Towards a Multi-Representation Database Approach to On-Demand Mapping and Continuous Zooming

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1 Introduction

On-demand mapping, as the process of creating customised maps upon request from map users to meet their specific requirements, has attracted increasing research interests in recent years.

Arguably, an ideal on-demand mapping system should be able to process requests from non-expert users and generate high quality outputs at (near) real time and with minimum human intervention.

In this paper, we propose an approach to on-demand mapping based on the multi-representation spatial data model presented in [1]. This approach also facilitates multi-dimension continuous zooming.

2 Two approaches to on-demand mapping

The majority of approaches (e.g. [2]) proposed for on-demand mapping may be regarded as process-driven. Such approaches, as illustrated in figure 1, attempt to orchestrate multiple map processing services (MPS) and diverse data sources to create maps in response to user requests. Theoretically speaking, process-driven approaches have the potential to offer maximum flexibility and best quality. Nevertheless, there are also some significant technical challenges:

- Mapping user requests to map specifications
- Mapping map specifications to appropriate map processing services and parameters
- Response time

To an extent, the first two issues might be addressed by standardisation and AI techniques (at the expense of losing some flexibility and extensibility). The performance of such a system, however, is unlikely to be near real-time for any reasonably large dataset, due to the NP-hard nature of many generalisation algorithms.

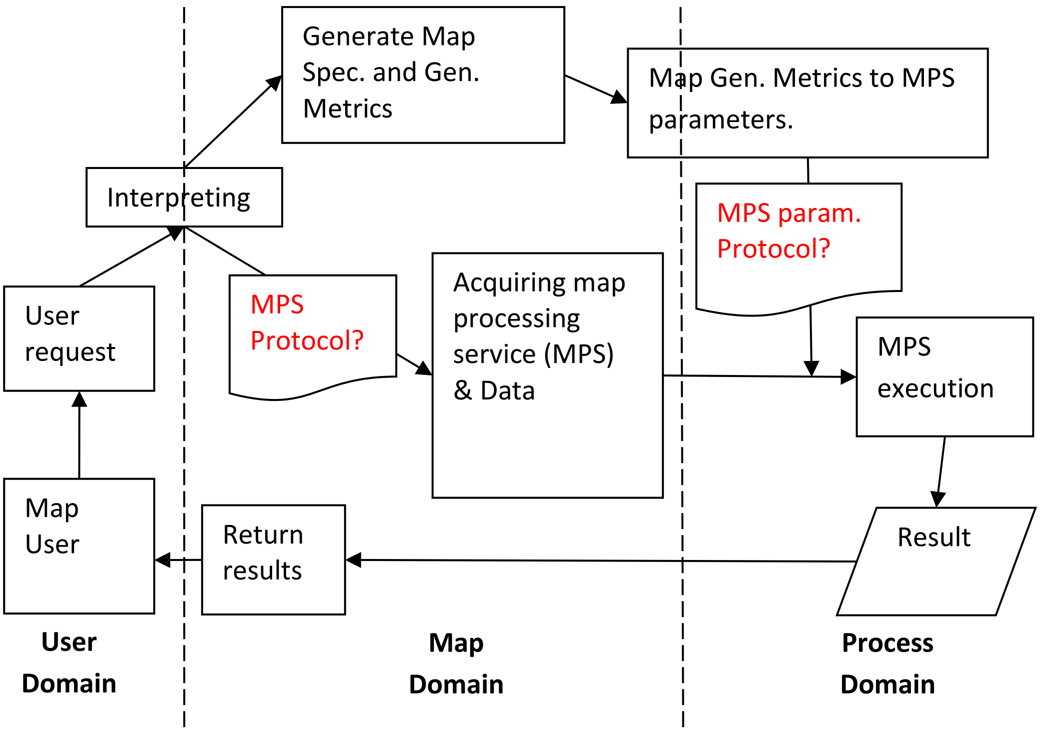

Figure 1: On-demand mapping: a process driven approach

Figure 2 illustrates an alternative approach which shares some components with the process-driven approach but differs in data processing strategy. It pre-generalises data to create multi-representation spatial databases and maps user requests to database queries to retrieve results on the fly (with optional real-time post-query processes).

