A Constraint Inductive Learning- Spectral Clustering Methodology for Personalized 3D Navigation

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Abstract. The recent advances in ICT boost research towards the generation of personalized Geographical Information Systems (p-GIS). It is clear that selection of a route based only on geometrical criteria, i.e., the route of the shortest distance or the minimum travel time, very rarely coincides with a "satisfactory itinerary" that respects users' preferences, that is their desires to navigate through buildings or places of his/her own particular interest. Additionally, 3D navigation gains more popularity compared with 2D approaches especially in virtual tourist and cultural heritage applications. In a p-GIS, user's preferences can be set manually or automatically. In an automatic architecture, user preferences are expressed as a set of weights that regulate the degree of importance on the route selection process and on line learning strategies are exploited to adjust the weights. In this paper, the on-line learning strategy exploits information fed back to the system about the relevance of user's preferences judgments given in a form of pair-wise comparisons. Then, we use a constraint fusion methodology for the dynamic modeling of user's preference in a 3D navigation system. The method exploits an active inductive learning approach that is combined with an adaptive spectral clustering scheme in order to avoid smoothing during the weight adjustment process.

1 Introduction

A Personalised Route Guidance System is a geographically-enriched decision support system that incorporates methods for automatic or semi-automatic, in the sense of minimum users' interaction, route selection by exploiting user, geographical and 3D object metadata [1],[2]. It is clear that selection of a route based only on geometrical criteria, i.e., the route of the shortest distance or the minimum travel time, very rarely coincides with a "satisfactory itinerary" that respects users' preferences, that is their desires to navigate through buildings or places of his/her own particular interest.

However, creation of an architecture for personalised route planning requires, on the one hand, (i) advanced knowledge methodologies able to facilitate efficient description of the geographical information,(i.e., *the feature extraction process*) and,

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on the other, (ii) dynamic *on-line learning strategies* that relate the extracted metadata with the user's preferences dynamics. However, it is clear that extraction of representational features is a challenging and application-dependent process [3]. This is mainly due to the so-called *"semantic gap"*; humans perceive content with high level concepts that cannot be modelled with the extracted low level features [4].

Another difficulty towards a truly personalised route planning arises from the *human's subjectivity* [5]. Different persons or even the same under different circumstances perceive the same visual content quite differently leading to several issues in user profiling [6]. This means that there is no a unique mapping scheme that relates the extracted low-level metadata (features) with the high-level concepts [7], [4]. The current, personalised route planning architectures use a set of explicit metadata (usually textual) to describe user's preferences [9]. Such systems are called "adaptable personalized route guidance systems". On the contrary, the systems that use an automatic procedure in the user's preferences estimation are called "adaptive personalized route guidance systems" [10]. In both cases, weights are used to regulate the degree of importance of each feature element on route selection [2]. In the manual case, the weight values are explicitly provided by the user, while in the automatic case, the weights are provided by the system based on an on-line learning algorithm. However, setting manually the weights is a very demanding process, since there is no a quantitative association between user's preferences and feature metadata. Our research, is focused on automatically setting the weights.

1.1 Previous Work

Usually, the current personalized route guidance systems exploit an explicit methodology for defining the weight values [2], [9], which are, then involved in multi-criteria optimization strategies for best route selection. To address the inconsistency of describing the rich geographical media content with low level descriptors, the work of [9] introduces an ontological framework. In this way, [9] provides a better description of the semantics of geo-referenced and contextual information, such as tourist attraction, road safety issues (telephone, medical assistance, etc) and road facilities (gas station, services, terminal). However, this work focuses only on the ontological representation and fails to provide on-line learning strategies, which are necessary for a truly adaptive architecture. Another approach incorporates symbolic information with visual components, extracted through the application of image processing tools to provide a cognitive spatial path planning [11]. However, again, this work is focused on a better organization of the metadata (textual or visual) that describes the geographical content, instead of modelling user's preferences. A different approach is presented in [2] where multi-criteria strategies are presented for best route selection.. However, again the focus is on the optimization for the best route instead of personalization. In the same context (e.g., route path creation) there are works that use agents for route planning [12]. However, still the personalization aspects are limited.

1.2 Contribution

In this paper, we propose an adaptive personalized route guidance system for cultural heritage purposes. The architecture exploits a constrained fusion methodology that combines active inductive learning with spectral clustering algorithm. In particular, our method, in contrast to the current approaches, estimates 3D paths which are more suitable for cultural heritage purposes. Additionally, our research automatically estimates the weight values which are associated with metadata elements used to describe the rich geographic media content. Automatic estimation of the weights values is performed through on-line learning strategies based on a pair-wise comparison methodology; the metadata weights are adjusted by information fed back to the system about the relevance of user's preferences judgments given in a form of pair-wise comparisons.

