as follows:

-All nodes assessed for 'proximity' to each input
-Winning nodes identified.
-Winning nodes adjusted, based on scaled input vectors. Scaling of vectors is based on winners learning rate
-Information of adjustment of winning node is passed along topological connections.
-All nodes are then adjusted, based on topological proximity to winning neurons, and the learning rate of non-winning neurons.

1.2 Dynamic Topologies

The basic SOM typically uses a fixed topology, although Kohonen proposes further adaptations, using varying topological structures.

Dynamically Defined Topologies [2]

'Dynamically defining topology' allows for connections between nodes can be active or inactive, depending on 'distance' [or difference] between nodes. If two nodes that would normally be connected become too 'dissimilar', then the connection between the two becomes inactive. If the two nodes return to within an acceptable threshold of 'similarity', then the connection becomes active. Whilst the connection remains inactive, learning between the two nodes cannot occur.

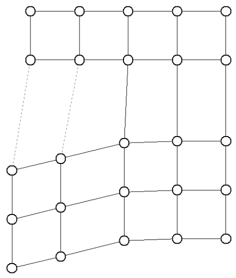


fig 2. Dynamically Defined Topology within grid based SOM

Growing SOMs

Kohonen also proposed a means of growing a SOM grid [3]. As topological connection become stretched' during learning, new 'rows' and columns' may be inserted. Conversely, rows and columns could be deleted if nodes came to close to one and other

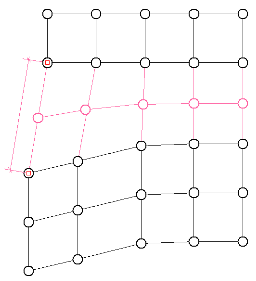


fig 3. Growing SOM - Kohonen

1.3 CECA – University of East London

Following Kohonen's SOM and the initial proposals for dynamic topologies, further work as been carried out investigating the principles and benefits of dynamic networks and growing neural networks. Neural Gas models have been developed by Martinetz [4], and Growing Neural Gas models by Bernd Fitzke. [5]
From this research the work of CECA at UEL has developed such models, within an architectural context.

Building a Synthetic Cognizer - C. Derix [6]
Self-organizing Topologies For Spatial Description - T Parvin [7]

The work of Christian Derix uses self organising spatial networks to map a large urban area in London. The system is based on the genre of spatial networks proposed by Kohonen. The study takes a simple geometric description of the massing within the architectural field. Vertices of buildings are used to create the training data. A significant development from the basic Kohonen model is the building in of node properties, specific to the problem of mapping architectural space. Nodes are able to 'perceive' corner conditions and 'next to' properties of nodes. Furthermore, the system has a 'bias' function for node behaviour. This allows nodes in the network to asses their condition in relation to their topological neighbours. Nodes are able to recognise localised clustering around themselves, of other nodes in the network. Nodes measure their 'stability' in terms of the clustering around them. A 'stable' node will be less

likely to make significant adjustments in relation to the inputs. As such, stable nodes are privileged in the network learning.
This model uses a fixed topology, however, the bias function in the nodes allows for more sophisticated network behaviour. Clusters of nodes within the network are able to adapt to the local conditions of the input space. This allows for 'specialisation' within the network.

Tahmina Parvin has proposed a growing neural gas for the mapping of internal architectural space, based on the topology preserving model proposed by Martinetz. This is proposed as tool for 'Spatio-temporal event mapping' within the Pompidou Centre, Paris.
The model uses a decay function. This removes unused elements within the network [i.e. connection that are no longer 'active']. The model uses a nested topological structure. In such cases, the number of nodes to which a node is connected increases and decreases sequentially. This allows for detailed mappings and clear understanding of network densities - increased numbers of neighbour imply high intensity of inputs.
Here, the growing neural gas model crucially enables the mapping of 'events' in space rather than simply the space itself.

These two models for the use of self organising feature maps in an architectural context provide important developments in neural computation. Both studies address the specific conditions of architectural space and the requirements for mapping it. Both models include adaptation sand developments of more 'traditional' neural networks specific to the notion of mapping architectural space, as opposed to merely mapping abstract data.