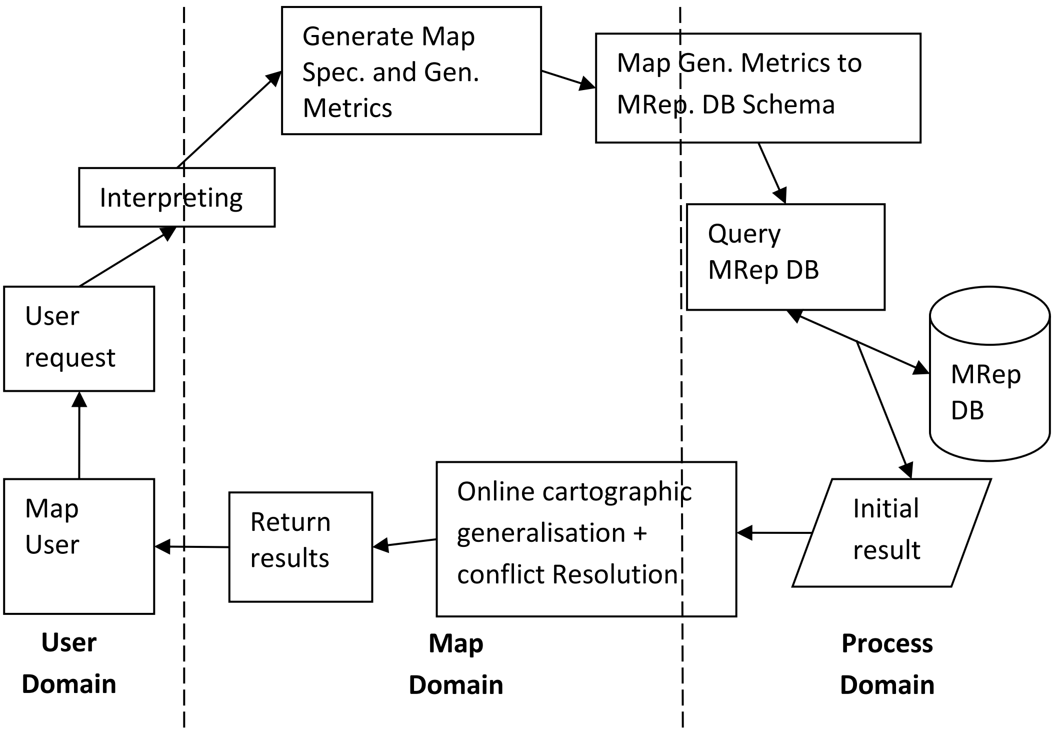

Figure 2: On-demand mapping: a multi-representation database approach

Although potentially less flexible and with quality compromise, this approach will offer much better performance, plus supports to local caching and continuous zooming as useful by-products.

3 A multi-representation view to maps

A map feature, as the depiction of a real world phenomenon, is generated at a specific spatial resolution to meet map users' certain demands. Generalisation is required when users' demand changes (figure 3). Generally speaking, user demands are reflected by generalisation criteria in the form of generalisation metrics (which are further mapped to parameters of generalisation algorithms) and spatial resolution (equivalent to scale in some cases).

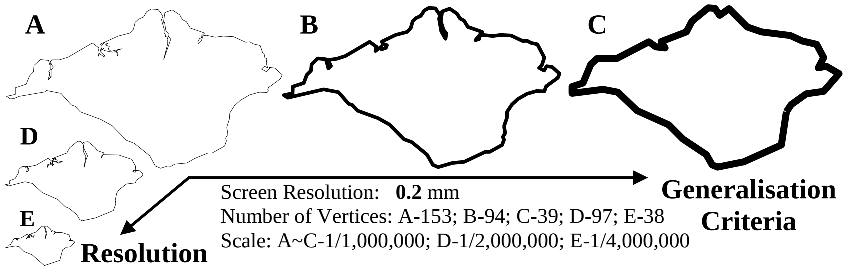

Figure 3: Effects of change on spatial resolution and generalisation criteria [1]

A map consists of points, lines and polygons (the latter two are defined by their constituent vertices which are also points). A map point can be defined as a tuple $(x, y, z, r, c_1, c_2, \ldots, c_n, \ldots)$ in a multi-dimension abstract space **S**$(X, Y, Z, R, C_1, C_2, \ldots C_n, \ldots)$ where dimensions **X**, **Y** and **Z** define the location, **R** represents the spatial resolution and $\mathbf{C_i}$ ($i = 1, \infty$) represents other map specification/generalisation criteria in various scales of measurement (nominal, ordinal, interval or ratio). In particular, we regard the sub-space $PS(R, C_1, C_2, \ldots C_n, \ldots)$ as the **presentation space.**

A multi-representational point p_{MRep} $(x, y, z, \{r_i\}, \{C_{1j}\}, \{C_{2k}\}, \ldots)$ is located at (x, y, z) and with a presentation range $(\{r_i\}, \{C_{1j}\}, \{C_{2k}\}, \ldots)$ containing a resolution value set $\{r_i\}$ and/or other generalisation metric value sets $\{C_{1j}\}$, $\{C_{2k}\}$, … Multi-representation lines and polygons are constructed from multi-representation points as their vertices. Their presentation ranges are the unions of presentation ranges of the constituent vertices.

This model may be illustrated by the example in [1] where multi-representation geometries are defined in **S**(X, Y, Z, RDP, WEA) where Ramer-Douglas-Peucker tolerance RDP [3] represents the spatial resolution dimension and the weighted effective area[4] WEA represents a single generalisation metric dimension. Consequently, a multi-representation point $p_{MRep}(x, y, z, [r_f, r_c), [w_1, w_2))$ will appear in any map specified by spatial resolution $r_q \in [r_f, r_c)$ and generalisation criterion $w_q \in [w_1, w_2)$.

By retaining only the spatial resolution, this model will be down-converted to S(X, Y, Z, R), the special case of multi-resolution model which is the focal point of most previous multi-representation researches.

4 Progressive generalisation for constructing multi-representation geometry

A multi-representation geometry, like a hologram, covers a range of spatial resolutions as well as generalisation metrics. It should contain many representations but remains compact storage-wise. Conventional generalisation method, which generalises map from resolutions A to B under a fixed set of generalisation metrics, is obviously inadequate for creating such a multi-representation geometry and a different paradigm of generalisation is needed. We believe the "progressive generalisation" approach [5] may provide a solution.

The motivation of progressive generalisation came from the simple fact that:

The minimum difference between two maps is one point.

This point could be a point feature or a vertex on a linear feature or the boundary of an area feature.

Consequently, if we can sweep through resolution/generalisation metric dimensions to detect the "event horizons" when changes to spatial resolution and/or generalisation metrics triggers addition/removal of map points, we will be able to pre-compute all the representations of map features in the presentation space. In spirit this is very similar to the well know algorithm family of sweep-line in computational geometry.

