Exhibition-Area Segmentation Using Eigenvectors

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Abstract

In the information age, people feel overwhelmed by information. Large museums are often overwhelming for first time visitors, especially people with limited time. Without professional assistance in exhibition design and arrangement of objects, this issue becomes impossible for them to narrow down the most significant pieces to see. This paper introduces a systematic approach by collecting the visitor information such as the circulation in exhibition space. Then, we can exploit the visitor information to segment exhibition space inherent in circulation behavior of visitors. The segmentation of exhibition space can be achieved with the eigendecomposition of the covariance matrix of the characteristic vectors obtained from visitor dwell time for each time slot. Eigenvectors take advantage of the capability of showing the (first, second, third, and forth) most important circulation behavior of visitors as well as examining the degree of dominance of their corresponding. We, then, adopted the theory of graph spectra for partitioning the exhibit spaces. In experiments, we applied the segmentation approach to the data set obtained from the virtual and real museums: 36 avatars at the Ritsumeikan gallery in Second Life and 45 real visitors at the MIT museum in order to discovering groups of strongly coherent exhibits. The implications are also discussed in the paper.

Keywords*: Visitor Circulation, Eigendecomposition, Museum Environment, Virtual Worlds*

1. Introduction

In museums and galleries, the arrangement of their collections is one of the most important key factors that affect visitor impression and satisfaction. The curators, who are in charge of the collections, decide how the objects will be displayed and arranged. They present the collections in an exhibit based on the coherence between objects so that the well-arranged exhibit can tell the story to the visitors. Consequently, the efficiency of the exhibit arrangement has depended upon curators' experience.

The visitor circulation through museums and galleries will determine what visitors will see, where they focus their attention, and, ultimately, what they learn and/or experience [1, 2]. The move of visitors is not dominated by exhibits but implicitly driven by the space syntax as investigated by [2]. However, the observation time that a visitors spends on a particular exhibit corresponds to the visitor attention and interest. A number of researches have been published on how people move through museums for many years but none of them addressed the exhibit arrangement correlating to the observation time of visitors.

Related to on-site activities, people plays the games related to their location via their GPS-based device [3, 4, 5] as well as they can interact with robots and enjoy seeing the robot show [6]. Such activities have a purpose to improve museum visits and entertain visitors especially school kids. The visitor records during their museum trip are also useful for enhancing the functionalities of exhibitions including collecting, organizing, displaying, etc. On the other words, the byproduct of these activities is an implicit indicator reflecting to the engagement and enjoyment of visitors.

In this paper, we introduce how to apply eigendecomposition to a problem of exhibit arrangement. Eigenvectors are derived from the covariance matrix of visitor circulation. We can partition off the exhibit space by grouping together similar objects in the same partition. The objects in the exhibit judged as the same or different groups are determined by the set of primary behaviors of the visitors.

The primary behaviors are derived from the repeating and common movements of visitors in the same space. For example, in a museum, the most popular objects where a number of visitors spend more time are a potential factor to construct the common behavior structures.

To validate our proposed approach, we tested the approach against the synthesized data of 36 visitors following the four characteristics of visitor styles as well as the real visitor data from a MIT museum.

2. Previous work

In our previous works in [7], the analysis of the visitor circulation in museums and galleries has been investigated in a virtual world. Their findings can take advantage of classifying and identifying the visitor types for a guide system in museums and exhibitions. In terms of information visualization, that paper introduced the visualization for guiding curators to rotate the museum items and arrange the sequence of items. The approach indicated the interesting or skipped items associated with the visiting styles.

Eigendecomposition is adapted in many applications as follows: As Eagle and Pentland [8] concluded, the behavior structures become more apparent when the behavior is temporally, spatially, and socially contextualized, the visitor circulation in the museum space will be dominated by a set of primary structures. Ref. 7 introduced an eigenbehavior-based approach to determine the primary behaviors of players' movements by extracting their repeating structures. The repeating and common structures are identifiable movement directions of players in the same virtual space. Their proposed technique is employed in a Massively Multiplayer Online Game (MMOG). This is because the locations where players go to receive a service, such as, a quest or assistance, are a potential factor to construct the common behavior structures.

Eigenplaces are named by [10] who applied eigendecomposition to extract the discriminant features from the time-series data (the aggregated network usage). They analyzed and categorized wireless access points based on common usage characteristics that reflect real-world, place-based behaviors. The resulting eigenplaces have implications for research across arrange of wireless technologies as well as potential applications in network planning, traffic a tourism management, and even marketing.

