SEMI-AUTOMATIC PARTITIONING BY VISUAL SNAPSHOPTS

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Abstract: It is stated that a closer intervention of experts in knowledge discovery can complement and improve the effectiveness of results. Normally, in data mining, automated methods display final results through visualization methods. A more active intervention of experts on automated methods can bring enhancements to the analysis; No meanwhile that approach raises questions about what is a relevant stopping stage. In this work, efforts are made to couple automatic methods with visualization methods in the context of partitioning algorithms applied to spatial data. A data mining workflow is presented with the following concepts: data mining transaction, data mining save point and data mining snapshot. Moreover to display results, novel visual metaphors are changed allowing a better exploration of clustering. In knowledge discovery, experts validate final results; certainly it would be appropriate to them validate intermediate results, avoiding, for instance, losing time, when in disagreement, starting it with new hypnoses or allow data reduction by disable an intermediate cluster from the next stage.

1 INTRODUCTION

A geospatial dataset (in Geographic Information Systems (GIS) a layer) is compounded by semantic and spatial attributes and emulates the design of some kind of phenomena that occurs in the surface of the earth. An organization can collect many geospatial datasets all large in volume and high-dimensionality. Many factors contribute to the accumulation of spatial data in organizations. For instance, the mobility of people increases the development of Location Based Applications that monitors people and goods. Organizations always have collected information with a geographic component, for instance: addresses, phone numbers and events (where did something happen). Also disciplines related to earth sciences have a strong spatial component.

The unprecedented large size and dimensionality of existing datasets make the complex patterns that potentially lurk in data hard to find (Guo, Peuquet, & Gahegan, 2003). Spatial data has a complex and specific nature bringing particular issues to the discovery of hidden patterns – extracting knowledge from spatial datasets is a multivariable, multilayer and multi data type problem. No meanwhile, the spatiality can enrich the analysis by bringing graphic elements (like thematic maps).

There are three main approaches to extract knowledge from geospatial datasets (Demsar, 2006): (*i*) **spatial data mining**. Invent new spatially aware data mining algorithms; (*ii*) **spatial pre-processing**. Model spatial properties and relationships in pre-processing followed by the application a common data mining algorithm; and (*iii*) **exploratory geo-visualization**. Apply visual data mining to spatial data allowing the analyst, by visualization, to interact directly, identify patterns, and draw conclusions.

In this work the last approach is used. A partitioning algorithm is chanced in order to display intermediate results so that experts can interact more deeply with the automatic method.

Only experts can interpret and validate the results produced by clustering. The high dimensionality and volume of datasets makes it difficult to find the right clusters. Frequently, results are in disagreement with specialists' intuition (Guo,

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Gahegan, MacEachren, & Zhou, 2005) and (Nam, Han, Mueller, Zelenyuk, & Imre, 2007).

The involvement of users (experts) in intermediate stages allowing then to understand the flow of the automatic process can bring interesting results to the analysis, since, experts have a more comprehensive view about attribute values and attribute combination. In their knowledge domain they are the better agents to explore attribute combination. Moreover, different experts can have different interests in the analysis. They can formulate new hypotheses after exploring attributes or attribute values, focus on one know pattern and continue the process in order to make some conclusions.

In this paper a semi-automatic approach to cluster spatial data is presented. A partitioning algorithm is monitored. Through visualization experts can make conclusions observing both spatial and non-spatial results produced in intermediate stages of execution. They can, for instance, conclude that a cluster has already been found. Because, in knowledge discovery, results have the expert validation, in this kind of system experts should also validate, previous, intermediate results.

For instance, the expert detects that objects, of a cluster, have similar geographic location and confirms some logic in attribute combination. Then he considers that a cluster has been found. In this scenario, the implicated objects can be removed, making the next stage, of the automatic method, lighter.

Displaying intermediate results has a main problem: when and how the automatic method should be stopped. Moreover users should have an interactive interface to allow a convenient exploration of attribute combination (discovering relevant values for cluster formation).

This paper pretends to answer the following questions: (*i*) What is the workflow of semi-automatic process?; (*ii*) What is a stopping condition?; (*iii*) How to display and allow the exploration of intermediate results produced by spatial clusters?. This paper is organized as follow: the next section makes an overview of spatial clustering algorithms, visual data mining and related work. In section 3 we propose an interaction model for visual and spatial clustering. In section 4, as prove of concepts a case of study is presented. Finally we make some conclusions and point out future work.