Some classic generalisation algorithms are inherently progressive (e.g. Visvalingam-Whyatt algorithm [6] and the RDP-based BLG tree [7]). It will be more difficult to make many other algorithms progressive so new algorithms may have to be designed to process certain feature categories.

In case of multi-dimension presentation spaces (e.g. the RDP-WEA space in the previous example), a priority hierarchy should be specified among different dimensions. For example, we sweep the RDP dimension and computed RDP intervals first; subsequently on each RDP interval we computed the WEA intervals. This also applies to multiple feature classes where some feature classes will take priority over other classes in case of interactions among features from different classes.

The resulting multi-representation information is in the form of rectangular regions in the presentation space. Normally the number of regions is small (3.12 in the sample dataset and less than 30 bytes of storage space is required if single-precision is used). From the multi-representation dataset created (initially containing 5 objects and 2376 vertices), more than half a million distinctive representations may be retrieved by different combinations of query RDP and WEA values.

5 Degree of Generalisation

The difficulty to map user requests to parameters of generalisation services is two-fold:

- For the same request (say "give me a thematic representation of Isle of Wight") at different scales (due to size variation of display devices), the appropriate generalisation metrics are scale/resolution dependent;
- Many generalisation services may have multiple parameters which are hard to understand even for human operators.

The concept of **degree of generalisation** (DoG) introduced in [1] might be able to address these issues to some extent. The idea of DoG is to define a function DoG = $f(\boldsymbol{g}_i, \mathbf{r})$ for generalisation metrics

$\boldsymbol{g}_i$ (i=1, n)and spatial resolution $\boldsymbol{r}$ such that for the same value of DoG the representation retrieved from the multi-representation geometry is consistent in style and level of details .

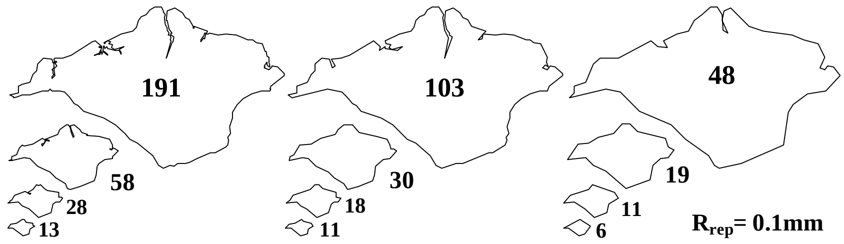

Figure 4: DoG-based intelligent zooming (number of vertices retained is as labelled)

Figure 4 shows the effect of “intelligent zooming” [1] which uses the DoG defined as $(1 – r/wea^{1/2})$ to retrieve appropriate representation from a single set of RDP-WEA multi-representation geometry. Clearly, for the same DoG value (left to right, DoG = 0.0, 0.5, 0.75), the style of representation remains roughly consistent regardless the change to scale (from $1{:}10^6$ to $1{:}10^7$). At the same scale, larger DoG results in retrieval of more heavily generalised, simpler representations.