2. Proposed Growing Neural Network Model

The initial model is based on a 3 level dimensionality [i.e. Euclidean]. Outputs are visualized as networks in 3D test space, representing an approximation to what will be considered 'architectural space' in further experiments.

2.1 Characteristics

'Loose-Fixed' topology – The nodes have a predetermined number of neighbours to which they will connect, however there is no organisational structure that determine these connections. Instead, a node is connected to the *n* closest of the other nodes ion the network.
Adaptive topology – The model is also capable of using an adaptive topology. Each node has an 'energy' threshold. The node is capable of making connections with as many other neighbours as possible, as long as the total length of those connections remains below this constant.
Mono –directional Connections – Each node makes its connections independently from the nodes to which it connects. A connection between one node and another is 'mono – directional', and is only 'active' with regard to the node that has created the connection.

Each node redefines the neighbourhoods themselves during every loop of the code. Connections are deleted and remade with new neighbours after all nodes have been adjusted.

2.2 Behaviour

Learning

In Kohonen's model, all learning parameters are a factor of time, and the network 'activity' lessens, effectively settling into a state. In this model, the learning parameters are fixed

Growing - Insertion/ Deletion

The model is capable of 'growing' new nodes and 'deleting' dead nodes. Each node evaluates the distance between itself and each of its neighbours. If this distance is above a predetermined threshold, the node inserts a new neighbour. The deletion process is also based on proximity - if the neighbour of a node moves within a give threshold, the initial node deletes itself.

2.3 Initial experiments - Simple Shapes

The network is presented with the vertex of simple 3D shapes. The initial state of the network is 4 nodes.

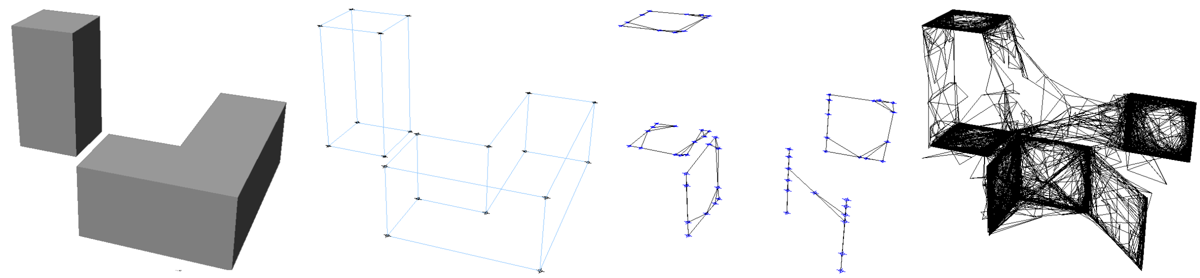


fig 4. Inputs shape, vertices, and final mappings

The network has maps the relationship between the vertices, as minimal spanning surfaces, rather than the 'solids' one sees in the original 'shapes'.

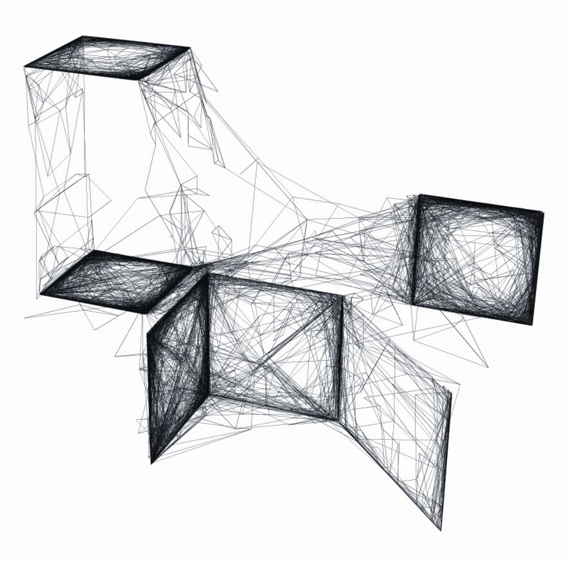


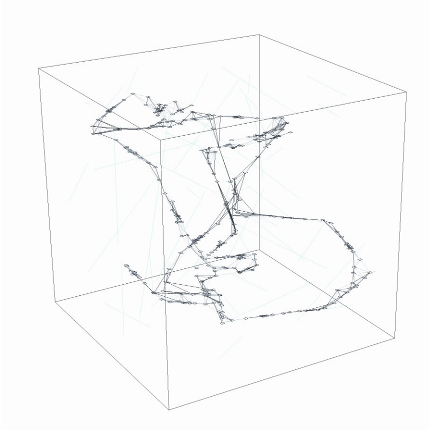
fig 5. 'History' of network states overlaid

