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Spatial Inference Based on Geometric Proportional Analogies

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Abstract

This paper addresses the domain of qualitative spatial reasoning, addressing two distinct domains of spatial information: namely geometric proportional analogies (GPA) and topographic (land-cover) maps. We present an analogy-based model that unites two distinct models that were developed, one for GPAs and the other for topographic maps. We describe how this new *generalized* model solves GPAs and also solves some inference tasks associated with topographic maps. We then describe how the new model makes use of additional categories of spatial information such as point features, which have received comparatively little attention. Finally, we present a new category of problem related to the identification of irregular structures, which lay beyond the scope of previous models but which is solved by our newer model.

1. Introduction

Spatial reasoning involves reasoning about locations and areas in both the real world and in representations of it, such as diagrams, maps, and schematics. It underlies our ability to understand and reason about the world. There are two basic approaches to spatial reasoning. First, a quantitative approach emerged from reasoning about quantitative information in spatial data. These formal models improve our understanding of locations, distances, areas etc. More recently, there have been attempts to reason qualitatively about spatial information. These aim to reason about non-quantitative spatial information, such as adjacency, containment and dis-connectedness.

Two basic approaches to qualitative spatial reasoning (QSR) have emerged from this work. First, the formal approach aims to support deductive reasoning about spatial relations. The main spatial algebra are E9DEM [9] used by IBM's DB2 Spatial Extender, RCC8 [13] and Oracle 10g. The second approach to QSR explores non-deductive reasoning, typically exploring more cognitively aware inference techniques [1, 6, and 7].

QSR gains even greater significance when we consider that the spatial domain frequently acts as the source domain through which we interpret other domains, most notably time [8]. So, while this paper does not specifically address temporal reasoning, our work does have extension to the temporal domain.

Our approach is applied to problem of enriching the classification of existing topographic maps and in particular OS MasterMap® which is a large scale digital map of Great Britain. Whilst OS MasterMap provides classification for individual features such as buildings it does not yet explicitly represent complex structures such as schools. Text exists to identify the location of such features but there is no explicit association between the individual simple features and the complex feature.

The remainder of this paper is organised as follows. First, we describe the specific problems within qualitative spatial reasoning. Secondly, we describe Geometric Proportional Analogy problems (GPA) and give a brief explanation of how they are solved. Finally, we show how *Jess*, our model, can be used both to resolve GPA problems and to solve problems identified in topographic maps.

2. Background

The first qualitative spatial reasoning problem we examine concerns GPA problems. GPAs are a type of analogy formed between two collections of geometric figures and are of the form A:B::C:D, where A and B are described as being the source domain, and C and D are the target domain. In a GPA problem, A, B and C are known and D, the solution, is unknown. The objective is to use the information contained in the source domain (A and B) as a basis for completing the partial description (C) – thereby generating the missing solution D.

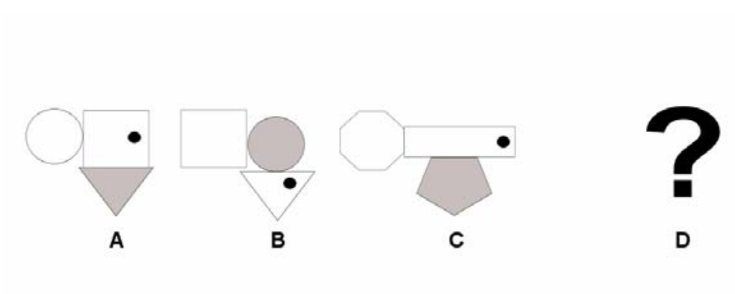

Figure 1. A GPA

The first computational model to solve GPA problems was created by Evans [1]. He examined a way of automatically solving the “Miller Analogy Test” problems, which are a set of intelligence test questions. Evans computational model used visual shape matching to process the problem and select a solution from a list of five potential solutions (D1..D5). Additionally, Evans model only operated on plain GPAs that had no colour or pattern information.

Gentner developed the Structure Matching Engine (SME) to solve analogy problems, which has also been applied to GPAs [2, 3]. SME represents the source and target domains using predicates, generating the A to C mapping by finding the largest isomorphic mapping between the predicate structures of A and C.

Tomai [3], like Evans, solved GPAs by processing the images representing the source and target domains, choosing the best from a list of five possible solutions. Tomai's solution looks at the overall shape of the image as well as using any of its rotation and reflection information. Like Evans model, Tomai's model is also limited to addressing plain GPA problems (without colours, patterns etc).