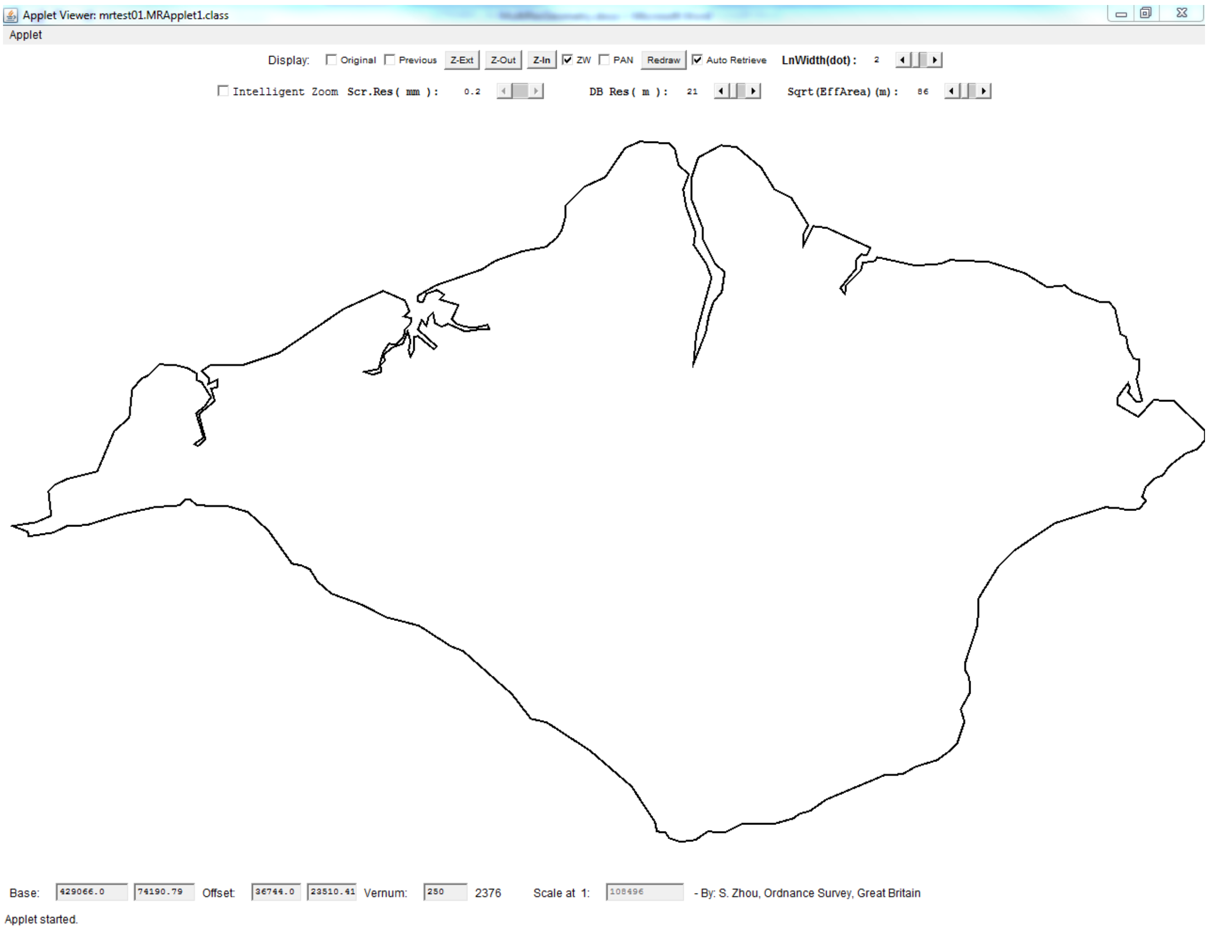

Figure 5: A demo system for RDP-WEA based multi-representation geometry

As illustrated by a demo system we developed (figure 5), if multi-representation data are transmitted to and cached on client-side, efficient and genuinely continuous spatial/semantic zooming can easily be facilitated.

DoG may be at any scale of measurement. Indeed, a nominal DoG (e.g. {TOPOGRAPHIC, THEMATIC, BACKDROP, SCHEMATIC}) may serve many purposes perfectly and it can be more easily mapped from user request via an ontological approach.

DoG hides away a lot of complexities in the process of parameter value selection. Nevertheless, for many algorithms it is not trivial (if ever possible) to design a good DoG. Also, DoG is normally designed from a map maker's point of view initially so it is almost certain that some training/learning process is required to calibrate a DoG to reflect map users' views.

6 On-going work

Previous research on multi-representation geometry [1] used just one feature theme (coastline). Currently a more complicated prototype with multiple feature themes is being developed to support on-demand mapping. The goal of the project is to implement a multi-resolution map server to address the issues of scale-sparse product stacks and inconsistent cartographic styles among different products.

OS MasterMap data for Isle of Wight is used as sample dataset in the project. In the initial stage, only a subset of feature themes is used and they are grouped into three sets: natural features (mean high water line as coastline, inland water line and inland water area), road network (ITN road links) and buildings. Our aim is to be able to process a complete theme set of OS MasterMap data eventually, before experimenting with additional generalisation criteria.

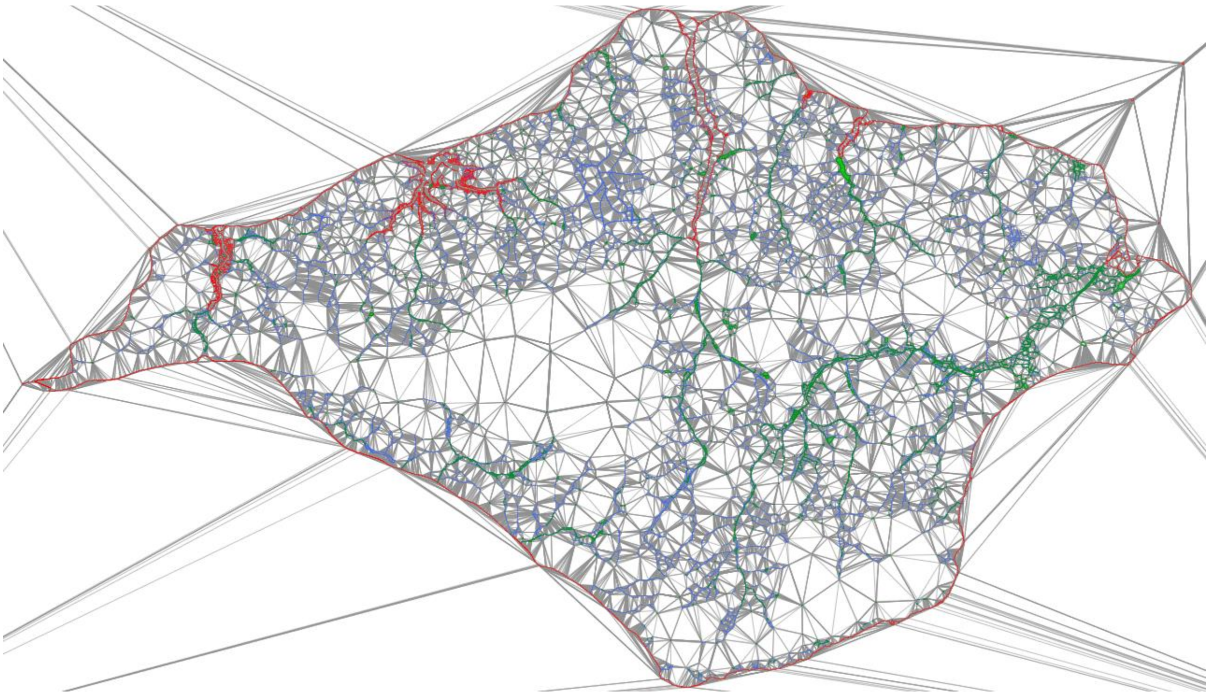

Figure 6: Sample data: OS MasterMap mean high water lines, inland water lines and areas

In our current process, natural features take the highest priority. A graph is constructed to handle the inter-connectivity among natural features. RDP is used to generate initial resolution range for vertices inside individual features. A dynamic constrained Delaunay triangulation is used to detect topological conflicts. At this stage, collapse of area details into new linear features, although required (e.g. the case shown in figure 7), are not used yet. For selection of water line and water area features, pre-defined simple ratios between their initial length or area and resolution are used at present. In the future, we wish we will be able to take into consideration the distribution of features and network topology (when a clean hydrological network can be built upon the rather noisy data we have at the moment).