2 BACKGROUND CONCEPTS

In this work, our automation method, is a *medoid* algorithm, namely, PAM (Partitioning around Medoids) (Kaufman & Rousseeuw, 1990). It makes an exhaustive search in order to produce effective results. Commonly *medoid* algorithms are applied in problems that process distances between geospatial entities. For instance, discover the most central points of a metropolitan region; discover the best location for water pumps, in a city, with thousands of buildings, (being the water pumps considerer the *medoids*).

Visual data mining combines concepts from data mining and information visualization, and integrates algorithms with graphic elements enabling data display and user interaction.

There are a large discrepancy between computers and humans. Computers can automatically process large amounts of data faster than humans but are incapable of interpreting results. On the other hand humans are able to interpret visual results recognizing patterns more efficiently then computers (Demsar, 2006), (Nam, Han, Mueller, Zelenyuk, & Imre, 2007) and (Keim, 2002). The process of clustering could be improved if both automated and visual capabilities were more deeply integrated enabling an additional active participation of experts in the knowledge discovery process.

Next we make a closer look at PAM. Later we make an overview of visual data mining. Finally, we identify related work of relevance.

2.1 K-medoids Algorithms applied to Spatial Data

Partitioning methods reallocate iteratively objects to clusters in order to gradually improve the quality of the final result. The more known partitioning methods are: *k-means*, *k-medoids* and *fuzzy* clustering. *k-means* and *k-medoids* find disjoint clusters; in *fuzzy* clustering all objects have some probability of belonging to all clusters. *k-means* and *k-medoids* algorithms differ in their central object – the first uses a gravitational point, the later a representative object (*medoid*).

The most know *k-medoids* algorithms are: *Partition Around Medoids* (PAM) (Kaufman & Rousseeuw, 1990), *Clustering Large Applications* (CLARA) (Kaufman & Rousseeuw, 1990) and *Clustering Large Applications Based in Randomized Search* (CLARANS) (Ng & Han, Efficient and Effective Clustering Methods for Spatial Data Mining, 1994).

In PAM: **First** a proximity matrix is computed storing the distance between all pairs of objects. Normally the distance is the Euclidian and expresses absolute differences in values of dimensions. **Second** a first group of *medoids* are randomly chosen. **Third** the distance of all objects to all *medoids* is computed (cost matrix) and objects (called *non medoids*) are associated to the closest *medoid*. **Fourth** verify for each *medoid* if there is a *non medoid* that produces a better cluster. If so, a permutation must be done (*non medoid* is promoted to *medoid* and the *medoid* passes to *non medoid*). A new cost matrix is computed and *non medoids* are reallocated again. The process continues until permutations no longer exits.

Because of the exhaustive search PAM is considered effective and efficient for small datasets. To overcome PAM efficient problems CLARA and CLARANS have been proposed. In CLARA, PAM is applied to samples extracted from a dataset. CLARANS is compared to a search in a graph where each node represents a group of medoids; two nodes are neighbors if they differ in one medoid and a jump between two nodes is persecuted if a neighbor of a node produces better clusters. CLARANS is considered better than CLARA because the randomize search is applied to all dataset being independent of the quality of samples.

In partitioning methods, attributes are projected in space and objects are represented in a plane by points. Their distance mirrors their similarity. The adaptation of traditional partitioning algorithms to spatial data is trivial since spatial data is commonly represented by points and distance is one of the most important spatial relationships. Even though particular changes in algorithms have happen because of the spatial data types (beyond points there are lines and polygons); and spatial relationships (beyond distance there are direction or topology). For instance particular algorithms addresses: (*i*) **spatial object heterogeneity**. Computing distances between points, lines and polygons needs particular attention. Polygons have irregular shape and occupy a region. The similarity function can't be computed using the Euclidian distance and the irregularity of polygons has computational costs. In (Ng & Han, CLARANS: A Method for Clustering Objects for Spatial Data Mining, 2002) three ways for computing polygons distances are compared. They conclude that the best way is to compute distances between polygons using the closest points between polygons approximations (*ii*) **obstructions**. When computing distances between two spatial objects, others spatial objects can obstruct the way, for example, two buildings can be separated by a river being their distance dependent on the location of the bridge. In (Wang & Hamilton, 2005) and (Tung, Hou, & Han, 2001) changes are made in PAM, CLARA and CLARANS for dealing with obstruction; and (iii) **roads and paths**. In the surface of the earth, human's movements are made using roads so, distances between two spatial objects can be a function of the distance within roads (Ibrahim, 2005).

2.2 Visual Data Mining: Architectures, Visual Tools and Issues

Large datasets cause serious problems for visualization techniques and these problems can be divided in two groups (Guo, Gahegan, MacEachren, & Zhou, 2005): (*i*) **computational efficiency problem** (time needed to process the data); and (*ii*) **visual effectiveness problem** (display of large datasets makes patterns hard to find and perceive).

