Intelligent Road Network Simplification in Urban Areas

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ABSTRACT
This research is concerned with the automatic generalisation of road networks from a single detailed database. The challenge of representing networks at changing scales is that we retain the essence of connectivity and continuity throughout the network, whilst reducing the level of detail. The algorithm builds on prior work concerning the perceptual organisation of map objects, and has as its focus the urban network (rather than the rural) where particular challenges exist. When simplifying the city network, it is important to retain its links with the surrounding rural region. The algorithm focuses on identifying and retaining those parts of the network that best define and demarcate the various regions that typically comprise the city. It does this through the use of both graph theoretic constructs, and analysis of the areal partitions created by the existence of a network. The implementation, within an object oriented GIS is outlined, and the effectiveness of the technique illustrated and evaluated.

1.0 INTRODUCTION
Generalisation is a complex process that attempts to mediate between, on the one hand detailed spatial data and on the other cartographically represented geographic information. The task is one of trying to maximise the display and visualisation of the information contained in the data within the constraints imposed on the display by factors such as, scale, purpose, medium, resolution and user perception of cartographic symbols. Within the generalisation process different atomic operators act to transform the information representation in different ways, principally either by the omission of data or by the reorganisation of data. Urban network simplification or street selection is an example of the former category of operator. Urban streets are selected from the set of all streets of an urban network in such a way as to retain the underlying qualities of the network, but to remove detail that is imperceptible or otherwise not possible to display. The criteria used to perform this selection are based on an understanding of the properties of the composite entity the 'urban network'. These properties determine the levels of detail of the network structure and characterise the overall shape which it is sought to conserve. The research reported here, adopts the approach to generalisation that considers the generalisation of a geographic phenomenon as consisting of three components; measures, constraints, and algorithms. Measures relate to the analysis and description of spatial form and spatial relationships of geographic phenomena. As such measures
represent the mining of geographic information from a detailed spatial database. Constraints relate to the constraints on the representation of spatial data as geographic information, for example through a map. Hence, they relate to the focusing of the solution of generalisation to conform to a set of conditions. For a map, these conditions are determined by the map specifications, cartographic knowledge of map symbols and geographic knowledge of represented phenomenon. Constraints are violated when geographic information undergoes a change of scale, theme or representation medium, resulting in a loss of available space with which to display all the data. Algorithms translate between a geographic form represented by measures and a geographic form that satisfies the set of pre-declared constraints. These three components represent constraint-based generalisation. (c.f. Weibel, 1999 – lecture notes in CS).

