# On-line Spectral Learning in Exploring 3D Large Scale Geo-Referred Scenes

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**Abstract.** Personalized navigation of 3D large scale geo-referred scenes has a tremendous impact in digital cultural heritage. This is a result of the recent progress in digitization technology which leads to the creation of massive digital geographic libraries. However, an efficient personalized 3D geo-referred architecture requires intelligent and on-line learning strategies able to dynamically capture user's preferences dynamics. In this paper, we propose an adaptive spectral learning framework towards 3D navigation of geo-referred scenes. Spectral clustering presents advantages compared to traditional center-based partitioning methods, such as the k-means; it effectively categorize non-Gaussian, complex distributions, present invariability to shapes and densities and it does not depend on the similarity metric used since learning is performed through similarity matrices by exploiting pair-wise comparisons. The main difficulty, however, in incorporating spectral learning in a 3D navigation architecture is its static implementation. To handle this difficulty, we propose in this paper an adaptive framework through the use of adaptive spectral learning which tailors 3D navigation to user's current needs.

**Keywords:** spectral clustering, 3D navigation, adaptation, personalization.

## 1 Introduction

With the recent progress of digitization and information technology 3D geo-informatics have emerged and entered in their digital era [1], [2]. Google Earth and Microsoft Virtual Earth are house hold names towards this direction. The conception and construction of 3D urban and building models lead to the creation of massive digital geographic libraries with tremendous impact perspective in digital cultural heritage. Examples include the Virtual City (V-City) project supported by the EU with the aim of research, develop and validate an innovative system for the rapid and cost-effective reconstruction and visualization of complete, large-scale and interactive urban environments [3]. The use of a 3D interactive framework for navigating cultural heritage sites and artefacts allow a closer adhere to the real world, increasing user's cultural experience and revealing the relationships among cultural heritage parts.

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However, an intelligent personalized 3D geo-informatics architecture requires, apart from semantically enriched knowledge tools able to facilitate the description of cultural heritage objects, on-line learning algorithms able to capture the user's preferences dynamics, required for the creation of user centric geo-referred routes [4]. Currently, personalised route planning systems use a set of explicit textual metadata to describe users' preferences [5]. However, such approaches present the drawback that the textual metadata cannot describe the rich geographical content [6], [7] and users' preferences cannot be modelled through a simple set of keywords. To address the aforementioned difficulties, the work of [8] introduces an ontological framework to better describe the properties of 3D cultural heritage objects. However, again ontology is a static description framework.

An approach towards this direction has been presented in [9]. The method presents an efficient and personalized route planning system based on the incorporation of an active learning algorithm able to model user's preferences through few training samples. The learning algorithm exploits an inductive-based methodology using ordering tools through pair-wise comparisons. A set of two 3D cultural heritage models are projected to the user, who evaluates them as a strong recommendation of being the one more preferred (or less preferred) than the other. Then, an overall ordering is obtained from the set of pair-wise comparisons [10]. Marco and Micro path route planning is proposed that exploit the inductive learning and a combination of optimization strategies, personalized entropy criteria and metadata propagation tools.

One shortcoming of the approach of [9] is that learning simulates *an ordering rather than a clustering methodology*. Thus, with [9], we are not able to provide similarities / dissimilarities between the 3D models by grouping them into clusters of common entities. Another shortcoming of [9] is that ordering method in not *adaptive*. Each time a new preference judgment is provided by the user, as a feedback for updating user's preferences, object ordering is performed from scratch, decreasing computational efficiency.

To address these shortcomings, in this paper, we propose an innovative adaptive spectral clustering algorithm suitable as regards personalized 3D navigation of 3D cultural heritage items. Spectral clustering presents advantages compared with traditional centred-based methods, such as the k-means algorithm. This is mainly due to the fact that spectral clustering is able to categorize effectively non-linear, complex distributions [11]. Traditional centred -based approaches explicitly or implicitly assume a metric or a similarity structure over the space of configurations [11]. However, the success of such methods heavily depends on the choice of the metric, but this choice is not a part of the learning process. To alleviate the metric influence, constrained k-means methods have been proposed in the literature, like the one of [12]. Spectral clustering introduces a different framework; learning is performed through the construction of similarity matrices [13].