Software architectures that integrate visualization in data mining can be classified as (Ankerst, 2000): (*i*) **visualization of final results**. Helps interpret results allowing their comparison and verification. An algorithm extracts patterns from the data and patterns are displayed for human observation. Based on the interpretation, the user may want to return to the data mining algorithm and run it again with different input parameters (figure 1.a); (*ii*) **visualization of intermediate results**. An algorithm performs an analysis of the data but at some intermediate step results graphically displayed. Then the user retrieves interesting patterns and make decisions about the next step (figure 1.b); and (*iii*) **visualization of data**. Data is visualized immediately without running a sophisticated algorithm before. Users explore the dataset and can, for instance, reduce data or attributes that are used as input for algorithms (figure 1.c).

Visual data mining can bring greet enhacements to the analysis, no meanwhile it is a challenge task, since a multidimensional space has to be displayed in a 2D screen. Furthermore human visual system can´t process system simultaneously a large number of graphic elements. Example of information visualization techniques are scatter plots, histograms and bar graphics.

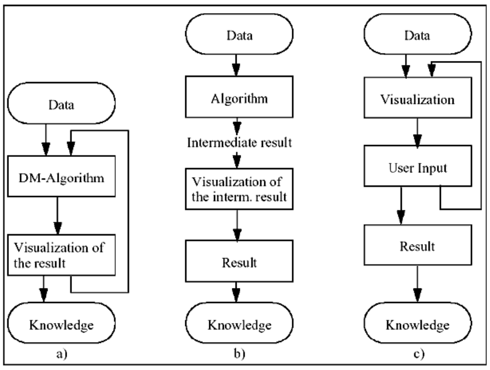
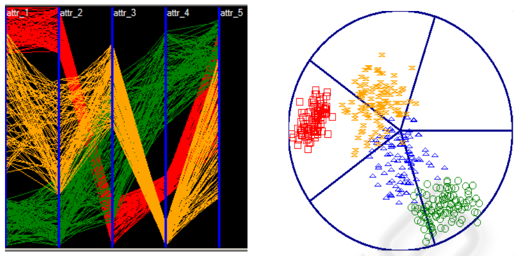


Figure 1: Architectures for Visual Data Mining.

Novel information visualization techniques have been defined allowing a better exploration analysis of large and multidimensional data sets. Most know techniques are (Kantardzic, 2003): (*i*) **Geometric projection techniques**. Projections for multidimensional datasets; normally concerned with the display of multidimensional spaces in a 2D plane; (*ii*) **Icon-based techniques**. Display small icons to represent attribute values; (*iii*) **Pixel-oriented techniques**. Each object in the dataset is represented by a pixel; and (*iv*) **Hierarchical techniques and graph**. Information is displayed like in a graph or hierarchy. Works like (keim 2002) make an overview of these tecnhiques and tools.

Next we describe some visualization tools related to this work. They are: (*i*) **Parallel Coordinate Plots (PCP)** (Inselberg, 1985). The objective is to represent a multivariable dataset in a 2D plane (like a screen of a computer). A backdrop is drawn consisting of *n* equally spaced parallel lines each one representing a dimension (figure 2.a)). For each object a polyline is drawn and the position of the vertex on the *i-th* axis corresponds to the *i-th* coordinate of the object;
(ii) **Radial Visualization** (Hoffman, 1999). Its goals are similar of PCP but the plane is represented by a circle with axes equally spaced. The number of axes is equall to the number of dimenions. An object makes a physical strength in the *i-th* axe similar to the *i-th* coordinate and a representative point is drawn where the sum of all forces is zero (figure 2.b)). This tool enables an analysis of the efforts made by dimensions. It is also a way to visually display the structure or geometry of clusters; (*iii*) **Self Organized Maps** (SOM) (Kohonen, 1990) produces low dimension representation of training samples while preserving the topological properties of the input space. Useful to visualize, in a low dimensional space, high dimensional data. It consists in two steps. First a traning stage is made to build the map with samples. Then a mapping stage is performed to classify the input data. Each object is represented by a vector with values from dimensions. The object is associated to the cell with the most similar vector



a)Parallel Coordinate Plot b) Radial Visualization

Figure 2: Example of geometric techniques.