2.0 BACKGROUND

A number of researchers have explored ways of automating the reduction in the level of detail of urban networks as part of the automated map generalisation process. Typically, the structural properties of the network are viewed as one of two dual forms; linear or areal. Linear representations consider the network as consisting of a set of linear connected 'street' objects. Whereas, areal representation considers the network as a surface of areal 'city blocks', generated by minimum cycles of the streets. Perceptually, the two dual forms represent different views of what the network is. On the one hand, the linear representation focuses on the entities that make up the network, on the other, the areal representation focuses on space between the entities and hence on how the network in its entirety extends in space. Ultimately, the distinction becomes entangled into the dichotomous figure-ground relationship (MacEachren, 1995). In the application of generalisation each representation has its own advantages. The linear representations are readily integrated with graph theoretic techniques since the network is readily transposed into a graph representation with the links as roads and the nodes as junctions. Mackaness and Beard (1993) and Thompson and Richardson (1995) describe the utility of this representation to generalise the structural properties of a network. They describe how Minimum Spanning Trees and Shortest Path algorithms may be used to characterise and classify the nodes and links in terms of their importance to the overall network and the application of this information to generalise the network ensuring that these relationships are maintained. Reynes (1997) and Morrisett and Ruas (1997) also use a linear graph representation, but instead focus the process of generalisation on the selection of streets of a network that will be used most frequently and hence the description of the network in functional terms. Reynes (1997) describes a technique to generalise the network by electing attractive nodes within a network, such as train stations or post offices, and then determining the shortest paths between each attractive point and all others. The frequency of use of a road in each of the shortest paths is then used as a criterion for classifying its relative importance. Morrisett and Ruas (1997) use a similar technique, but attempt to determine frequency of use by simulating traffic flows using a multi-agent system, rather than shortest path. The linear representation also allows for urban network to be considered graphically, as consisting of sets of cartographic symbols that have, both individually and in composite, perceptual properties. This representation underlies a description of various graphical qualities such as the connectivity and 'shape' of the network and these qualities have been used in a number of research areas such as urban
design (Penn 1993) and network generalisation (Mackaness 1995). Thompson and Richardson (1999) demonstrate how perceptual grouping by 'good continuity' can be employed to generalise the 'shape' of a network. The mechanism groups together individual streets into continuous best 'straight' lines, termed 'strokes'; a metaphor to espouse the idea that they are made by the continuous stroke of a cartographer's hand. Through this grouping process, through-roads and arterial roads are identified without the need for detailed semantic information. In their research, generalisation is then performed by the successive attenuation of the least important strokes. Meaning that those arterial streets that have the greatest bearing on the 'shape' of the network are maintained. The main disadvantage of using a linear representation is that it provides no obvious method for integrating graphic constraints with which to guide the generalisation process. For example Thompson and Richardson (1999) use the controversial Radical Law (Topfer and Pilwiezer 1966) to approximate the number of entities that must be removed and then attenuate based on this value. Constraints are useful in order to provide a description of the solution to a given generalisation problem. As such, they tie generalisation algorithms to specific issues that must be resolved in representing geographic information cartographically at different scales. Graphical constraints are concerned with issues such as information congestion, levels of perceptible detail and conflict of symbology. As they relate to linear entities, these would include such things as minimum length of an edge that is perceptible and the level of sinuosity that is perceptible. Such constraints relate to the entity in isolation. However, within the context of an urban street network constraining entities in this way is not particularly useful. For example, a street in isolation may be less than the minimum edge length, though within the network it will be connected at both ends to other streets above the minimum edge length. This makes an atomic measure of edge length problematic. In addition removal of such an edge always carries the risk of disconnecting the network. Constraints on the broader contextual properties of the network are much more useful. These will include issues such as network connectivity and the minimum allowable distance between two linear symbols. The use of an areal representation, provides a better representation with which to integrate such contextual constraints. This is because the areal units consists of sets of surrounding roads in local contextual situations (Ruas, 1995), termed city blocks. The city block provides a basis for controlling network attenuation. In generalising such a representation, aggregation of city blocks is commonly used. Aggregation is triggered when one of the blocks is found to violate a constraint such as the minimum perceptible area. Care is required in the management of successive aggregations across the network and criteria used to determine which adjacent city block a violated city block should aggregate with. Peng and Muller (1996) describe a rule-based technique to guide aggregation using attribute information, in such a way as to preserve chains of streets with the same road classification attribute. In this way global semantic information is integrated with local processing. The danger with their technique is it relies on the robustness of the semantic information to guide processing. However, this information will often not be present nor in a form conducive to the methodology. Ruas (1999) also uses aggregation, though the triggering is based on symbology conflict between the roads of the city block and the contents of the block, rather than simply the size of the city block. Her approach again attempts to preserve main streets but has the additional criteria
that aggregated blocks should ‘look’ the same, e.g. they should have similar building
densities inside them.

In summary, there exist dual modes of considering an urban network for generalisation.
On the one hand, the linear representation offers the advantage that a better appreciation
of the importance of each individual street within the global context of the network can
be made. This may be through an analysis of the structural (by graph theory), functional
(by simulation of traffic flow) or graphic (by perceptual grouping) properties of the
network. On the other hand, the areal representation offers the advantage that it is better
placed to characterise levels of detail within the network and hence integrate constraints
with the generalisation operations. The approach reported here builds on the philosophies
described in the preceding discussion but attempts to bridge the gap between the two
representations by handling them simultaneously. Thus, bringing together global
contextual information with local processing, and integrating constraints and measures
within the generalisation process.

3.0 METHODOLOGY

The algorithm can be viewed as an eight step process. These steps are summarised in
table 1 and illustrated figuratively in Figure 12.

Measures
1. Stroke formulation by linear grouping
2. Determination of the city boundary and urban network
3. Creation of the partitions
4. Creation of weighted adjacency graph of the partitions

Parameterisation of constraints
5. Determination of the parameters for the generalisation process

Generalisation algorithm
6. Construction of an MST based on the adjacency graph
7. Sequential fusion of the partitions by inspection of the MST
8. Termination, when partition size is above minimum required