Using a small set of pair-wise compared elements, we construct a graph that dedicates the degree that one object is preferred against another. In this way, our research exploits an on-line inductive learning algorithm that based on constructed preferred judgments graph calculates an overall ordering of the depicted to the user objects according to his/her information needs. The overall object ordering is used to initially estimate the weights of metadata elements provided an initial estimation of user's preferences. Then, an adaptive spectral clustering algorithm is implemented to partition the ranked objects into a set of disjoint classes. We select spectral clustering as it provides good classification capabilities for non-Gaussian, complex distributions. The outcome of the spectral clustering is constrained with the outcome of inductive learning to formulate a non-linear best route selection scheme being optimized on the use of a genetic algorithm. In contrast with previous approaches like [13], the proposed constrained methodology increases the capabilities of modeling user's preferences. This is mainly due to the fact that few extreme preferred objects are classified into different classes and therefore their influence on the route selection is not averaging by the remaining many preferred objects.

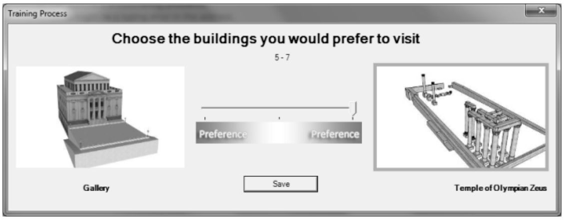

Fig. 1. The *pair wise comparison process:* The National Gallery of Athens is presented against the Temple of Olympian Zeus and the user selects the Olympian Zeus Temple

2 Modeling User Preferences through Pair-Wise Comparisons

The first step of the proposed architecture is to extract features, that is, metadata, that describe the attributes of the cultural objects. In this paper, we use as features the ones presented in the [13]. For clarity of presentation, we briefly describe, in the following section, the features used. Following the feature extraction process, the second step of the proposed architecture is to automatically estimate the weight values that regulate the degree of importance of the feature elements involved in the route selection process. In this paper, the automatic estimation of the weight values is performed through a pair-wise comparisons scheme. In particular, initially the system depicts to the user two randomly selected cultural heritage objects and forces the user to select the most preferred one between the two. Fig. 1 indicates an example of our pair-wise process adopted in this paper to trigger the on-line learning algorithm used for the automatic estimation of the weight values that model user's preferences.

2.1 Cultural Heritage Attributes

Quantitative and qualitative metadata are used to describe the attributes of a cultural heritage object [13]. Qualitative metadata includes the type of building use, the building style, the construction material, the building location, attractive content and the type of city block. Each of the aforementioned qualitative metadata get predefined values. For example, construction material can be wood, marble, clay etc. On the other hand quantitative metadata includes the building cost of visit, interactivity, popularity, age and geometry. In the following, we denote as $\mathbf{m}_{o_i} = [m^1_{o_i}\ m^2_{o_i}\ ...]^T$ the metadata vector of an object o_i, where $m^i_{o_i}$ is the i-th attribute of the object o_i.

3 Active Inductive-Based Learning Process

Let us also denote as $g(\cdot)$ a user preference function defined as

$$g(u,v): SxS -> [0\ 1]. \tag{1}$$

where $u, v \in S$ are two selected objects (see the previous Section). Function $g(u,v)$ defines the order between the object pair (u,v) with respect to user's preferences. Variable $g(u,v) \to 1$ means a strong recommendation of being u more preferred. The opposite is happened in case of $g(u,v) \to 0$, whereas a value around ½ indicates an abstention of making any recommendation.

Using the pair-wise recommendations, we form a graph $G = \{V, E\}$ where variable V indicates the vertices while variable E the edges of the graph. It is clear that the vertices of the graph coincide with the number of objects depicted to the user for the pair-wise comparison, denoted as N. Instead, the graph edges coincide with values of function $g(u,v)$ of Eq. (1). An example of the constructed graph is depicted in Fig. 2.