The above image shows the 'history' of the network states during the learning sequence overlaid.
The network has mapped the two objects as a collective object, rather than a collection of

individual objects. The mapping is relational, the classificational, implying a topological, and of course topographic relationship between the two.
This is an important capability of any neural network, to understand an input, and visualize it, in a different way than may have already been perceived.

2.4 Initial experiments - Dynamic Inputs

The GNN model is suited to mapping dynamic inputs. The first experiments with dynamic inputs uses initially random training points with a speed and trajectory that determine their movement. The nodes use 3 vectors [defining their position in 3D space] and winners/ losers are determined by Euclidean distance. The trajectory of the training points is fixed and the network learns whilst the training points
behaviour loops.



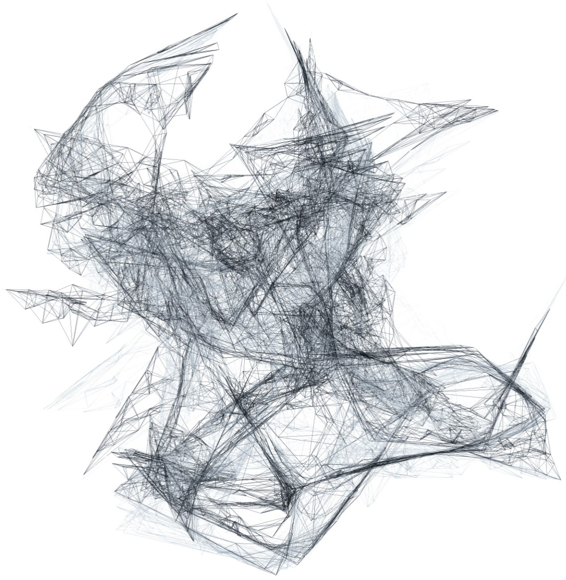


fig 6 & 7. Final mapping of dynamic inputs and 'history' of network states overlaid

The network 'settles' into a fluid loop, optimised to the training points movement. The map to represent the topological relationship between the 'near-misses' of the training points as they pass by one another. The image above-right represents all of the connections made by the network during the mapping. It is possible to see the network beginning to 'learn' the behaviour of the training points, developing a more and more accurate representation.

2.5 Initial experiments - Observations

From the initial studies the following can be said of the model:

- The network can produce useful global outputs using only local conditions
- Adaptive topology networks are capable of creating generalised mappings that contain local conditions of node and connection density
- The network model is capable of mapping both 'fixed' inputs and 'dynamic' inputs
- The output maps are 'fuzzy' generalisations that are capable of highlighting topological and topographic conditions.

3. Network Analysis

The capability of the network in mapping complex conditions through dynamic inputs suggests that the behaviour of the network in mapping such conditions may be useful means of understanding the input data, and output mapping.
Three properties inherent in complex systems are used as a means of analysing the network.

3.1 Flow

Flow *within* a network, rather than the flow *of* the network is a feature of complex networks. It is typically a condition that can only be identified within areas of the networks and cannot be evaluated to the network as a whole. Flow is defined by the learning function of the nodes - the 'flow of information' along the connections.

3.2 Cliques

A common definition of a clique may be a close-knit group, possibly of friends, whose relationships are principally limited to other members of the group, entry to which is difficult and controlled.
In graph theory, cliques typically relate to undirected graphs [i.e. without 'flow'] in which all nodes are connected to each other.
Connections are prioritised rather than nodes and it is the structure of the network that is the subject of analysis.