The main drawback to incorporate spectral learning in a personalized 3D navigation architecture is its static implementation. Spectral learning is an off-line algorithm, meaning that it cannot incrementally update clustering results as a small change of the data set is concerned. To handle this aspect, we propose an incremental spectral clustering methodology that permits dynamic modelling of user's preferences [14]. In particular, we adopt an eigenvalue updating strategy [14] that exploits aspects of perturbation theory and allows spectral clustering evolution as new preference judgments is feedback to the system. In the following, we exploit the results of the adaptive spectral learning for creating groups of relevant/ irrelevant objects (according to current user's preferences) which are then used for the creation of personalized routes.

## 2 Cultural Heritage Object Characterization

Initially, all the 3D objects are modelled through a set of quantitative and qualitative parameters (i.e., features). Table 1 presents an overview of the metadata adopted in this paper. The qualitative metadata are included in the feature vector as Boolean values indicating the existence or not of the specific property. Pre-defined values has been adopted as regards the presentation of the qualitative metadata. In the following, we denote as $\mathbf{f}_u$ the feature vector which is used for representing the metadata of a 3D cultural heritage object $u$.

**Table 1.** The Qualitative and Quantitative Metadata used to describe a 3D geo-referred object

| Metadata of a 3D Geo-referred Object | | | | | | |
|---|---|---|---|---|---|---|
| Qualitative | | | | Quantitative | | |
| Building Style | Construction Material | Building Location | Used for | Geometry | Age | Other |
| Modern, Neoclassical | Wood, Marble, Clay, Glass, Stone, Metal, Cement | Downtown, Suburb | Office, construction business, Museum, Gallery, School, University, Shop, Town mall, Restaurant, Church, Monument, Archeological site | Length, Width, Height, altitude, Latitude | Ancient, Medieval, Contemporarily, … | Cost of visit, interactivity, additional multimedia content, popularity |

## 3 On-line Spectral Learning

In this section, we describe an on-line spectral learning strategy, which is used for modelling the dynamics of the user's preferences. On-line learning addresses the semantic gap problem arisen during the development of a personalized 3D navigation architecture; the low-level features extracted to represent a 3D object (see Section 2) are not able to represent the high level concepts that human use to interpret these objects. The proposed on-line learning strategy exploits user's interaction feedback as regards the preferred judgment between two objects and, in the sequent, incorporates advanced adaptation mechanisms able to dynamically modify the significance of the object's metadata with respect to the user's preferences.

Our on-line learning approach is based on a pair-wise object comparison. In particular, a user evaluates the importance of a 3D object with respect to another based on a highly interactive framework. We adopt this strategy, since it minimizes user's interaction and thus providing a convenient way in implementing a personalized 3D navigation; each time a user compares only one 3D object versus another. Then, the algorithm propagates the feedback information to all the stored objects in the scene.

### 3.1 Spectral Representation

Spectral representation in classification presents many advantages compared to the traditional center-based approaches (see [13]). In particular, spectral representation has the advantage of performing well with non-Gaussian clusters as well as being easily implementable. Another very important advantage of the spectral clustering is its invariability to shapes and densities, increasing, therefore, the performance in complex classification scenarios. Fig.1 presents the advantages of a spectral representation. As is observed, spectral clustering is able to classify more complex distributions compared with the traditional partition based approaches. The Red colored point of clouds is supposed to belong to one class, while the Blue colored to another.

(a) (b)

**Fig. 1.** The advantages of the spectral representation algorithms. They are able to cluster efficiently the above illustrated distribution where the conventional center based approaches fail. The Red colored distribution is supposed to belong to one class, where the Blue one to another.

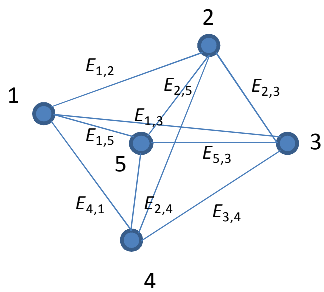


**Fig. 2.** A graph is created by a pair wise user's interaction process. Each time a user compares two 3D object again one each other. This way, we create an association between the two selected objects.

In spectral representation, a graph is considered as the most appropriate mathematical structure. In particular, let us denote a G={V, E} the respective graph. The vertex of the graph V indicates the selected 3D objects, while the respective edge the relationship between the two respective objects (provided by the preference judgments of the user through pair-wise comparisons). Fig.2 illustrates the respective graph formulated among, say five 3D objects, without loss of generality.