Figure 7: inter-dependent geomorphological details: sand spit or stream?

After pre-process to join adjacent lines and merge split areas, there are 8105 features (495405 vertices) of the three types in the natural dataset. Below is the data displayed at around 1:100K in the demonstrator (note that a 38% scaling is applied on the original screenshot image).

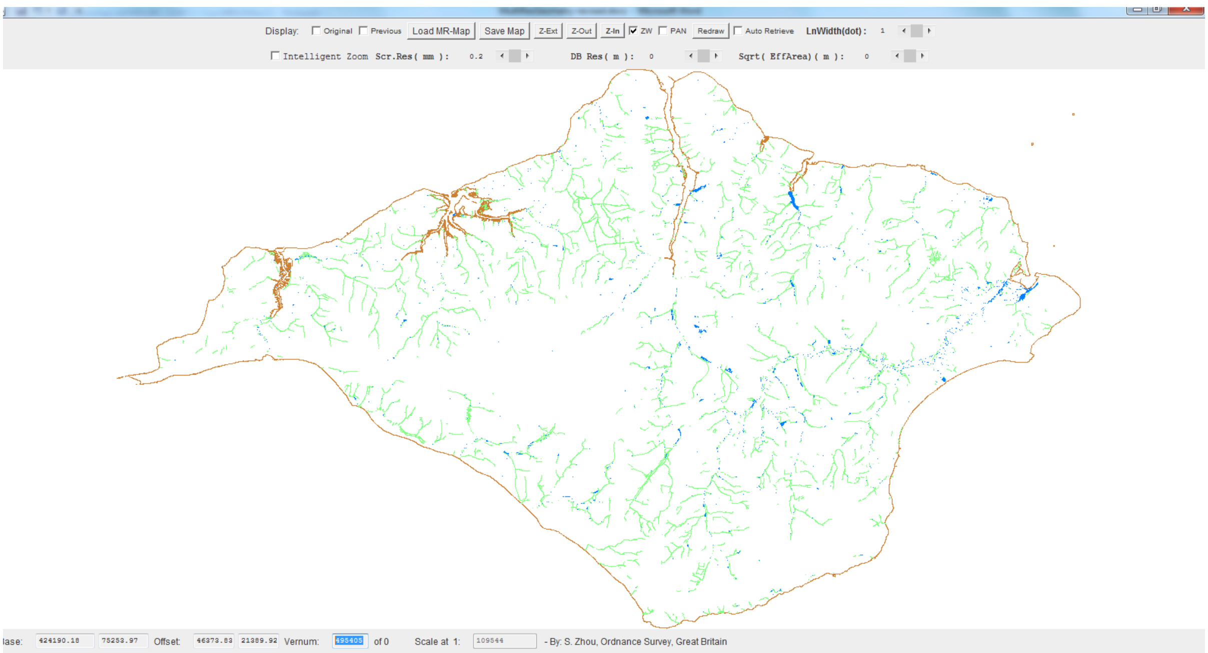

Figure 8: MHW, water line and area at about 1:100K (38% scaling on original screenshot image)

This demonstrator inherits the “intelligent zoom” feature in the MRep-geometry prototype it is based. An adjustable screen resolution (representing the visual characteristics of display media) and the current scale (the physical extent of current display media against the extent of the data to be displayed) are mapped to a data resolution which is subsequently used to filter out vertices on geometry to generate properly simplified representation for the specific scale. Figure 9 shows a less cluttered display of the data at the same scale and screen resolution (0.2mm), after “intelligent zoom” was switched on and data were filtered.