2.3 Related Work

In (Nam, Han, Mueller, Zelenyuk, & Imre, 2007) a visual tool, called *cluster sculptor*, is presented for exploring large and high dimensional datasets. The clustering engine implements a *k-means* algorithm. Users are allowed to tune parameters interactively, like: geometry, composition and spatial relations. Their environment has tools for visually explore hierarchical classifications by means of an interactive dendrograma (operations like zoom, merge and moving object between clusters).

In (Guo, Gahegan, MacEachren, & Zhou, 2005) an integration of computational, visual and cartographic methods is studied in order to visualize multivariable spatial patterns. SOM is coupled with a colour scheme to summarize a large amount of data. Other novel visual data mining tool is PCP: used to help interpreting multivariable patterns.

In (Demsar, 2006) investigates if combining automated and visual data mining is suitable approach for exploring geospatial data. The work proves that novel visual elements, like snowflake graphs, and SOM can be integrated with automatic data mining algorithms like helping experts investigate geodatasets.

In (Guo, Chen, MacEachren, & Liao, 2006) present a novel geo-visual analytical strategy for exploring and understanding spatial-temporal and multivariable patterns. They also develop a methodology to cluster, sort, and visualize large datasets with spatial data allowing experts to investigate large and complex patterns in spatial and temporal dimensions.

3 A MODEL FOR VISUAL AND SPATIAL CLUSTERING

As already stated, in a spatial cluster there are objects with both semantic and spatial attributes; it means, that clustering can be applied in miscellaneous approaches. We propose the following approaches, to get spatial clusters: (*i*) **non-spatial oriented**. Apply the algorithm only to semantic attributes. The spatial attribute is displayed in a thematic map (spatial object, of the same cluster, are drawn with the same color). This spatiality of clusters enables the identification of regions with similar behaviors. Inside a spatial cluster, objects can be near, spread all over the space or have some pattern correlated with some relationship with another geographic phenomenon; (*ii*) **spatial and semantic oriented**. Apply algorithms both to semantic and spatial attributes (separately). A thematic map is generated with two different iconographic elements: one for semantic patterns and other with a spatial pattern; (*iii*) **spatial oriented.** Apply the algorithm to the spatial attribute. For instance, identify the most central entities of a layer (e.g., in a large area, where are urban centres?); and (*iv*) **multi-spatial oriented**. Apply algorithms to different layers tracking spatial relationships, like topology, distance and directions. This approach avoids pre-processing relations between layers, making it possible to parameterize spatial relations on-the-fly.

In this work, we use the **non-spatial oriented approach**, and implement a visual data mining architecture based on the **visualization of intermediate results** (as presented in figure 1.b). .

In the context, of intermediate results visualization, we formulate the following questions: What is a stopping condition? How to handle more than one stopping condition? When visualization should be persecuted? What visual elements should be used? Which actions should be allowed?.

We make the following considerations: **First** experts are responsible for specifying relevant stop condition, since they have more experience and intuition about datasets; **Second** there must be some flexible but controlled form to specify those stopping stages, protecting the automatic process against meaningless setting; **Third** in algorithms an unit of work should be enclosed, to watch and check his state; **Fourth**, since there are a large numbers of dimensions and objects users can configure many stopping condition.

Next we make some definitions about concepts for a spatial and visual data mining system. We call the **visual data mining workflow**.

3.1 Visual Data Mining Workflow

In a semi-automated method a visual data mining workflow is a group of visual data mining transactions (one for every stop condition). A save point detect a stop condition whose state can be displayed through a visual snapshot. Next we make a detail explanation of those concepts.

Definition 1. **Unit of work**. In *medoid* oriented algorithms, a step is a unit of work that ends with clustering (group of clusters) and has a timestamp. The clustering state is measured computing: (*i*) **inter-cluster and intra-cluster similarities**, for instance, the number of objects, min, max and average distance, distance between *medoids*, cohesion and separation; (*ii*) **is_link_pattern.** Intermediate patterns about values in dimensions considerer relevant.

Definition 2. **Visual save point**. Happen when a clustering has a state in agreement with a stop condition, parameterized by experts. The automatic method stops and gives rise to the visual method, expressing the status of the current clustering.

Definition 3. **Visual and spatial snapshot**. Graphic elements that express the state of a visual save point and enables some level of interaction.

Definition 4. **Visual data mining transaction**. A relevant condition. In the context of a visual data mining workflow experts can configure many visual data mining transactions (conditions). No meanwhile the can be none or many save points.

Figure 3 shows the concepts associated to the visual data mining workflow. The automated method is coupled with the visual method.