Using this graph, we are able to perform an overall ordering of all objects depicted to the user according to his/her preferences [14]. As mentioned in [14], to derive the overall order is a NP-hard problem. To overcome this problem, the authors of [14] present an approximate algorithm to compute the overall ordering of the depicted CH objects to the users. Let us denote as $\beta(u)$ a value that indicates the difference between the outgoing and ingoing edges. It is clear that large value for the outgoing metric means that object u is highly preferred, while the opposite is held for the ingoing metric. Variable $\beta(u)$ is estimated through the following equation

$$\beta(u) = \sum_v g(u,v) - \sum_v g(v,u). \tag{2}$$

Using variable $\beta(u)$, we can define a greedy algorithm to approximate the overall ordering of the CH objects depicted to the user. In particular, the greedy algorithm proceeds as follows: Initially, we select as the most suitable object, the one that maximizes the value of $\beta(u)$ and therefore, the respective node is removed from the graph. In the next step, the values of the remaining objects (vertices) of the graph are potentially updated and the node is the next maximum value of $\beta(u)$ is selected as the most appropriate. This process is iteratively repeated until no nodes are included in the graph. The aforementioned recursive approach is presented in Fig. 2. .

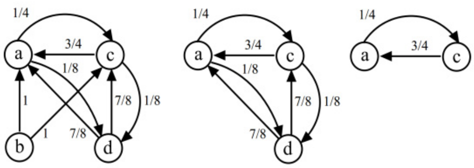

Fig. 2. The greedy algorithm used to estimate the overall ordering. In the leftmost graph object b will assign the maxima value and will be deleted, resulting to the middle graph. Then, node d will assign the maxima value of $\beta(u)$ and thus it will be deleted, leading to the rightmost graph. Finally, node c will be ranked ahead a. Therefore, we have b>d>c>a [14].

The main advantage of the proposed algorithm is that it can provide an estimate of the overall ordering of the objects of the graph, by exploiting only pair-wise comparisons. The main limitations is that the inductive learning algorithms a) fail to direct estimate the weight values associated of the metadata elements of the objects to model users' preferences and b) therefore is not able to generalize the results to objects that are not depicted for judgment by the user. To address the aforementioned limitation, we combine in the following a clustering algorithm with the active inductive learning in order to categorize the ordered objects into clusters of similarity.

4 Spectral Clustering

Spectral representation in classification presents many advantages compared to the traditional center-based approaches (see [15]), since it has the advantage of performing well with non-Gaussian and complex clusters as well as being easily implementable. Using the graph representation presented in Section 3, we are able to apply the spectral clustering algorithm with the purpose of detecting the common distributions among the selected preferred objects. In contrast with the aforementioned described active inductive learning algorithms, spectral clustering partitions the depicted objects to the user into groups of common properties. In the continuous case the algorithm optimize the following equation

$$(\mathbf{D}-\mathbf{E})\cdot\mathbf{x}=\lambda\cdot\mathbf{D}\cdot\mathbf{x}\,. \tag{3}$$

where **E** denotes the matrix of the edges of the graph (see for example the graph of Fig.2 as created by the feedback of the user in the form of preference judgments between pairs of selected 3D objects), while **D** is a diagonal matrix $\mathbf{D}=diag(\cdots d_i \cdots)$, whose elements d_i, i=1,2,...are the cumulative degrees of $d_i = \sum_j e_{ij}$.

Rounding the aforementioned solution into the district space of the K available classes, we result the final clusters of the spectral algorithm. However, rounding is an NP-hard process [16]. A simple rounding process is to set the maximum value of each row of the eigenvector matrix, derived as a solution of (3), equal to 1, while the remaining values equal to zero.

5 Best Route Selection

Using the active inductive learning algorithm, we have the order of the objects selected by the user. let us rank objects u in descending order according to their values $\beta(u)$. Let us denote as $u_{i_1}, u_{i_2}, u_{i_3,...}$ the first, second, third, … ranked object of S respectively. It is held that $\beta(u_{i_1}) \geq \beta(u_{i_2}) \geq \beta(u_{i_3}) \geq \ldots$. Then, we can select $M<N$ (recall that N refers to the total number of objects depicted to the user) objects according to the energy of the M first ranked objects, defined by the values of $\beta(u_{i,j})$.

On the other hand, using the spectral clustering algorithm, we are able to estimate a set of K classes that contain objects of similar properties.

The first step of the fusing algorithm is to estimate the weights of the metadata that regulate the degree of importance of the features-elements to the selection score.

$$S(u) = \sum w_u^j f_u^j \ , \tag{4}$$

where f_u^j denotes the j-th feature element for object u, while w_u^j the respective weight. The weights w_u^j are estimated by the first M ranked objects as provided by the inductive learning algorithm. In particular, the weight factors w_u^j are estimated as the inverse ratio of the standard deviation of the respective feature element over all the M selected objects.

$$w^j = \frac{1}{std\,(m^j_{u_{i_1}}, m^j_{u_{i_2}}, ..., m^j_{u_{i_M}}) + \delta}, \tag{5}$$

where the $std(\cdot)$ denotes the standard deviation operator, while the $m^j_{u_{i_m}}$,m=1,2,…, M the j-th element of metadata vector $\mathbf{m}_{u_{i_m}}$.