Table 1: The essential steps of the algorithm

3.1 Measures Linear Grouping
The authors’ approach builds significantly on the work of Thompson and Richardson
(1999), who developed a technique for ranking the importance of a street amongst a set of
streets of a network based on its continuous form. The technique groups streets into
subsets by concatenating streets into chains of the most similar attribute classification and
for which, at any junction the continuation of the chain is the best approximation of a
straight line, with respect to all the streets meeting at the junction. These chains are
termed ‘strokes’, to espouse the idea of a continuous stroke of a cartographer's hand.
Hence, two principles are adhered to; the principle of grouping by similarity and the
principle of grouping by good continuity. Figure 1 describes three streets meeting at a
junction with which to illustrate these principles.
In Figure 1, if the three streets are all assumed to be of the same attribute classification, e.g. ‘B road’, then \( b \) can be said to continue \( a \) by principle of grouping by good continuation. This is because the angle \( ab \) better approximates a straight line, i.e. 180°, than the angle \( ac \). If however the streets \( a \) and \( c \) were of type ‘A road’ and street \( b \) was of type ‘B road’ then \( c \) would continue \( a \) because of the principle of grouping by similarity. Grouping by similarity always takes priority over grouping by good continuity.

The algorithm reported here follows the implementation of Thompson and Richardson (1999), but differs in that it enforces symmetry in the grouping relation, i.e. \( c \) continues \( a \) implies that \( a \) continues \( c \). This is done since otherwise the order in which the streets are processed by the grouping algorithm will have an effect on the result. For example, in figure 1 if the grouping algorithm selects \( c \) first then, without symmetry, \( c \) will be concatenated with \( a \), since \( a \) provides the best continuation of \( c \). However, assuming all streets are of the same class, this relationship is asymmetric since the best continuation of \( a \) is \( b \) and vice versa. Thus, enforcing symmetry ensures that \( b \) and \( a \) are always grouped, with \( c \) terminating, whatever the order of processing by the grouping algorithm. The symmetry relationship is achieved by computing, for each road meeting at a junction, a preference order for grouping with each of the other streets. Grouping relationships that are too dissimilar, either in terms of semantic similarity or continuity are ignored. For example, in Figure 1, \( b \) and \( c \) have no preference to be grouped with each other since their continuity is too dissimilar. A depth first recursive search, centred on the node, is then used to match up the preference orders so that they satisfy the condition of symmetry. Table 2 describes the algorithm. The use of a search tree is required, since for any choice not reciprocated, e.g. the first choice of \( x \) is \( y \) and the first choice of \( y \) is not \( x \), then there exists another choice that prevents the relationship, e.g. the first choice of \( y \) is \( z \). However, if this choice is not reciprocated, e.g. \( z \) does not choose \( y \), then it is still possible to establish symmetry in the original choice, e.g. the second choice of \( y \) is \( x \). This can only be determined by testing every choice to a symmetric conclusion.
road_in – road to find partner for; road_out – symmetric partner of road_in returned
is_matched: boolean - true if partner found; false if no partner, i.e. road_in terminates, road_out ignored

find_pairing (road_in, partner_road_out, is_matched) {
    if (partner_road_out == NULL) then partner_road_out := road_in //executed on very first call
    current_road_in := road_in; current_partner := partner_road_out //local scope variables setup
    for each preference in [current_partner, preference_list] {
        if (preference == current_road_in) { //if true, symmetric pairing found
            is_matched := TRUE; RETURN } //only true for current scope
        else {
            road_in := current_partner; partner_road_out := preference // test choices of preference
            find_pairing(road_in, partner_road_out, is_matched) // using recursive call
            if (is_matched ) and (road_in == current_road_in) { //if matched, check local variable
                is_matched := TRUE; RETURN } //if same - match found for this scope
            else if (is_matched) and (road_in != current_road_in) { //if local variable is different
                is_matched := FALSE; RETURN } //false match for this scope
        }
    } // if is_matched false continue looping through preferences
    is_matched := FALSE // end of preference_list - no grouping found for road_in
    RETURN
}

Table 2. Symmetry enforced grouping algorithm

In order to assess good continuity it is necessary to elect representative vectors with which to measure the angle between two digitised lines at the point that they meet. One solution is to simply use the edge closest to the junction. However the ability of this edge to represent the general trend of the digitised line as it enters a junction is very much dependent on the scale at which the map is to be displayed. Figure 2 describes the effect of scale on the perception of the angle.

Figure 2. Scale effects on the perception of angles (after Thompson and Richardson 1999)

To provide a better approximation of this vector a least squares was used to estimate the angle of entry into the junction. Figure 3 describes the method used to estimate this angle.
Perceptible area vectors computed using least squares on portions of the lines within the perceptible area.