2.1 GPAs using attributes

This paper focuses on GPA problems that are more complex than those used by Evans and Tomai. Our GPA problems include objects with attributes, such as colour or pattern information. In solving these problems it is central that this *attribute* information is identified and dealt with correctly. Neither Evans nor Tomai are concerned with this category of problem.

Two previous models do incorporate attribute information in GPA problems. Bohan and O'Donoghue [6] examine a variety of GPA problems involving attributes. However, this model is specific to GPAs and does not deal with topographic maps or with the complex polygon clusters we shall describe later. Mulhare [4] describes a model for classifying objects in topographic maps, but this model does not specifically address GPAs nor does it use point information or deal with complex polygon structures.

3. Representation

The first step in our solution to these GPA problems is to represent each image in symbolic form using predicates. These predicates detail how the objects in each image are spatially related. They also detail any attributes that an object may have. Each part (A, B and C) of the problem is treated as a Voronoi diagram, from which a Delaunay diagram is created by placing a node in each object in A and B. The nodes are then joined if a relationship exists between the objects. Examining the edges allows the relationship between the objects in each part of the image to become clear.

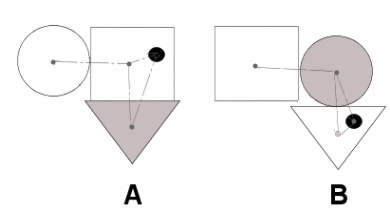

Figure 2. Delaunay Diagram

Figure 2 shows the Delaunay diagram for parts A and B. Two relationships are used to describe the topology of parts A, B and C. `line-adjacent` represents objects that share a common boundary, while `inside` represents an object that exists completely within the boundaries of another object. Attributes are represented by either `plain` or `shaded`. The predicates describing these images are listed below. Examining the changes in the predicates describing A and B show the transformation that was applied to A in order to produce B.

Predicates Describing A	Predicates Describing B
lineAdjacent(circle, square) lineAdjacent(square, triangle) inside(point, square) shaded(triangle) plain(circle) plain(square)	lineAdjacent(square, circle) lineAdjacent(circle, triangle) inside(point, triangle) shaded(circle) plain(triangle) plain(square)

Table 1. Predicates Describing A and B

The next step is to identify the inter-domain mapping between A and C. This means finding the largest isomorphic mapping between the descriptions for A and C. In order to do this, it is necessary to scrutinize the predicate lists for A and C. The size, shape and rotation of the objects are not taken into consideration; instead the emphasis is on the relationships between the objects and the attributes associated with each object. Figure 3 shows how each object in A is mapped to its counterpart in C.

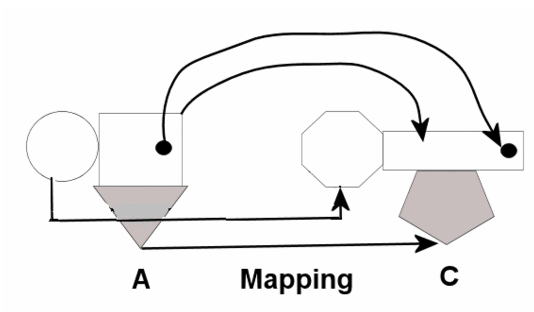

Figure 3. Mapping A to C

Finally, the transformation between A and B is applied to C, generating D. This method allows D, shown in figure 4, to be generated without a list of possible solutions.

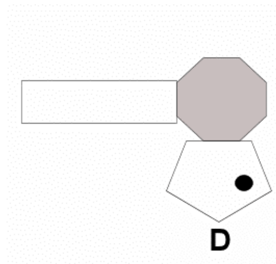

Figure 4. The Solution

4. Generalised Spatial Problems

Next we examine how the same solution that solves the above GPA problems is also used to solve problems in topographic maps. Like many GPA problems, topographic maps are also composed of collections of polygons, each with attribute information in the form of a category, like *road*, *rail*, *building*, *inland water* etc.

Currently, the information that is contained in a map is generated manually and so is expensive to process. Automatic processing of this spatial data is desirable to both reduce costs and make the information available to computational processes. In the below examples the OS MasterMap data for Port Talbot (containing around 5000 polygons) has been used in order to illustrate the solution to some spatial reasoning problems.

Both Bohan [6] and Mulhare [4] have looked at problems involving simple collections of coloured polygons, thus we shall not concern ourselves with these problems in this paper (such solutions conform to the regular structure of the Delaunay graph of the problem). Our model's solution to some of these problems can be found in Mullally and O'Donoghue [11].