Using the graph representation, we are able to apply the spectral clustering algorithm with the purpose of estimating groups of 3D objects that simultaneously satisfy the following two basic properties

1. The degree among all objects in a class is as maximum as possible, while simultaneously
2. The degree among all objects between two separate classes is as minimum as possible.

Usually, a normalized cut spectral graph partitioning algorithm is adopted. This choice was made because the traditional spectral graph partitioning min cut algorithm [15] would favor the creation of too many small partitions. Let us denote as $D(A,B)$ the similarity between two arbitrarily sub-graphs $A$ and $B$. The distance $D(\cdot)$ is denoted as follows

$$D(A,B) = \sum_{i \in A} \sum_{i \in B} E_{i,j} \, , \tag{1}$$

where we recall that $E_{i,j}$ indicates the relationship between the 3D objects $i$ and $j$ respectively. Let us now denote the degree metric $d_i$ as

$$d_i = \sum_j E_{i,j} \, . \tag{2}$$

Then, for each sub-graph A and B, we can denote the volume of the graphs Vol(A) and Vol(B) respectively.

$$Vol(A) = \sum_{j \in A} E_{i,j} \text{ and } Vol(B) = \sum_{j \in B} E_{i,j} \, . \tag{3}$$

The normalized cut aims at minimizes the following inter-cluster metric

$$\min: InterCut = \frac{D(A,B)}{Vol(A)} + \frac{D(A,B)}{Vol(B)} \, . \tag{4}$$

It has been proven in [15] that minimization of eq. (4) simultaneously lead to the maximization of the intra-distance relationship between all the sub-graph nodes

$$\max: IntraCut = \frac{D(A,A)}{Vol(A)} + \frac{D(B,B)}{Vol(B)} \, . \tag{5}$$

Therefore, equation (5) lead *to min-max optimization solution*. The solution to the aforementioned normalized cut problem is obtained through the usage of an generalized eigenvalue problem of the form

$$(\mathbf{D} - \mathbf{E}) \cdot \mathbf{x} = \lambda \cdot \mathbf{D} \cdot \mathbf{x} \, , \tag{6}$$

where E denotes the adjacent matrix of the graph of the Fig. 2 as created by the feedback of the user in the form of preference judgments between pairs of selected 3D objects. Matrix **D** is defined $\mathbf{D} = diag(\cdots d_i \cdots)$, whose elements $d_i$, i=1,2,...,$N$, are equal to the cumulative comparison degrees of $d_i = \sum_j E_{ij}$ [see eq.(2)].

### 3.2 Recursive Implementation

As we have stated above, in a personalized navigation and geo-referred architecture the data points and their similarities are dynamic. This means that the similarities between two objects can be dynamically changed through time due to the dynamic nature of user's preference. Therefore, the main question is how we can recursively solve the aforementioned system by taking into account new user's feedback as a result of new user's judgment statements. Fig.3 presents an example as regards the evolution of the data expressed through a graph similar to the approach adopted in Fig.2.

In Fig.3 (a), we have presented the graph of Fig.2 along with the similarities values between the five compared 3D objects. Instead, in Fig.3 (b), we have presented an updated graph with two value of two edges have been modified. This is presented in the graph as Red colour. Therefore, a question is how we can estimate the new spectral classes from the graph (groups of nodes -3D objects- of maximum Inta-similarity, and simulteneouly minimum Inter-similarity) by taking into consideration the information provided by the initial graph. This results in a recursive implementation of the spectral graph clustering problem, which is very important for the proposed 3D personalized navigation architecture due to the dynamic nature of the user's judgments.

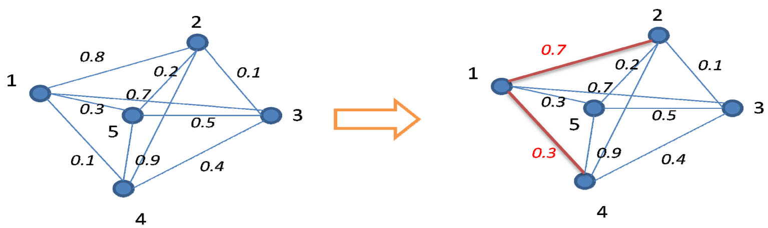


**Fig. 3.** An example of the evolution of the graph created through a dynamic pair-wise comparison process. a) The initial graph and b) the updated graph. We have indicated as Read color the edges and the values of the graph that have been changed from the initial state.