Equation (5) means that feature elements that share similar values among all the M objects lead to large weight values (small standard deviation) since in this case the respective feature element seems to be consistent with respect to user's preferences. The opposite happens in the non consistent case. Using Eq. (4), the best personalized route is selected as the one that optimizes the following equation

$$C = \gamma_1 \cdot S(\vartheta(r,1)) + \gamma_2 \cdot S(\vartheta(r,2)) + \ldots, \tag{6}$$

where $\vartheta(r,m)$ is an operator that returns the m-th object of route r and γ_i weight factors. In [13], a genetic algorithm is used to solve the aforementioned optimization problem. It should be mentioned that, in contrast to this work, in [13] additional terms have been included to estimate the best route, such as affective properties. Other alternatives exist in the literature (see [2]) a quantifier-guided ordered weighted averaging (OWA) aggregation operator is adopted for selecting the best route.

5.1 Inductive Learning Constrained by Spectral Clustering

The aforementioned procedure for estimating the best route does not take into account the results obtained from the spectral clustering algorithm. In other words, the values of the weight metadata are estimated by the order of the selected objects as provided only by the inductive learning. The main limitation of this approach which is also adopted in [13] is that a cultural object that significantly differs from other similar objects but it may be salient for the user, it cannot affect the weights in such a degree to play an important role in route selection. This is mainly due to the fact that Eq. (5) is in fact an averaging operator that smoothes extreme user's preferences.

To compensate this drawback, we fuse in this paper, the results obtained by spectral clustering on the solutions provided by the inductive learning. In particular, we classify the *M* ranked objects according to the available clusters provided by the spectral method. Therefore, we can define a probability distribution of user's preferences with regards to the *K* available classes.

$$p(i) = \frac{n_i}{M}, i = 1,.., K \text{ , with } \sum_{i=1}^{K} n_i = M \tag{7}$$

Using eq.(7) we can define the probability distribution of a route *r*. In particular, let us denote as *r* a route that consists of *M* objects $r = \{u_1, u_2, u_3, .., u_M\}$. Then, we can define the probability f the route *r* to belong to one of the *K* available classes provided by the spectral clustering algorithm,

$$p_r(j) = \frac{\sum_{i=1}^{M} Index(u_i, j)}{M} \tag{8}$$

where operator $Index(u_i, j)$ =1 if the object u_i belongs to the j-th cluster out of *K* available and $Index(u_i, j)$ =0 otherwise. Having estimated the probability of a route *r* to belong to one of the *K* available clusters, we can estimate the probability distribution as the concatenation of the probabilities $p_r(j)$ over all clusters *j*=1,2,…,*K*.

$$Pdf(r) = \{P_r(1), P_r(2), ...P_r(K)\} \tag{9}$$

Using the previous equation, we can modify the route selection process as follows;

$$C = \begin{cases} \gamma \cdot S(\vartheta(r,1)) + \gamma_2 \cdot S(\vartheta(r,2)) + & if \;\; Pdf(r) \approx Pdf^{(user)}(r) \\ 0 & otherwise \end{cases} \tag{10}$$

In eq. (9), *Pdf(r)* is the probability density of the route *r* as defined in Eq. (8), while $Pdf^{(user)}(r)$ denotes the targeted probability density of the route *r* provided by the user's judgments.

6 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 of Section 2. Furthermore, we assume that all the 3D models have five faces only (the face that points to the ground is not evaluated).

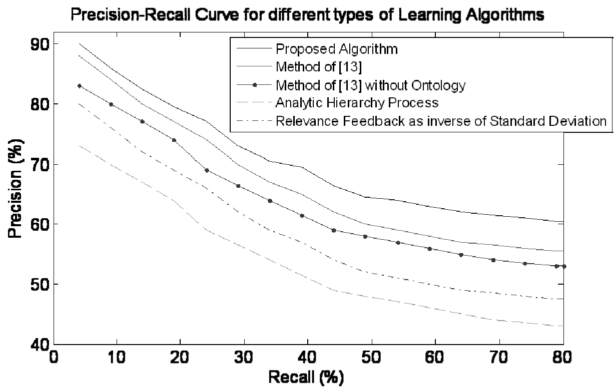

Fig. 3. Comparisons of the proposed personalized route selection algorithm with other approaches