3.3 Borders

A theoretical approach to networks and network analysis is adopted by multi-disciplinary research group Multiplicity [lead by Architect Stefano Boeri] and explored in the project Border Devices. [8]

"Wherever one looks living spaces today, in fact offer a proliferation of borders, walls, fences, thresholds…virtual frontiers…specialised zones.[it] is an inevitable – if not surprising – outcome of any mapping of territory." [9]

The project 'Frontiers' looks for metaphors for the observed network conditions of territories.

"…Boundaries are not merely lines or walls. Some boundaries are like funnels that channel disorderly flows…others seem to be pipes…There are boundaries that emerge between the folds of two territories in conflict…but also boundaries the, like spongers, attract…Phantom limbs…continue to function when they no longer exist." [10]

These descriptions of globalised border conditions, themselves the product of complex networks, offer a theoretical approach to the understanding of complex, artificial networks.

Flows, Cliques and Borders are interrelated conditions – the border represents the extent of a flow, the clique may block or divert flow and cliques may form at border conditions. In order to track these behaviour characteristics, following analysis methods are proposed for the growing neural network model. They are calculated locally by each node, as the network grows and learns, and, as they are output, offer detailed insight into the pattern of growth and response of the network to the dynamic input data.

Flow Out/ Flow In - Flow is determined by data passing through the node. A node may 'receive' or pass on data.
Borders and Boundaries – Analysis of flow conditions of a node can be used to determine the edge of data flows and therefore the identification of subsystems within the network

Cliques – These are a type of specialised subsystem, within which nodes are connected only to other nodes within the clique. Cliques are calculated through analysis of a nodes neighbourhood condition, and that of its neighbours, in order to determine is 'cliqueness'. These 'specialists' may be privileged with higher learning rates, or more stable connections within the clique.

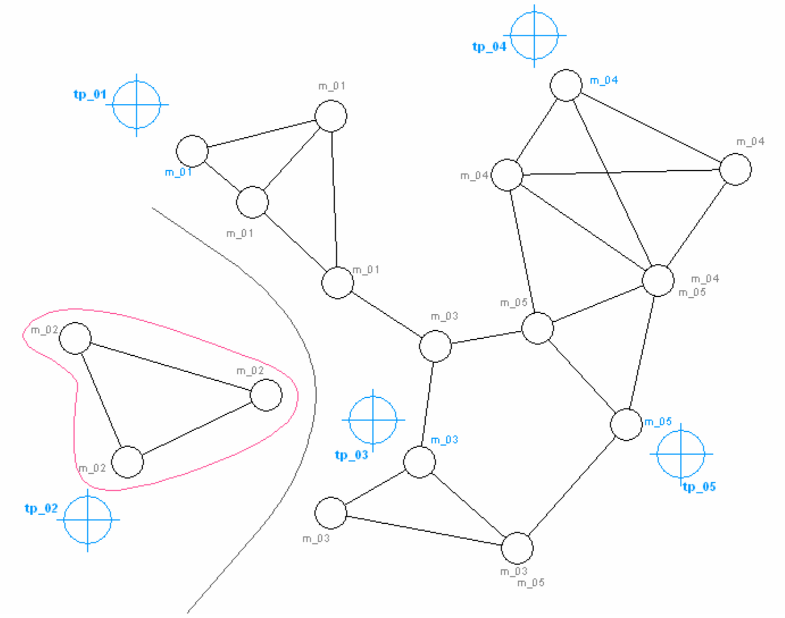


fig 8. Cliques and border conditions

4. Use of Growing Neural Network in Urban Mappings

4.1 Territories

'Species of Spaces' by Georges Perec, attempts to map spaces through written descriptions of the systems from which they are produced. Perec addresses space at all scales, 'the bedroom', 'the apartment', 'the street', 'the neighbourhood', 'the world'. Perec not only describes these notions of space in their generic form, but also as personalised space. He recognises himself as part of the system through which these spaces are defined, created and sustained.

"Contrary to the buildings, which almost always belong to someone, the streets in principle belong to no one. They are divided up into a zone for motor vehicles known as the roadway and two zones, narrower obviously, reserved for pedestrians, called pavements..." [11]

For Deleuze and Guattari, 'Milieus and Refrains'[12] are the means through which territories are created. The refrain is the bird song - used to define its territory, and a milieu is described by its repetition.[13] The territory 'is the product of the 'territorialization' of both of these things. This approach is at odds with what is normally considered 'architectural space'. It attempts to describe the process through which space is appropriated [or more specifically territorialized], rather than simply the space within which this process occurs.