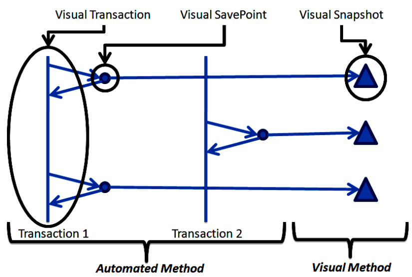


Figure 3: Visual Data Mining Workflow.

How to stop the automatic method? We propose three main parameterizations: (*i*) **Using 'must link'**. Subdivide into: *Stop using semantic states* – some combination of values in a sub group of attributes;

Stop using spatial states – geographic objects can have specific relationships with other geographic layers. For instance, in urban crime experts can declare that violent crimes happen near old buildings (the system looks to the relationship, in each cluster, between the location of crimes and old buildings); (*ii*) **stop with periodicity**. Use a regular step interval; and (*iii*) **stop using similarities between steps**. Verify if a constant metric is present between clustering (from step to step) – if so maybe a cluster has already been found.

Figure 4 presents a diagram showing the interaction between automated and visual methods.

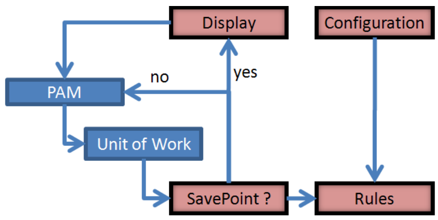


Figure 4: Stopping the process.

3.2 Exploring Clusters

An abstraction of a cluster is made using an ellipse, whose **size**, **colour** and **position** are in agreement with properties of clusters. A thematic map is generated by cluster (each cluster has a different colour). If the dataset is large, instead of displaying geographic objects, a geometric approximation can be computed, for each cluster, allowing a more suitable observation.

The visual elements for exploring clusters are: (*i*) **Cluster Abstraction.** A group of ellipses represents a group of clusters; (*ii*) **Interactive PCP.** Understand the data distribution inside and between clusters; and (*iii*) **Interactive RV**. Understand data distribution and structure inside and between clusters.

The interaction model has synchronized granularity managed and controlled by a central component (controls the parameterization of colours and the display of clusters and attributes).

3.2.1 Visual Abstraction of Clusters

The ellipse is rendered on screen on a position computed by the spring model stated in section 2.2. The spring model enables the computation of central points in screen using values of *medoids*. Figure 5a) shows an ellipse where the number of axes is equal to the number of attributes (four). In each axe the strength is equal to the attribute value. Figure 5b) shows the equilibrium point (central point).

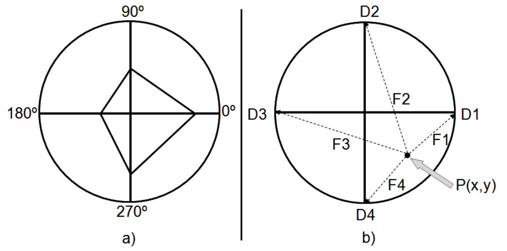


Figure 5: Computing the screen central point of a cluster using the *medoid.*

In equation 1, α represents an angle, β is the angle step and d_α is the value made, at α, by a dimension d.

$$\omega \sum_{i=1}^{n} F_i = 0 \Leftrightarrow \begin{cases} x = \omega \sum_{\alpha=\alpha+\beta}^{360°} \cos(\alpha) \times d_\alpha \\ y = \omega \sum_{\alpha=\alpha+\beta}^{360°} sen(\alpha) \times d_\alpha \end{cases} \quad (1)$$

3.2.2 Interactive PCP

PCP is a component that projects the spectrum of clusters through dimensions translating an *n* dimension space in a 2D space. Using a colour scheme is possible to distinguish clusters from each other. By observing the map and the PCP users have a legend for interpreting the projection of dimensions in the map (Guo, Gahegan, MacEachren & Zhou (2005)). No meanwhile, more can be done.

In this work, interactive exploration is improved by allowing: (*i*) **attribute reorder**. The expert sets relevant attributes side by side in order to compare them and conclude, for instance, that in a cluster the combination of some attribute values are correct; (*ii*) **attribute zooming**. The expert makes a closer look at some detail in a dimension in order to better understand how values spread over the dimension. If all clusters have a similar value in a dimension then users can conclude that the dimension doesn't have a strong influence in the identification of clusters and so can be removed in a subsequent step; (*iii*) **attribute hide**. Similar to reorder but dimension disappear from the component; (*iv*) **cluster cut**. Turning clusters visible or invisible allowing a better observation of one or some clusters; and (*v*) **attribute move**. Automatic had-doc position ordering by exchanging plane positions allowing the observation of all possible combinations in dimensions; (*vi*) **store the picture**. In a black box execution, the current projection of clusters in PCP, can be stored as an image in disk enabling a future analysis; (*vii*) **values cut**. Using the mouse users can draw a rectangle in order to watch, in the PCP, only objects whose values are inside some selected area excluding values that are not interesting; **change**

layout. Experts can make a new thematic parameterization of clusters changing colors, size of lines.