Instead, this paper looks at two different categories of problems that have not been previously solved by any model. The first category of novel problem that we look at concerns the use of point information in conjunction with polygons. The second category relates to complex "incremental" structures involving multiple polygons. We will now look at some common problems in topographic maps and GPAs that have not been seen before.

4.1 Point in polygon classification

Point in polygon classification is a method of using a point feature to classify an object. Figure 5 shows how point in polygon classification can be used to solve a GPA problem.

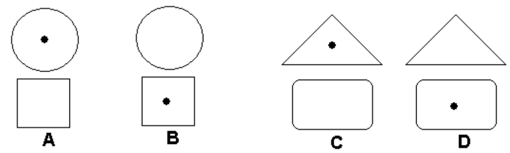

Figure 5. GPA showing Point in Polygon Classification

Examples of point features in topographic maps are benchmarks, spot height, text identifying a road, names of prominent buildings and addresses. Each point feature is anchored to a point on the map and can be clearly read when looking at the map. However, it is not directly associated with any object and it can only be used to identify an object when it is being read by a human.

4.1.1 Dwelling Sub-categorisation using Point-in-Polygon

One problem associated with categorising polygons in topographic maps is finding all of the dwellings in the map. Figure 6 shows semi-detached houses and garden sheds that are all currently categorised simply as buildings. One method of categorising a semi-detached house is to construct a template [4]. Although this solution may identify every semi-detached house, it will also misclassify garden sheds as they too fit the semi-detached house template.

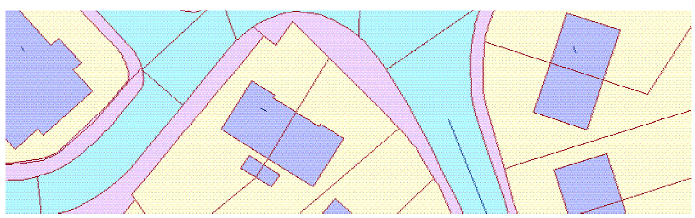

Figure. 6. Semi-detached houses.

Another way of solving this problem is to look at the point features associated with dwellings. OS MasterMap has an address layer that contains an address for every dwelling. Each address is represented as a point feature. If an address point feature is added to the original template, it is possible to remove the misclassified garden sheds from the results.

The results below detail the identification of semi-detached houses in the "Port Talbot" dataset. They detail the number of buildings found in the map, the number of semi-detached houses found by hand and the number of semi-detached houses found using the methods detailed above.

Total Number of Buildings in Map	Semi-D identification without point info	Semi-D identification with point info	Human Semi-D categorisation results.
2123	1142	960	952

Table 2. Accuracy of "Semi-D" Identification Strategies

The results above show that without using the point information, 182 buildings are incorrectly classified as houses. These misclassifications are mainly garden sheds that conform to the semi-detached house template. However, adding in point information containing the address of each house solves this problem as garden sheds do not have addresses.

In this case eight buildings were incorrectly identified when using the address point. These were composite buildings that appeared to be houses as they had addresses and appeared to fit the semi-detached house template. However, even though they were misclassified as houses, it is possible to correctly classify them later when looking at incremental structure matching, detailed below in section 4.3. Other possible applications of "point-in-polygon" include road junction identification and house number to polygon assignment.

4.2 Incremental Structure Matching

Incremental structure matching is a means of assigning a better classification to a polygon once additional information is known about its surrounding area. Figure 7 shows how incremental structure matching can be used to solve a GPA problem. It consists of two parts: root identification and root elaboration [10].

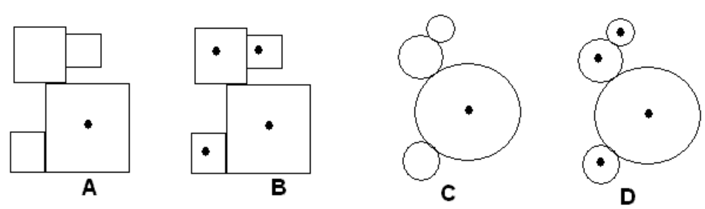

Figure 7. GPA showing Incremental Structure Matching

An example of a problem that can be solved using incremental structure matching is cluster identification. This means identifying all of the polygons that are part of the same cluster, and categorising them accordingly. In the below example, a cluster of buildings that form a college is being considered.