"The marker (wall, road, line, border, post, sign) is static, dull, and cold. But when lived (encountered, manipulated, touched, voiced, glanced at, practised) it radiates a milieu, a field of force, a shape of space. Space is in continual motion, composed of vectors, speeds" [14]

This idea of spatial impermanence, through its definition as formed by the observer can be seen as an idea of space as territory, and is becoming a new paradigm in architecture. The notion of the refrain defining territory becomes more complex when such refrains are overlaid, spaces are shared and territories overlap. The nature of these territories is such that although discrete in some way, they are still co-dependant and relational and require new ways of mapping and analysing. By mapping the overlapping territories within space they occupy, there emerges an unseen and as yet unknown network.

4.2 Case Study

The case study used is an ongoing research project based on a section of Kingsland Road/ Stoke Newington high Street, in north London, and involves territorial mappings of the local immigrant communities.

fig 9. Kingsland Road/ Stoke Newington high Street, north London

The area lies between the 'established' centres of Stoke Newington to the North and Dalston to the south and, in contrast to these two areas, is rather fractured. Furthermore, the road in this area lacks a major intersection and is a funnel between the two areas.
Lacking the strong immigrant community identity of Dalston [African/ Caribbean] or Stoke Newington [Turkish/ Kurdish], the space displays the influence of both, and the 'border' condition it defines provides the street with a variety of uses, that may be less common, affordable or popular in other parts of the street.
The area contains of the typical shops and services one would expect to find in London. Food shops, a mosque, pubs, a church, cafes, restaurants, laundrettes. But also there are uses that describe the space as one of negotiation. A large Kurdish community centre occupies a prominent position, and from it are organised protests against the Turkish government. The protest takes place, a march along the middle of the road, regularly and occupies a space that is used by the local Turkish community. In this way, the road represents an area of negotiated territories.
The spaces used by individuals are the definition of the territory and the negotiation lies in the complex overlaying of the varying territories of those users. Here, the refrain discussed earlier, is the repetition of behaviour, of use. The place one goes for bread, for coffee, for beer, for friends, for family. Relationally, the refrain also describes those places one doesn't go, either because there is no need, no desire or because one knows them as places for others.

4.3 Encoding Input Data and Learning

The network is used initially in the mapping of the 'complete' existing condition. The road has been mapped conventionally, recording building use at street level. The street contains a wide variety of commercial and social uses, which are typically open for different periods during the day. The initial inputs are based on the spaces that are open [active] and the times at which they used [occupied]. This data is converted into training points that contain information relating to physical position along the street, the spatial nature of the a specific premises, and the times of day at which it is used.

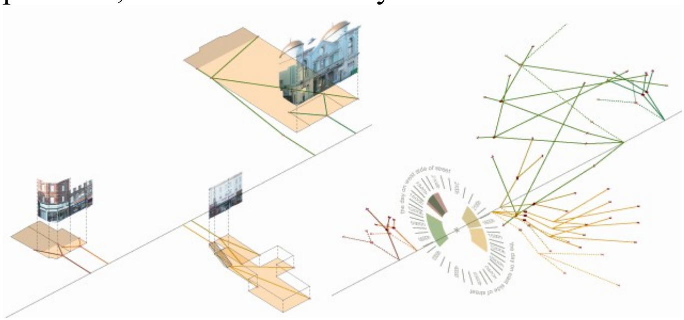


fig 10. Encoding physical spaces along street into training point data

The encoding method is an attempt to combine the notion of a 'territory' as something that is not only an understanding of the physical, with a geometric representation of the space that the territory occupies.
The network is presented with hour-by-hour data and has a period of learning before the input data is updated. The learning phase is determined by the networks behaviour, and a notion of 'steady-ness' in the network. The network 'learns' the input data for one hour and then must adjust as the new data is presented. The mappings are therefore cumulative, and can describe the relationships between overall maps at different times of the day, as well as the 'active space data' at a specific time.