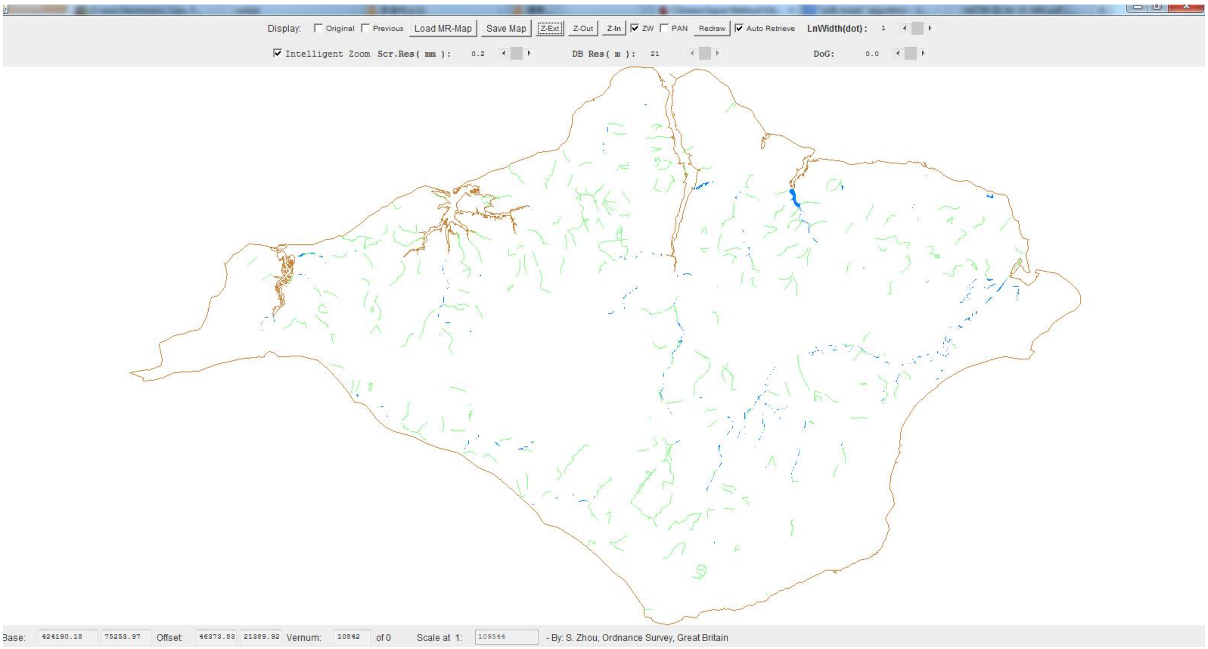

Figure 9: Generalised data (10642 vertices) at 100K (38% scaling)

When we zoom in, scale increase and more vertices are “re-activated” and more details are visible (Figures 10-12).

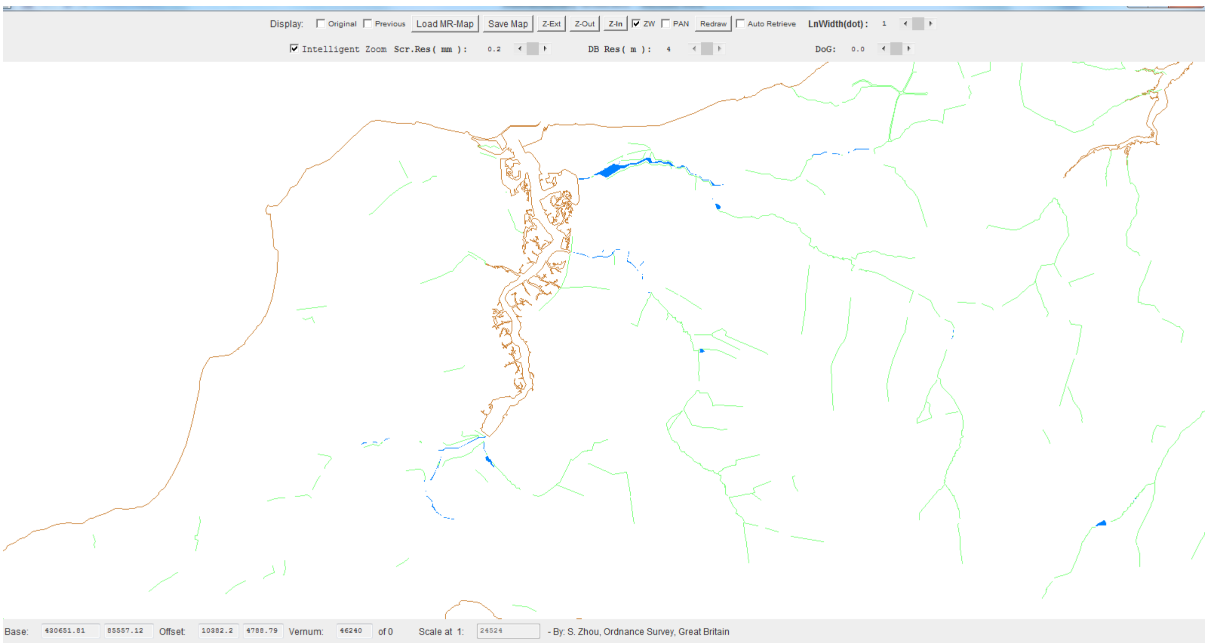

Figure 10: at about 1:25K (46240 vertices) more details are revealed (38% scaling)