4.2.1 Incremental Structure Matching in Topographic Maps

Using incremental structure matching in topographic maps allows objects such as schools, universities, hospitals and depots to be identified. These objects are irregular structures that are made up of clusters of polygons. They do not have set sizes or shapes and therefore a normal template cannot be used to identify them in the same way that a semi-detached house can be identified. This means that previous map classification techniques would not work for this type of polygon identification. Incrementally categorising map objects will ultimately lead to a better overall categorisation in topographic maps.

4.2.2 Root Identification

The first part of solving the problem is finding a polygon that is part of the cluster. This is then described as the root polygon. Identifying the root means taking a closer look at point features, or more specifically, text point features. Text point features are points, which are anchored to the map, that contain information about a polygon. For example, the text may contain the word school, hospital, university, depot, church or, in this example, college. However, it is not always the case that the relevant text is positioned inside the correct polygon. Often the text is positioned in a neighbouring polygon. For example, a text point associated with a college may appear somewhere on the college grounds as opposed to on the building itself. In this case it is necessary to assign the text to the nearest building.. It is also essential to ensure that the text is sufficiently close to the building, i.e. the text should be within 2km of the building.

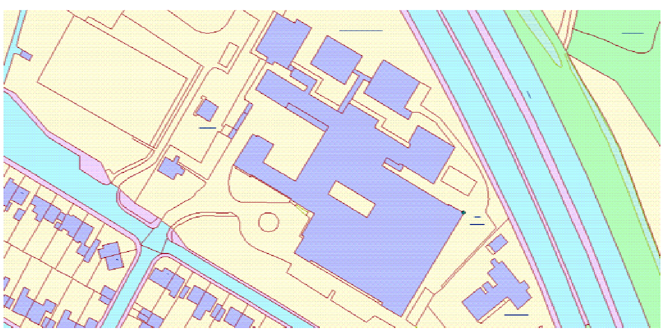

Figure 8. An Irregular Cluster of Polygons Forming a College

4.2.3 Root Elaboration

Once the root polygon has been identified, some constraints must be satisfied before the root can be elaborated. The first constraint is that no building that is being considered for classification should be more than 2km away from the root. The second constraint is that all of the buildings should be contiguously linked topologically with each other. If both of these constraints are satisfied then it is most likely that the building is part of the same structure as the root, and should be classified accordingly and included as part of the root.

In the college example there are a total of eight buildings that are part of the college structure. Both of the above constraints are satisfied. *Jess* initially identifies all of the buildings that are directly adjacent to the root and re-classifies them. Once this is done it is then possible for *Jess* to reconsider other buildings in the area for re-classification. The buildings that are adjacent to the newly classified buildings can also be re-classified. This continues until all of the buildings in the cluster have been identified. An additional way of confirming the identity of the cluster is to use address points. If the text point has been assigned to the correct group of buildings, then at least one of the buildings should have the relevant text in its address.

For this dataset, *Jess* successfully identifies all of the building clusters. We are currently testing *Jess* on larger datasets. Preliminary results suggest that this method is effective in identifying over 90% of building clusters.

4.2.4 Other Uses

Incremental structure matching permits dynamic polygon clusters to be formed. This allows ad hoc categories [5] to be used. Ad hoc categories are categories that are created to suit a precise need, as opposed to a category such as *semi-detached* which is more general. For example, an auctioneer might be interested in finding all semi-detached houses in his area that are situated in a cul-de-sac. He could define an ad hoc category to this effect, which would return the results he needed. This is just one example of how categorisation can be useful to businesses.

5. Conclusion

In the beginning of this paper it was stated that qualitative spatial reasoning could be used to solve GPAs. This was achieved by examining the spatial relationships between objects in GPAs, along with the attributes that each object has. *Jess* allows the solution to each analogy to be inferred, independent of any set of possible solutions. The solution generated is independent of size, shape and orientation.

Although *Jess* can be used to solve regular GPA problems, topographic maps were focused on in order to show how this technique could work successfully with real-world applications. Point in polygon classification and incremental structure matching were looked at in detail. Classifying houses using point in polygon classification yields results that are more accurate than template matching alone.

Incremental structure matching allows composite structures, such as schools and hospitals, to be identified. These structures could not be identified using previous methods as they are irregular and thus do not conform to a template.

The use of point information in both examples is essential in order to obtain accurate results. Ignoring point information reduces the ability to successfully categorise objects in topographic maps.

Although further testing is needed, it appears that *Jess* provides a successful method for solving both regular GPAs and GPAs in topographic maps.

Acknowledgements

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