4.4 Results

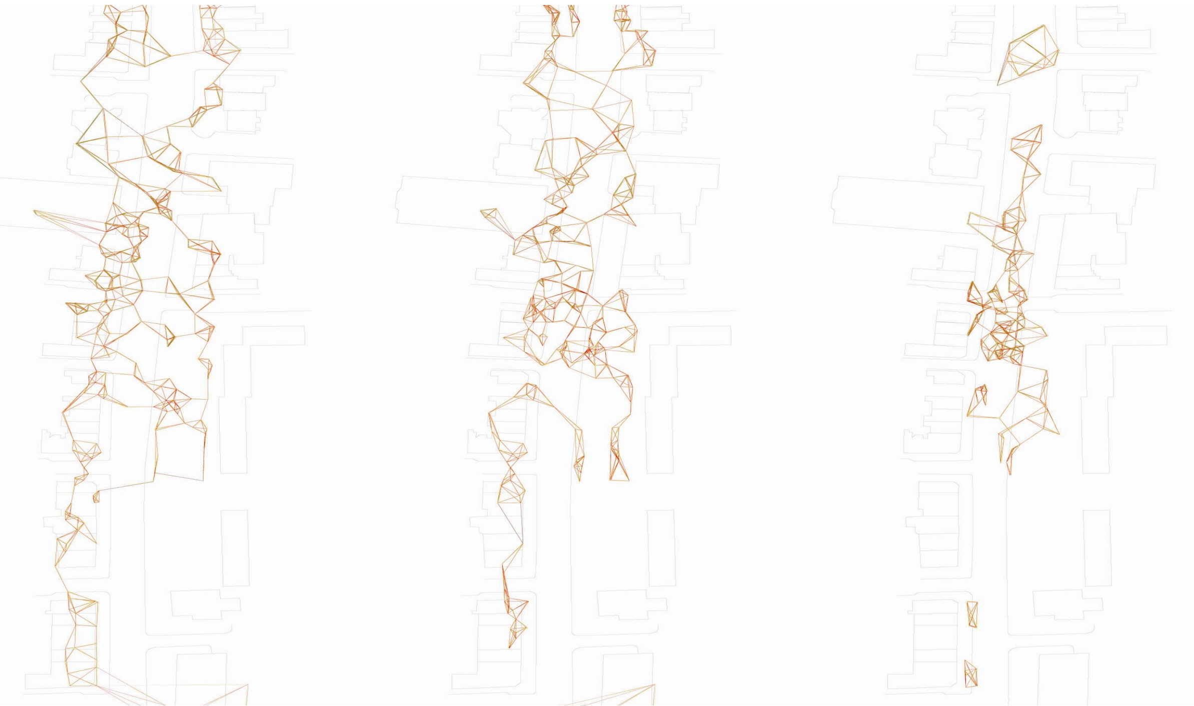


fig 10. Hourly output maps of high street at 1800h, 2100h, 2400h

The network outputs maps for each hour of the day that represent the change in the 'active' spaces along the street. This is different from a simple 'classification' map, as at each stage, the network must represent the topological relationship between the 'active' inputs. These are mapped as zones, clustering of activity, linked or isolated. Importantly the network must 'react' as the training data is updated, rather than learning each input independently.

4.5 Output Maps

The early stages are characterised by localised clustering. These clusters become conjoined to form a more recognisable totality. However, areas of disconnect remain throughout the learning. This is partly caused by the network being continually presented with data, and having to adapt to the new set, rather than start from scratch each time. What we see are latent connections, similar to the notion of a 'phantom limb' described previously. There is a significant level of redundancy in the network and this is reflected in the maps, where we can see connection remaining after the inputs have changed.

fig 11. Hourly output maps of high street at 0300h, 0600h, 0900h, 1200h, 1500h, 1800h, 2100h, 2400h