Figure 3. Angle estimation in assessing continuity.

Rather than ‘mean-centring’ the co-ordinate systems, as is common for least squares computations, the co-ordinate system was instead centred on the junction vertex. This was to ensure that the vector would always pass through this junction point. The least squares formulation was then performed using the equation shown in table 3, where I is the number of points within the perceptible area, x and y are the co-ordinates of each point, and m is the gradient of the vector.

$$m = \frac{\sum_{i=1}^{I} y_i x_i}{\sum_{i=1}^{I} x_i^2}$$

Table 3: least squares computation for assessing the degree of continuity

It should be noted that whilst this approximation technique worked well for urban roads, where the shape of the roads are fairly well-behaved, there are many conceivable situations where the technique would not work. For instance, theoretically, the road could cycle around the central vertex resulting in a very poor approximation.

Using this principle for perceptual grouping, the road network of the entire region can be analysed and road segments assigned values based on the significance of the 'stroke' of which they are part. The greater the continuity of the road, the higher its importance in conveying essential connectivity across the map. In the simple example of Figure 4, the annotations show membership and simple ranking for this set of roads.

Figure 4: A section of the region showing the 'stroke' values for each segment of the network.
In the algorithm of Thompson and Richardson (1999) the ‘strokes’ generated by the grouping were then ranked and selection performed by the successive attenuation of the least important strokes. This is done in such a way as to ensure that the network remains connected. Their approach produced some interesting results, though the authors admitted that the technique could be improved, for example, by the removal of unwanted ‘hanging’ streets generated by the process. However, it is argued in this paper that, in the context of an urban road network, the grouping is better used as a measure for characterising the network in order to provide global information to the generalisation process, rather than as an end in itself. This is because, as a linear representation, the technique is difficult to integrate with constraints and doesn’t provide sufficient consideration of the contextual properties of the urban network, such as its consisting of cycles (city blocks). To overcome these problems, the approach outlined here adopts the areal dual of the network as another data structure for characterisation, using the two structures simultaneously to perform the generalisation.

3.2 Measures - Urban area characterisation
The research outlined here deals exclusively with the generalisation of an urban network. As a preliminary it is therefore necessary to define what is meant by this term and hence how this geographic phenomena may be determined. An urban network is that portion of the entire road network that services urban or built-up areas. The definition of an urban area used here is taken from the (UK) Office of National Statistics (1991) that describes it as an area of land extending for 20 hectares or more, where separate areas of land are linked if less than 50 metres apart. The ‘city’ is therefore defined by the density of buildings and the end result is a cookie cut region defining the region within which generalisation will take place. The algorithm designed to implement this definition uses a morphological aggregation technique based on a method devised by Ormsby (1998, pers. comm.). This generates areas by buffering buildings and geometrically union-ing the generated areas where they overlap. Where the resultant areas are less than that defined for urban area they are then removed. Intersecting these urban areas with the road network then segments the entire network into sections that are ‘inter-urban’ and sections that are ‘intra-urban’. This allows for differential treatment that better addresses the specific properties of each of the geographic phenomena. Figure 5 illustrates an urban area boundary overlaid on a road network from the IGN x database.
Figure 5. Road network and boundary of urban area. Copyright notice ref for IGN

After generalisation of the urban region we wish to re-connect this region back into the rest of the map. It is therefore necessary to ensure the preservation of all roads that intersect the city boundary (irrespective of 'stroke' or other attributes). This is required to ensure reconnection with the inter-urban network. This requirement is illustrated in Figure 6. Figure 6a shows the city boundary superimposed on the entire network, and used to create 6b, the urban road network. The urban street network is generalised (figure 6c), and reconstituted with the inter-urban network (Figure 6d).

3.3 Measures - Areal Partitioning

A partitioning is a discretisation of space using cycles formed by linear objects (c.f Ruas, 1995). In this research the linear objects used were the streets and the boundary of the urban area. Figure 7 illustrates the partitioning. Partitioning space in this way is useful for a number of reasons. Graphically, it provides a mechanism to group objects that in composite share a common shape property by their arrangement. As such, the partitioning represents the dual of the linear representation of the network. The matrix of areas generated thus has explicit perceptual properties useful to generalisation. For example it can be used to define levels of detail of the network and these can then be used to validate graphic constraints within the generalisation process.
The partitions also provide units for spatial analysis. In terms of topology, different relationships can be found between the partition objects and non-partition objects, (e.g. by inclusion), between partition units, (e.g. adjacency), and significantly, amongst the objects used to generate the partition, (e.g. connectivity). Deducing the connectivity amongst parts of a network is possible by considering the topological relationships between partition units. In general, if a set of partitions can be shown to be continuous in terms of adjacency and touching, then the network they represent must be connected. In practice, special cases are generated by cul-de-sacs and these must be handled explicitly. Clearly, maintaining connectivity is essential in generalising a street network. Partitioning can also be used to create new forms of geographic phenomena and hence new forms of representation with which to understand the data. An example of this is the geographic entity a ‘city block’. Within the database these phenomena may be augmented with semantic or statistical information and the geographic relationships amongst entities explored.