According to the results of [14], we can solve a generalized eigenvalue problem recursively. More particularly, we have that the perturbation of the generalized eigenvalues satisfies the following formula

$$\Delta\lambda = \frac{\mathbf{x}^T(\Delta\mathbf{A} - \lambda\Delta\mathbf{B})\mathbf{x}}{\mathbf{x}^T\mathbf{B}\mathbf{x}}, \tag{7}$$

where $\mathbf{x}$ refers to the generalized eigenvectors of the generalized eigenvalue system of the form $\mathbf{A}\mathbf{x} = \lambda\mathbf{B}\mathbf{x}$, while $\Delta\mathbf{A}$ and $\Delta\mathbf{B}$ indicates the small perturbation of the matrices **A** and **B** respectively of the generalized eigenvalue system. Matrices **A** and **B** is equal to the matrices **A=D-E** and **B=D** of eq. (6). Using equation (7) and the fact that **A=D-E** and **B=D**, we can derive an algorithm for updating the generalized eigenvectors according to the small perturbation of the values of matrices **A** and **B**. In particular, according to the results of [14], we can estimate that

$$\Delta\mathbf{q} = (\mathbf{K}^T\mathbf{K})^{-1}\mathbf{K}^T\mathbf{h} \quad . \tag{8}$$

where $\mathbf{K} = \mathbf{D} - \mathbf{E} - \lambda\mathbf{D}$ , $\mathbf{h} = (\Delta\lambda\mathbf{D} + \lambda\Delta\mathbf{D} - \Delta\mathbf{L})\mathbf{q}$

However, the main drawback of (8) is that **K** still remains high. To overcome this difficulty, we adopt an approximate approach. As similarity change of two objects *u* and *v*, we expect little influence on data far from *u* and *v*. Therefore, matrix **K** is formulated only for the nodes (objects) within the sub-graph over which the graph is updated. Thus, we have a much small matrix $\mathbf{K}_s$, obtained from the sub-graph $\mathbf{D}_s$ which is used in eq. (8).

# 4 3D object Importance Estimate

The aforementioned algorithm is used for estimate a set of *M* classes that contains objects of similar properties with respect to user's preferences. In the following, several variations can be used for estimation of a route to satisfy user's profile.

*Scenario 1*: One solution is to select one 3D object from the *M* discrete classes. This leads to a selection of *most uncorrelated* 3D objects covers a spherical view of a city tour. In particular, let us denote as $R_i$, $i$=1,…,$M$, the *M* class representatives. Then, we can select these *M* 3D objects as the most salient to the user's preferences.

*Scenario 2*: Another version is to select all the 3D objects that belong to the most important class (according to the user's profile). The most important cluster can be estimated through the exploitation of user's interaction. In particular, the most representative 3D object of a class, say the $R_i$, can be compared against the remaining representatives. Among the two compared, the one of the greater value wins. Thus, in case of comparing $R_i$ and $R_j$, we select the one that are ranked ahead of the other. The algorithm proceeds iteratively to the other representative classes. This way, we can estimate the most representative 3D objects and 3D virtually represented them according to the user's preferences.

## 4.1 Estimation of the 3D Object Importance

In order to estimate the importance of the 3D objects in the scene, we exploit the objects' metadata and we assign a weight for each feature element.

$$S(u) = \Sigma\, w_u^j f_u^j \ , \tag{9}$$

where $f_u^j$ denotes the *j*-th feature element for object *u*, while $w_u^j$ the respective weight. Our purpose is to estimate the weights through the results of the adaptive spectral learning algorithm.

In particular, let us estimate the most $\hat{K}$ relevant objects according to the user's preferences as provided by the adaptive spectral learning algorithm. Then, we can estimate the weight factors $w_u^j$ as the inverse ratio of the standard deviation of the respective feature element over all data $\hat{K}$ selected objects. In particular, let us denote as $\mathbf{f}_{ui_1}$, $\mathbf{f}_{ui_1}$, …, $\mathbf{f}_{ui_{\hat{K}}}$ the feature vectors for the first $\hat{K}$ selected objects. Then, the weight factor are given as

$$w^j = \frac{1}{std(f_{ui_1}^j, f_{ui_2}^j, ..., f_{ui_{\hat{K}}}^j) + \delta} \quad (10)$$

where the std(.) denotes the standard deviation operator, while the $f_{ui_m}^j$ ,m=1,2,…, $\hat{K}$ the j-th element of feature vector $\mathbf{f}_{ui_m}$ . Equation (10) means that similar values of a feature element among all the $\hat{K}$ preferred objects lead to a large weight factor since in this case the respective feature element seems to be consistent with respect to user's preferences. On the other hand, large deviation values indicate no significance for the respective feature element. To avoid instability issues occurred by a zero division, we have added a small constant value $\delta$ to the denominator of (10).