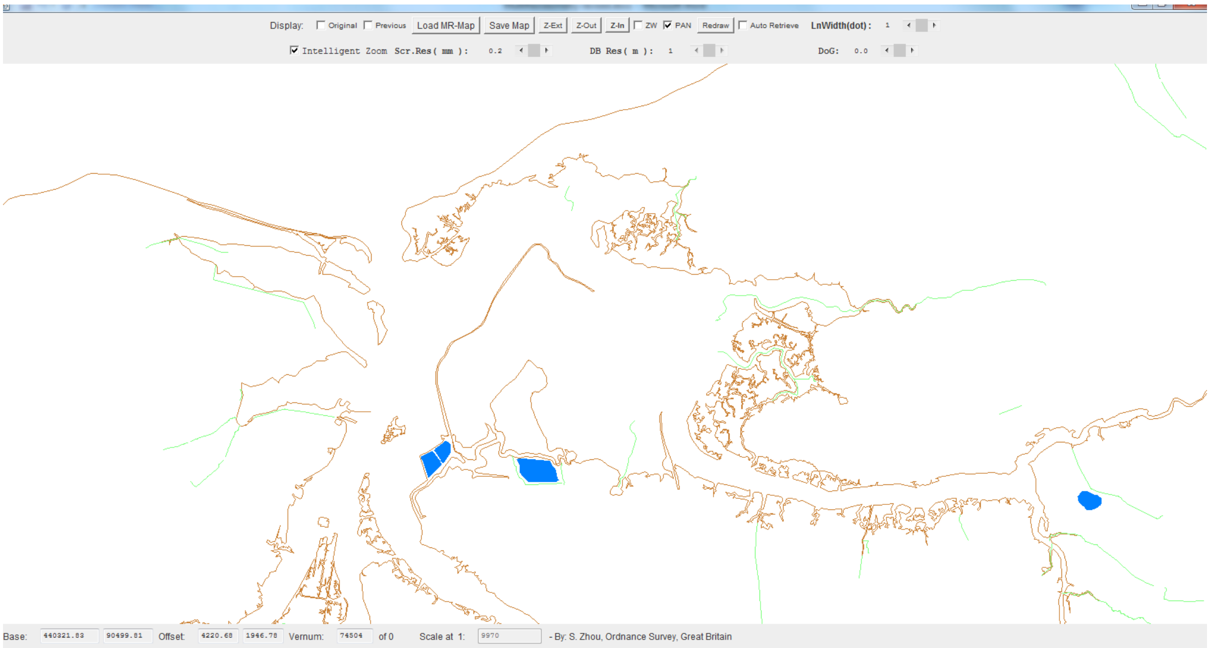

Figure 11: more details (74504 vertices) at about 1:10K (38% scaling)

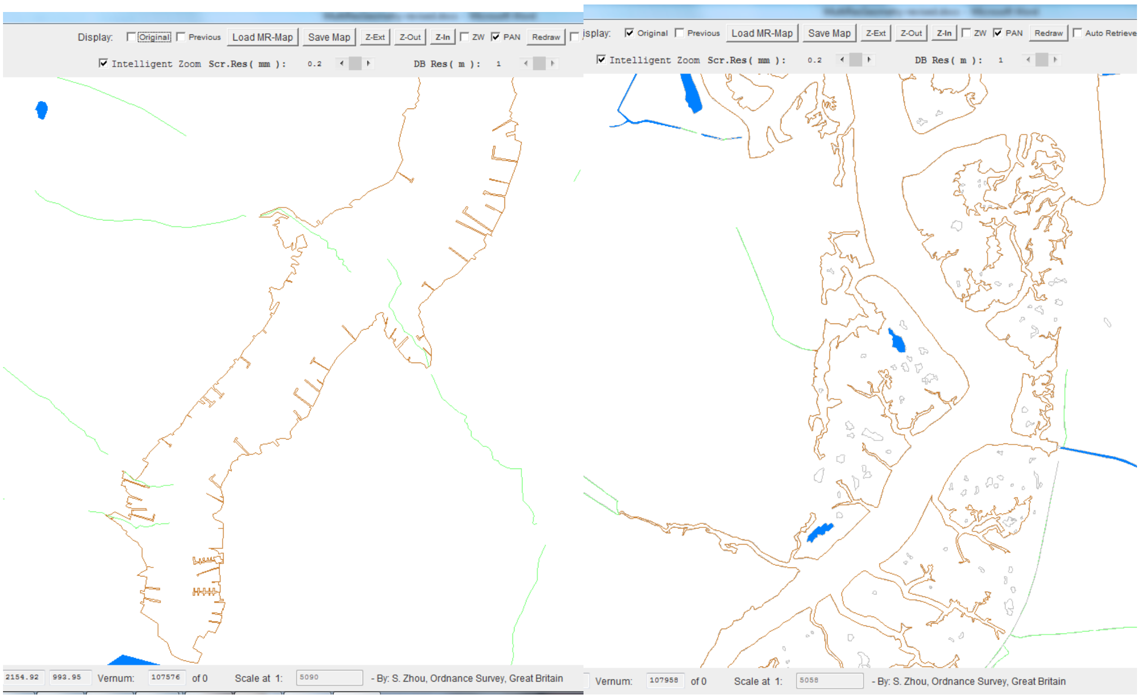

Figure 12: 1:5K (40% scaling). Note the filtered features (grey) in the sample at right.

We are currently working on generating resolution ranges for roads (figure 13) and buildings (figure 14). When we obtain further results from this ongoing research, we will create a supplement for this paper and make it online. Please search the authors on ResearchGate website in the near future.