3.2.3 Interactive RV

Interactive RV also projects an *n* dimensional space in a 2D space. In this case, dimensions are axes of an ellipse making it possible to observe the combination of strengths made by dimensions (higher or lower values). It uses colors and icons to render clusters.

This component has the same operations with the same meaning retracted in *Interactive PVP*, namely: (*i*) **attribute reorder**; (*ii*) **attribute zooming**; (*iii*) **attribute hide**; (*iv*) **cluster cut**; (*v*) **attribute move**; (*vi*) **store the picture**; and (v*ii*) **values cut**; (*vii*) **change the layout**.

The image produced by this component makes it possible to analyze the spatial structure of clusters in a 2D space. Tracking intermediate stages by storing images produced by this component enables a dipper comprehension about how clusters are formed along the time.

All actions in RV also have impact in the map and the PCP. Also in the map an operation (topology, distance, and direction) restricts the data that is displayed in others components.

4 CASE OF STUDY: ANALYSING AN URBAN INFRASTRUCTURE

In order to identify the benefits of the described concepts, a scenario related to an urban drainage infrastructure, implemented in small urban areas, is used for experiments. Users are allowed to identify correlations inside a spatial cluster and between spatial clusters. The approach is non-spatial oriented. The spatial dataset has a geographic attribute representing pieces of the network having each the following semantic attributes:

Year: (<1975, [1980-1985], 1[987-1994], >1994).

Status: A classification of the actual situation of a chunk (active, proposed, future).

Station: A classification of the type of station for residual water treatment (ETAR, FOSSA)

Material: (Material, Class). A classification of material used to build the network (GRES, PVC, PVCC).

The algorithm PAM was changed stopping at configured save points and displaying intermediate results. The dataset has 400 objects and 4 dimensions. Results for four clusters are presented.

Figure 6 shows an image with spatial clusters obtained after the application of the automatic method. The size of ellipses expresses the amount of objects allocated to clusters. In thematic maps, the color used to paint a geographic object identifies his cluster. In the ellipse a label identifies her *medoid*.

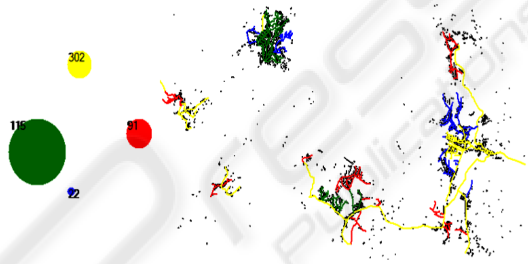


Figure 6: Visualization of spatial clusters.

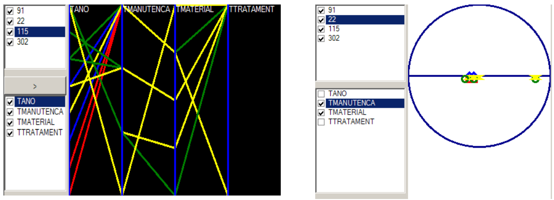
The **green cluster** (115) is the largest, being their spatial component concentrate in two areas; after overlapping the map with a layer of buildings, it can be pointed out that geographic objects are concentrated in the middle of urban areas. The **red cluster** (91) is located at non-dense regions (rural regions). **The yellow** (302) cluster is associated to the highest networks (the ones that are connecting small rural regions). Finally, the **blue cluster** (91) takes place in low concentrated regions.

After this visual interpretation, a closer look to semantic attributes can be persecuted allowing the interpretation of the semantic and spatial correlations.

In figure 7 the interactive PCP and interactive RV are displaying attributes and dimensions to users; through a set of checkboxes is possible to execute on the fly combinations of clusters with dimensions.

The image figure 7.a) shows that objects have very similar values at adjacent dimensions like **tmanutencao** and **tmaterial** since lines that connect them are overlapped (yellow lines belong to the last rendered cluster). This can have two meaning: (*i*) dimensions do not contribute to cluster formation; or (*ii*) small differences can be a factor to a cluster formation if the others dimensions are more similar.

In figure7.b) RV confirms object similarity in the two dimensions by showing that the distribution of objects along those two dimensions is concentrated.