## 5 Simulations

In this paper the personalized route planning platform have been developed using the Google Earth Building maker tools, which they have been integrated into the collaborative web GIS platform developed in our research laboratory. Each building was reconstructed as a 3D object model and each face of the 3D model was described using the metadata and the respective ontological model presented in this paper. The platform exploits the Google Earth plug-in and the Google Earth virtual environment to visualize 3D geographical data. In addition, we have developed a front end interface that contains the adaptive spectral learning algorithm.

Fig. 4 presents the results expressed as the precision-recall curve [16]. The precision-recall curves expresses how relevant is the selected 3D objects to the user's preferences. For a "perfect" system, both precision and recall should be high (ideally equal one). We, therefore, observe that the proposed method outperforms the compared approaches. This is mainly due to the advantages of the spectral learning method; it can partition complex non-Gaussian distributions and provides invariability in terms of shapes and densities.

Moving forward the two aforementioned different scenarios were simulated using real building from the downtown of Athens. In our experiment several 3D models of building were used. Figure 5 presented the distribution of buildings. The classification of the buildings has been marked with color on the bounding box of each. In this figure, we have examined the two different scenarios as discussed in Section 4.

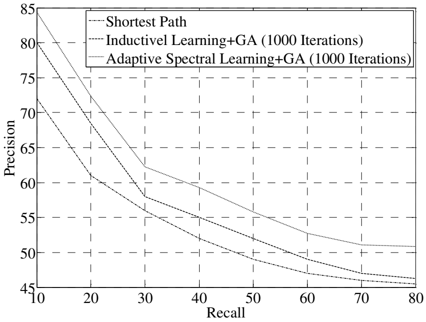


**Fig. 4.** The precision recall curve as regards the proposed algorithm compared with the shortest path optimization strategy and the inductive learning of [9]

**Fig. 5.** The generated paths as a result of the implementation of the two different scenarios discussed in Section 4; purple line indicates the scenario2, where the objects within a particular class are depicted; instead blue line indicates the case where one object from each of the 4

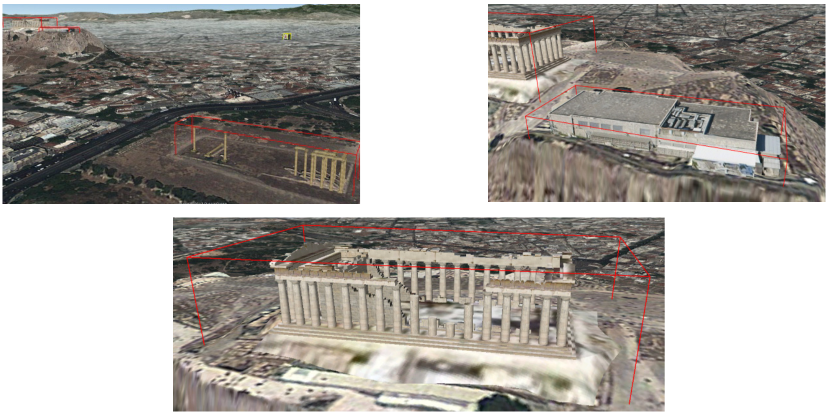

**Fig. 6.** The selected 3D objects of the scenario2 (Purple line Path of Fig.5)

In particular, the blue line presents the path with the most uncorrelated 3D models (Scenario 1); the extracted objects belong to each of the 4 created classes. On the other hand, the red line indicates the implementation of the scenario 2, where only the buildings of one class (and especially the historical objects) are presented. Fig. 6 zooms in the selected 3D object of the scenario 2 (purple line).

# 6 Conclusions

In this paper, we have proposed an adaptive spectral learning algorithm for capturing user's preferences dynamics. This is incorporated into personalized 3D navigation architecture of geo-referred scenes. Our results indicate the proposed methodology outperforms the current state of the art methods in estimating better the dynamics of user's preference under a computationally efficient framework.

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