3.4 Measures - Create adjacency graph of partitions

Discriminating the urban area and constructing the strokes and partitions, provides dual representations with which to view the geographic entity – urban network.

Figure 7 Partitioning using street network and urban area boundary

Figure 8: The problem viewed as both a connected network and a tessellation of space.
Figure 8 shows these duals. Viewing the map as in Figure 8b enables us to consider good continuity and to manage cul-de-sacs. Viewing the map as in Figure 8c enables us to ensure connectivity as we simplify the network and include graphic constraints within the generalisation process. In order to be useful these two representations must be integrated within an overarching structure with which to control the rate and sequence of generalisation. Thus, a weighted graph data structure is constructed, where the nodes represent the partitions, the links represent the adjacency relationships between partitions and the weights are used to integrate information from the ‘strokes’. Organising the partitions in this manner serves two purposes, it enables us to extract geographic features from the set of all partitions and it allows us to manage connectivity. To create the graph we need to define adjacency. Topologically adjacency is defined when two partitions have some of their links in common. However, from a cartographic perspective it is meaningful to define adjacency as being also dependent on the length of shared boundary. In Figure 9a, the boundary is too small to enable us to say that they are perceptually adjacent neighbours. In Figure 9b, the shared boundary is of sufficient length that we define them as neighbours. Clearly then, the perception of adjacency is scale dependent.

![Figure 9: What is meant by the adjacency of A and B, from a cartographic perspective](image)

Figure 10 describes in (a) a set of partitions (A - E) and in (b) their graph representation. The 'weight' assigned to the edge of the graph (Figure 10b), is that of the minimum stroke value found amongst the streets that form the boundary between two partitions. In the example all the boundary links belong to the same stroke, but for real data their may be several strokes that are represented in one boundary. In the figures the weighting is derived simply from an order of importance ranking.

![Figure 10: Assigning 'edge' values based on the stroke value of the partition boundary](image)
In order to define the conditions under which a generalisation solution has been found, we must first define the constraints to be satisfied and parameterise these constraints accordingly. Since the level of detail for an urban network was defined as being dependent on the area of the smallest partition, this was used as the constraint to terminate generalisation. Hence the constraint dictated that there should be no partitions smaller than the minimum visible or mappable area, where the area was measured as the partition area remaining after symbolisation. One exception to this rule was that those partitions that had been formed between the streets and the city boundary were artificial and therefore their area couldn't be measured, the area of these partitions was thus made to be infinity. The effect of this was to ensure the survival of any streets that crossed the city boundary. Thus preserving the links between the inter-urban and the urban network. In addition it is useful to ensure the connectivity of the network following generalisation.

3.6 generalisation

The basic principle of the simplification algorithm is that if a partition is too small to be represented then it must be aggregated with an adjacent partition. This principle is applied recursively until all partitions are greater than the minimum allowable size. The question of which partition to aggregate with is answered using the weights derived from the stroke information. A partition always aggregates with the neighbour with whom it shares the weakest boundary, i.e the weakest links are always removed from the graph. Hence the least continuous streets are removed from network under the condition that the cyclic nature of the network is maintained. The connectivity of the network is handled implicitly, since the aggregation of partitions in general cannot disconnect the network. However, there are two special cases; cul-de-sacs and multiple disjoint boundaries between two partitions.

**Construct a MST based on the adjacency graph**

In order to traverse the weighted graph and visit every partition a minimum spanning tree (MST) is used. The minimum spanning (MST) tree of a weighted graph is a collection of edges that connects all the nodes such that the sum of the weights of the edges is at least as small as the sum of the weights of any other collection of edges that connects all the vertices (Sedgewick, 1984). When used on a static partition structure, i.e a set of partitions that isn't being changed because of generalisation, the MST clusters groups of partitions along the branches of the tree. Hence the MST provides a tool for the abstraction of subsets of contiguous partitions that share common properties. These subsets form structures such as groups of city blocks surrounded by arterial roads. Figure 11 shows a minimum spanning tree of the test area.
For a dynamic partitioning, where the partitions are changing due to aggregation during generalisation, the MST provides a mechanism by which traverse through the partitions in a consistent order. It also ensures that the set of partitions after generalisation is connected.