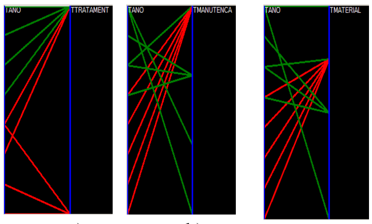


a) Interactive PCP (all dimensions and attributes)

b) Interactive RV (only some dimensions)

Figure 7: Interactive PCP and Interactive RV.

In figure 8 sample images of interactive PCP are presented.

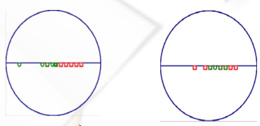


a) b) c)

Figure 8: Visual combining of attributes.

The user performs a **cluster cut** selecting only the two largest clusters (**green** and **red**), in order to comprehend then. Then it performs **attribute hide** in order to analyze the behaviour of the dimension labeled **tano**. It can be pointed that the two clusters have more similarities between labeled dimensions **tano** and **ttratamento** (figure 8.a)).

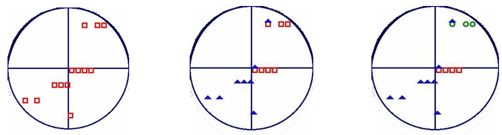
Users can be confused about which pair of attributes are more similar: **(tano, tmanutencao)** or **(tano, tmaterial)**. Using RV with only those dimensions users can, for instance, conclude that the pair **(tano,tmaterial)** is more dissimilar than **(tano, ttratamento)** since, in the first pair, objects are more spread over dimensions (figure 9).



a) b)

Figure 9: Using the interactive RV to visually discover similarities in dimension.

Figure 10 shows images about visual save points related to a visual data mining transaction. It is possible to observe the evolution of the clustering process along the time and make some conclusions. For instance, between save points 2 and 3 the structure of a cluster (blue triangles) is maintained which can mean that a cluster match has been reached.



a) SavePoint 1 b) SavePoint 2 c) SavePoint 3

Figure 10: The evolution of a clustering process displayed in RV and stored in disk.

In a large dataset, the process could be improved if a prior cluster is found. Users are allowed to stop the current automatic method and start it with a lower number of objects, by eliminating the ones that belongs to a validated cluster (data reduction) or eliminating dimensions that do not make a strong contribution to cluster discovery (dimension reduction).

In a large dataset, experts can stop the current automatic method and start it with a lower number of objects, eliminating the ones that belong to valid clusters already discovery.

5 CONCLUSIONS AND FUTURE WORK

In this work a visual data mining system is presented allowing some degree of interaction with intermediate stages of automatic methods. The concept of spatial data mining transaction is defined has a group of visual save points that are in agreement with a user stop condition. In a visual save point a visual snapshot is generated showing result of intermediate steps. In it experts can conclude that a cluster as been found by exploring attribute values combination. For that visual data mining tools like PCP and RV are implement with new operations allowing better attribute exploration (like reorder, zooming, hide). Future work will be done at the automatic method level by trying to improve the interaction with clustering enabling a more suitable way of attribute and data reduction.

REFERENCES

Ankerst, M. (2000). Visual Data Mining (PhD Thesis). Munich: Institute of Computer Science, University of Munich.

Demsar, U. (2006). Data Mining of Geospatial Data: Combining Visual and Automatic Methods. Stockholm: Royal Institute of Technology (KTH).

desJardins, M., MacGlashan, J., & Ferraioli, J. (2007). Interactive Visual Clustering. Proceedings of the 12th international conference on Intelligent user interfaces (pp. 361 - 364). Honolulu, Hawaii, USA : ACM Press

Gahegan, M., & Brodaric, B. (2002). Computational and Visual Support for Geographical Knowledge Construction: Filling in the gaps between exploration and explanation. Advances in Spatial Data Handling, Proceedings of the 10th International Symposium on Spatial Data Handling.

Guo, D., Chen, J., MacEachren, A. M., & Liao, K. (2006). A Visual Inquiry System for Space-Time and Multivariable Patterns (VIS-STAMP). Transactions on Visualization and Computer Graphics , 12 (6), 1461-1474.

Guo, D., Gahegan, M., MacEachren, A. M., & Zhou, B. (2005). Multivariate Analysis and Geovisualization with Integrated Geographic Knowledge Discovery Approach. Cartography and Geographic Information Science , 32 (2), 113-132.

Guo, D., Peuquet, D. J., & Gahegan, M. (2003). ICEAGE: Interactive Clustering and Exploration of Large and High-Dimensional Geodata. GeoInformatica (pp. 229-253). The Nertherlands: Kluwer Academic Publishers.