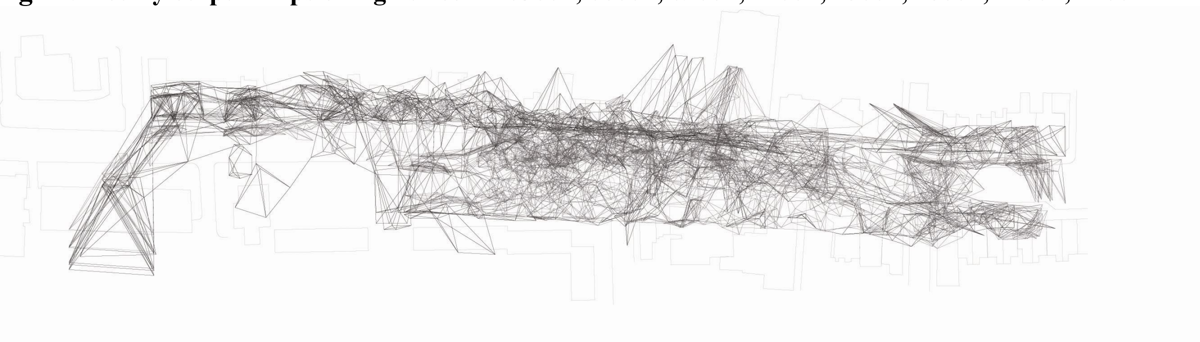


fig 12. 'History' of network states overlaid

4.6 Interpretations and Development

The output produced here represent an initial attempt at mapping urban territories. These are maps that describe 'occupy-able' space along the street. They do not, as yet, map the space that is occupied. The technique will be used to map the territories of individuals who live within the area, and for whom the street is place of contested territory. These first maps of the total space of the street are different to a traditional mapping. Rather than classifying, these maps describe relations between different spaces, both 'architectural' and 'urban', over time. The spaces are described only through there relationships to each other, and therefore offer a different understanding of urban space than a simple 'collection' of architectural spaces.

5. Conclusion - Growing Neural Network as Architectural Tool

Architectural and, in particular, urban data is commonly large and unwieldy. The initial use of this model, in mapping urban territories, offers a means of mapping such complex data.

The technique requires the reassessment of what constitutes 'architectural' conditions and data. Here, not only is the geometry of fixed space considered, but so is the more fluid condition of 'occupation' and 'use' over time and by different people. In this way the network does not produce tautological representations of 'known' inputs, but instead is able to produce relational, interpretive mappings that are capable of describing complex conditions in new ways.

This notion of 'territories', rather than 'space', describes a new paradigm that architectural practice must recognise and be capable of addressing. Tools such as these may begin to provide the means by which this can be achieved

References

1. Kohonen, Teuvo, *Self-Organizing Maps* (Berlin: Springer-Verlag, 1995)
2. Kohonen, Teuvo, *Self-Organizing Maps* (Berlin: Springer-Verlag, 1995)
3. Kohonen, Teuvo, *Self-Organizing Maps* (Berlin: Springer-Verlag, 1995)
4. Martinetz, Thomas & Klaus Schulten, 'Topology Representing Networks' in *Neural Networks* 7(3) (1994): 507-522
5. Fritzke, Bernd, 'A Growing Neural Gas Network Learns Topologies' in *Advances in Neural Information Processing Systems 7*, ed. G. Tesauro et al. (Cambridge MA: The MIT Press, 1995)
6. Derix. C, *Building a Synthetic Cognizer. Poster for the MIT Design Computational Cognition 2004 Conference, USA* (2004).
7. Parvin, T, *Growing Neural Gas With Self-oganizing Topologies For Spatial Description.* (London : University of East London, 2005.)
8. Boeri, Stefano, 'Borderdevices' in *Making Things Public: Atmospheres of Democracy*, *ed.* Bruno Latour
9. www.stefanoboeri.net
10. www.multiplicity.it
11. p47 Perec, Georges, *Species of Spaces and Other Pieces*
12. p345 Deleuze. G. & F. Guattari**,** *A Thousand Plateaus* -Translated by Brian Massumi. (London: The Athlone Press Ltd, 1988)
13. p344 Deleuze. G. & F. Guattari**,** *A Thousand Plateaus* -Translated by Brian Massumi. (London: The Athlone Press Ltd, 1988)
14. p297 Wise J. M, *'Home: Territory and Identity'*