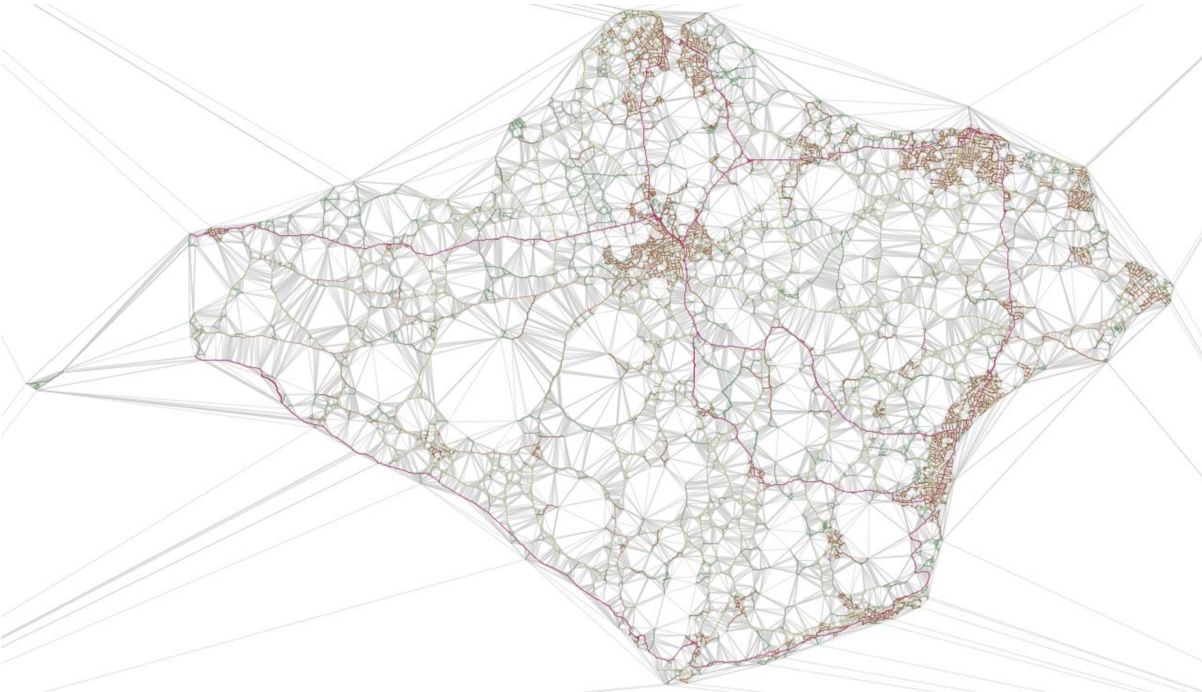

Figure 13: Sample data: OS MasterMap ITN Road links

Figure 14: OS MasterMap Buildings (details)

7 Discussion and Summary

7.1 Two important issues:

When generalisation criteria are used in addition to spatial resolution, two issues have to be addressed with extra care.

The first issue is consistency of feature details on the same feature. In general, a detail (e.g. a bay window on the profile of a building) that does not appear at a finer resolution and/or smaller degree of generalisation should not appear at a coarser resolution and/or larger degree of generalisation. This principle is quite obvious in theory but inconsistency can easily be introduced in implementation, especially when details are defined at the level of single vertex (e.g. the cases of RDP and Visvalingam). For this reason, it will be desirable to explicitly define details (and more importantly, hierarchy of details) on feature geometry. Some discussion on this issue can be found in [8].

The second issue is that topological or proximal inconsistency may arise between various representations (or details in representations) of different objects if their resolution ranges are overlapped. For example, in Figure 10, Rep_1 and Rep_2 are two representations of a village (the point object) at the south side of a road with a removable detail. Rep_1 will cause topological inconsistency if the detail is removed which will leave Rep_1 at the north side of the road. In this case, Rep_2 should be used instead. Rep_1 and Rep_2 may share the same PR and the retrieval of one of them depends on DOG value used for detail removal.

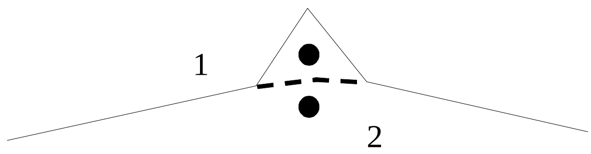

Figure 10 incompatible representation

The presentation ranges of the two representations may then be defined as:

$$PR_1 = \{(r, dog, dog_v) \mid (r, dog) \in PR \wedge (r, dog_v) \notin NPR_{dtl}\}$$

$$PR_2 = \{(r, dog, dog_v) \mid (r, dog) \in PR \wedge (r, dog_v) \in NPR_{dtl}\}$$

While PR is the initial presentation range shared by the two, dog_v is the DOG for detail removal and NPR_{dtl} is the non-presentation range of the detail in the road object.

Note that topological inconsistency in the example above may be removed the other way around, i.e. *dtl* is removed only if the point object does not present. We may also combine the two solutions together, i.e. *dtl* depends on rep_1 at finer resolution and at coarser resolution rep_1/rep_2 depend on *dtl*.

Proximal consistency is a much more complicated issue. When a multi-representation dataset is made, proximal consistency may be guaranteed based on some default resolution-dependent separation distance values. However, as different symbol sizes may be specified for multiple themes at the client side or a selection DOG value lower than default is used to retrieve more features, proximal inconsistency may still present after retrieval. From a data model point of view there might still be some practical but complicated solutions to this problem, or alternatively, proximal inconsistency may be removed by applying on-line proximal conflict resolution procedures on retrieved data.

7.2 Object vs space

The method we used to compute resolution range for vertices may be classified as object-based partition of the resolution space. Consequently, we may claim we have achieved support to genuine continuous zoom. However, it is not always easy or even feasible to implement some generalisation methods in an object-based partition manner.

An alternative approach is to pre-partition the resolution space into many fine ranges, generalise source data towards each range, and then merge the resolution ranges of common vertices to form a multi-resolution geometry. Using bit-array of sufficient size (e.g. a 32-bit integer provides encoding capacity of 32 ranges), the width of resolution range can be very small and make the result effectively "continuous". Some experiments on this approach may be found in [9].

It should be noted that following this approach, both the star and ladder models may be used to design the process flow. We believe for this purpose the ladder model (i.e. generalise result in one resolution range to create the result for the next coarser resolution range) has many advantages over the star model in maintaining consistency, identifying common vertices and merging resolution range.

7.3 Summary

The multi-representation database approach aims at circumstances that require quick response, output of reasonably good quality, and flexible visual presentation at client side. It is not a cure-all and will not replace a good process-driven system but rather complements the latter. Indeed, a practical on-demand mapping system may well combine these two approaches to offer a more versatile service.

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