Hoffman, P. (1999). Table Visualization: A Formal Model and Its Applications (PhD Thesis). Lowell LA, USA: University of Massachusetts Lowell.

Ibrahim, L. F. (2005). Using Clustering Algorithm CWSP-PAM for Rural Network Planning. Third International Conference on Information Technology and Applications (ICITA'05) (pp. 280-283). Sydney: IEEE Computer Society.

Imrich, P., Mueller, K., Mugno, R., Imre, D., Zelenyuk, A., & Zhu, W. (2002). interactive Poster:Visual Data Mining with the Interactive Dendogram. Information Visualization Symposium.

Inselberg, A. (1985). The plane with parallel coordinates. Visual Computer , 1 (4), 69-81.

Jiang, B. (2004). Spatial Clustering for Mining Knowledge in Support of Generalization Process in GIS. ICA Workshop on Generalisation and Multiple Representation. Leicester, United Kingdom.

Kaufman, L., & Rousseeuw, P. (1990). Finding Groups in Data: An Introduction to Cluster Analysis. John Wiley & Sons.

Kantardzic, M. (2003). Data Mining: Concepts, Models, Methods, and Algorithms. Danvers, MA, USA: John Wiley & Sons.

Keim, D. A. (2002). Information Visualization and Visual Data Mining. IEEE Transactions on Visualization and Computer Graphics , 100-1007.

Kriegel, H.-P., Kunath, P., Pfeifle, M., & Renz, M. (2006). ViEWNet: Visual Exploration of Region-Wide Traffic Networks. Data Engineering, 2006. ICDE '06. Proceedings of the 22nd International Conference on (pp. 166-166). Atlanta, USA: IEEE Computer Society.

Koua, E. L., MacEachren, A., & Kraak, M.-J. (2006). Evaluting the usability of visualization methods in an exploratory geovisualization environment. International Journal of Geographical Information Science , 20 (4), 425-448.

Liu, W., Seto, K. C., & Sun, Z. (2005). Urbanization Prediction with ART-MMAP Neural Network Based Spatial-Temporal Data Mining Method. 5th International Symposium Remote Sensing of Urban Area (URS 2005), XXXVI. Tempe, AZ, USA.

May, M., & Savinov, A. (2004). SPIN! AN ENTERPRISE ARCHITECTURE FOR DATA MINING AND VISUAL ANALYSIS OF SPATIAL DATA. In B. Kovalerchuk, & J. Schwing, Visual and Spatial Analysis (pp. 293-317). Dordrecht, The Nertherlands: Springer.

Nam, E. J., Han, Y., Mueller, K., Zelenyuk, A., & Imre, D. (2007). ClusterScultor: A Visual analytics Tool for High-Dimensional Data. IEEE Symposium on Visual Analytics Science and Technology 2007 . Sacramento, CA.

Ng, R. T., & Han, J. (2002). CLARANS: A Method for Clustering Objects for Spatial Data Mining. IEEE Transaction on Knowledge and Data Enginnering , 14 (5), 1003-1016.

Ng, R. T., & Han, J. (1994). Efficient and Effective Clustering Methods for Spatial Data Mining. 20th VLDB Conference. Santiago, Chile.

Schulz, H.-J., Nocke, T., & Schumann, H. (2006). A Framework of Visual Data Mining of Structures. 29th Australasian Computer Science Conference (pp. 157-166). Hobart, Australia: Australian Computer Society, Inc.

Tung, A. K., Hou, J., & Han, J. (2001). Spatial Clustering in the Presence of Obstacles. 17th International Conference on Data Engineering (ICDE'01). washington, DC, USA: IEEE Computer Society.

Torun, A., & Duzgun, S. (2006). Using Spatial Data Mining Techniques to Reveal Vulnerability of People and Places Due to Oil Transportation and Accidents: A Case Study of Istanbul Strait. Proceedings of the ISPRS Vienna 2006 Symposium, (pp. 43-48). Vienna.

Wan, L.-H., Li, Y.-J., Liu, W.-Y., & Zhang, D.-Y. (2005). Application and Study of Spatial Cluster and Customer Partitioning. Fourth International Conference on Machine Learning and Cybernetics (pp. 1701-1706). Guangzhou: IEEE.

Wang, X., & Hamilton, H. (2005). Clustering Spatial Data in the Presence of Obstacles. International Journal on Artificial Intelligence , 14, 177-198.

Zhang, X., Wang, J., & Wu, F. (2006). Spatial Clustering with Obstacles Constraints Based on Genetic Algorithms and K-Medoid. IJCSNS International Journal of Computer Science and Network Security , 6 (10), 109-114.