The principle of the MST algorithm is that the tree is built by finding from amongst the fringe edges, the edge with the lowest weight and then adding this edge and node to the tree. Once this new node is added to the tree the nodes that are adjacent to it, but not already on the tree, are found and added to the fringe. The algorithm terminates when all the nodes are represented in the tree. (after Sedgewick, 1984)

3.7 Sequential fusion of partitions
Generalisation occurs by the aggregation of partitions. This can be performed either after the MST has been built, using the information contained by its structure, or it can be performed during the building of the MST. Each approach has different advantages and
disadvantages. First building the MST has the advantage that generalisation can be performed very quickly and the tree can be used reactively (van Oosterom, 1995). We only need to search the tree for partitions that are too small and then aggregate them along the branches of the tree. However, the structure is static and cannot respond to the changes that occur because of the aggregation and thus street removal. Every time a street is removed the stroke information is changed, since there is a one to many correspondence between the stroke and the streets. Often a street will represent a single stroke (one to one correspondence) so its removal will have no side-effects. However, where a single stroke is composed of several streets, the removal of a street will affect the value of the stroke to which it belongs. Clearly, if the tree is static this information cannot be updated in the graph weights. The alternative method is to aggregate the partitions at the same time as the MST formation and update the stroke information dynamically as aggregation occurs. This method is more time consuming since the weights of the fringe edges must be re-evaluated every time a change occurs. However it means that if a stroke has become less important this is reflected in the future decision making. Often this leads to a feedback effect that sees an entire strokes eroded away because every time a street is removed the stroke becomes less significant and therefore more likely to lose a successive street. Which of the two techniques is better is debatable and the subject of current research. For the static situation it may be that errors incurred are quite trivial and it is often desirable to maintain the original stroke significance to prevent the erosion feedback. On the other hand the erosion can have a quite desirable symmetry-breaking effect, in areas where all the streets are of roughly the same significance.

3.8 Stop when partition size is above minimum required

As the examples in the results section show, the partition size governs the point at which merging stops. When no more partitions remain whose area is less than the prescribed 'minimum surviving area', the algorithms stops. Because the boundary partitions are determined to have an infinite area the algorithm must always stop and the roads that cross boundary will always be maintained. It should be noted that, having an infinite area does not mean that these partitions cannot be aggregated with. A partition which is too small may select a boundary partition to aggregate with, the generated aggregate partition will then also have an infinite area.
Stroke formulation
Determine city boundary
Determine parameters for amalgamation process
Create partitions
Create adjacency graph of partitions
Construct a MST based on the adjacency graph
Sequentially fuse partitions by inspection of the MST
Stop when partition size is above minimum required

Figure 12: The algorithm

4.0 RESULTS
Figure 14 shows a multiple of the city region at different values set for 'minimum surviving area'. As this value is increased, so less important roads (based on the continuity algorithm) are successively removed.

No generalisation 5000 m²
Figure 13: different generalised forms based on varying the minimum survivable area of a partition.

5.0 OBSERVATIONS

The following observations are made with respect to the quality of the results:
The continuity algorithm has successfully identified and retained the essence of the road network
The network is guaranteed to 'reconnect' across the city boundary to rounds outside the city in every case
Because the algorithm differentiates between the rural and the urban there is better inherent control of density between cities, and from region to region. In this sense, the research acknowledges that the way we generalise city streets is different from the way we generalise rural road networks (Mackaness and Mackechnie 1999).
The technique follows a constraint based approach to map generalisation. The idea that any given design is a compromise between competing criteria and can be modelled as gradual relaxation of constraints until a solution is reached.

5.1 Further work

Various researchers have acknowledged that the final design solution is a collective effort involving a myriad of other generalisation algorithms. This alone does not provide the 'final' solution. Algorithms are needed to control the generalisation of the network between the city regions (Mackaness and Beard), for displacement and simplification of linear features, as well as their appropriate symbology. It is anticipated that the cartometric information gathered during the process of generalisation goes on to govern the execution of other algorithms, behaviours of other map objects, and the key phase of evaluating the quality of the generalised map.
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6.0 REFERENCES