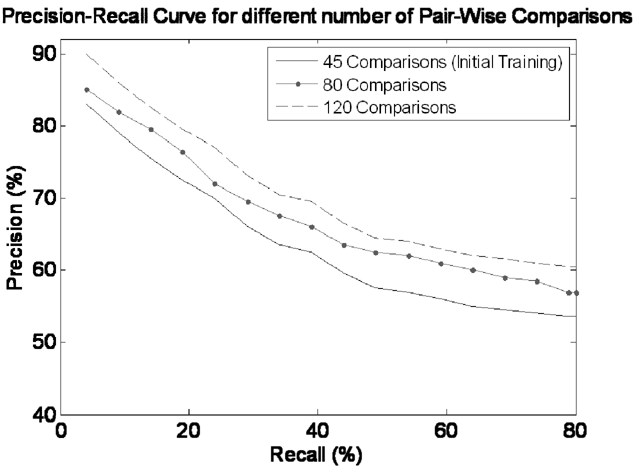

Fig. 4. The effect of the number of objects depicted to the user *N* on the system performance

In the following, we present experimental results that indicate performance of the proposed fusion algorithm that constraints inductive learning with spectral clustering.

Figs. 3 depicts the precision recall curve of the proposed algorithm compared with other approaches used for route selection, while Fig. 4 presents the precision-recall curve with respect to the number of objects depicted to the user, that is the number of pair-wise comparisons.

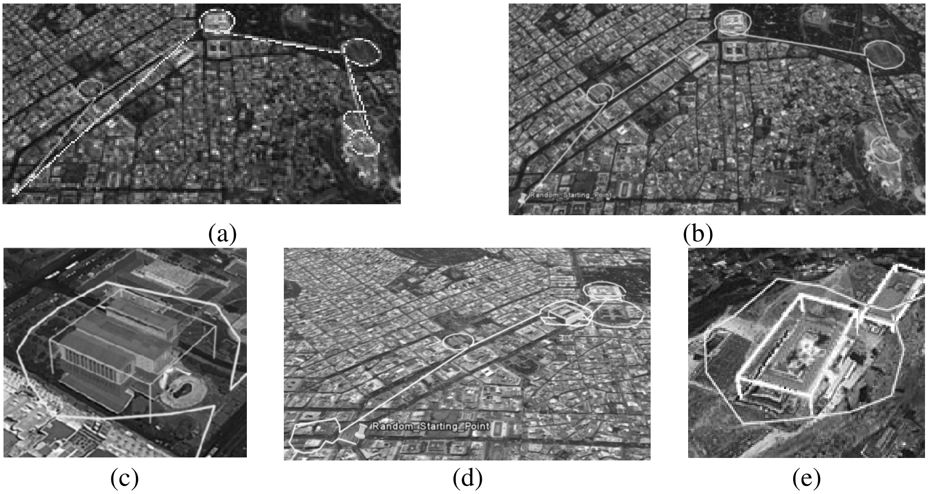

Fig. 5. (a) Generated path with the proposed algorithm compared with the method of [13], (b) Generated path using method of [13], (c,e) Zoom in two preferred 3D objects of the itinerary retrieved by the proposed genetic algorithm approach, (d) Generated path using Dijkstra shortest path algorithm.

Fig. 5 presents a subjective (qualitative) evaluation of the proposed genetic optimization strategy. Simulation results have been performed, according to the scenario that the user prefers archaeological places and buildings of neoclassical architectural style in his/her 3D navigation. In this figure we compare the results with the method of [13] and with the results of the shortest path using the Dijkstra's algorithm. In particular, the shortest path algorithm yields the shortest navigation route that connects SP and FP points. On the contrary, the proposed algorithm selects one building from the cluster with the green buildings (neo-classical buildings) and three from the cluster with the red ones (archeological sightseeing), as the user prefers more to visit archeological sightseeing than visiting neo-classical buildings. The path is presented with purple line on Fig. 5(a). On the other hand the according to approach of [13] includes in the itinerary objects that are most preferred by the user without any classification {yellow path Fig. 5(a,b)}. Fig. 5(c,e) zooms in two of the preferred objects of the itinerary extracted by the viewing algorithm.

As is observed, in the first case, the Temple of Olympian Zeus was selected as most appropriate as user prefer to see archeological sites more than visiting neo-classical buildings. The first building belongs to the cluster of archeological buildings which id more preferred by the user.

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