3. Purposed approach

3.1. Eigendecomposition

For segmenting a museum-like space, we represented the dwell time of visitor’s proximity to an exhibit as a vector and assembled the observations from all visitors into a single covariance matrix. Applying eigendecomposition to visitor circulation data yields many eigenvector and coefficient pairs; the latter's magnitude establishes the vectors' ranking according to their value in reconstituting the original data. Using the mean-square-error test, we can determine the number of pairs that is required to lower this error.

3.2. Theory of Graph Spectra

According to the Rayleigh-Ritz theorem [11], the components of the eigenvector with the second largest eigenvalue give a cluster weight assignment which is orthogonal to the cluster weight assignment (eigenvector) with the largest eigenvalue. Thus, we can use this orthogonality constraint to define disjoint clusters.

Any two exhibits (ξ_i, ξ_j) are in the same cluster by considering the components of an eigenvector that denotes the exhibit ξ_i in the associate cluster. Following the aforementioned definition, the function of testing whether two exhibits are in the same cluster, $\psi(\xi_i, \xi_j)$, is written below where the considering set of eigenvectors is denoted by V'.

$$\psi(\xi_i, \xi_j) = \begin{cases} 1 & ; \forall_{k \in V'} (sign(v_{k\xi_i}) = sign(v_{k\xi_j})) \\ 0 & ; \qquad\qquad other \end{cases} \tag{1}$$

Let us describe how to employ Equation (1) by example. Suppose that we have already obtained a set of eigenvectors of the visitor circulation at the MIT museum as shown in Table 1. Given $V' = \{v_1, v_2, v_3\}$, we will have four resulting clusters as follows: [1,7,12],[2,3,4],[5,6,11], and [8,9,10].

Table 1. Eigenvalues and the corresponding eigenvectors for the MIT exhibition space

			Eigenvectors (exhibits)											
Score(%)	**Eigenvalues**		ξ_1	ξ_2	ξ_3	ξ_4	ξ_5	ξ_6	ξ_7	ξ_8	ξ_9	ξ_{10}	ξ_{11}	ξ_{12}
55.91	35.80	V_1	-0.2	-0.3	-0.3	-0.2	-0.4	-0.3	-0.2	-0.2	-0.3	-0.3	-0.3	-0.3
64.11	13.70	V_2	-0.6	-0.4	0.0	-0.1	0.2	0.2	-0.1	0.2	0.4	0.3	0.0	-0.1
71.31	12.85	V_3	0.2	-0.3	-0.4	-0.4	0.4	0.3	0.4	-0.2	-0.2	-0.2	0.0	0.2
78.08	12.45	V_4	-0.2	0.1	0.3	0.2	0.4	0.2	0.3	-0.1	-0.2	-0.2	-0.4	-0.6
84.18	11.82	V_5	0.1	-0.1	0.1	0.0	-0.2	-0.2	0.5	0.3	0.2	0.1	-0.7	0.3
88.52	9.97	V_6	0.3	-0.1	0.1	0.3	0.0	0.2	-0.1	-0.4	-0.5	0.3	-0.2	0.5

3.3. Segmenting Exhibit Space Algorithm(SESA)

Given a set of visitor dwell time associated with various exhibits, our segmentation algorithm consists of the following steps:

1. Compute a visitor association with each exhibit by using the Logarithmic transformation of visitor dwell time.
2. Construct an association matrix representation, X, where each row referred to as a summary of a visitor's association with various exhibits during a given time slot.
3. Perform Singular Value Decomposition (SVD) of the association matrix X.

$$X = U.\Sigma.V^T \tag{2}$$

4. Compute the significance score ($score$) that is correlated with the percentage of power in the original matrix X captured in the rank-k reconstruction by using the equation below:

$$Score(\%) = 100 \times \frac{\sum_{i=1}^{k} \sigma_i^2}{\sum_{i=1}^{Rank(X)} \sigma_i^2} \tag{3}$$

5. Indicate a set of primary Eigenvector v_i with a desired significance score.
6. Partition the exhibits with the set of primary eigenvectors.

Note that the SESA algorithm uses the natural Log transformation of the visitor dwell time because there is evidence of substantial skew in the raw data as shown in Figure 1 (a) and Figure 2 (a). After applying the data transformation, the logarithm of the dwell time is called the visitor association and its histogram is shown in Figure 1 (b) and Figure 2 (b).

For Step 2, the association matrix is $X = \{x_{ij}\}$ where an entry represents the dwell time of i^{th} visitor stopping at the j^{th} object. In other words, each column vector corresponds to the popularity for an object across time as well as each row vector corresponding to an association vector for a time slot.

4. Experiments on two use cases

For validating the effectiveness of the SESA, we use two data sets:

1. The data set obtained from [5] and based on the four animal metaphors.
2. The data set obtained by Sparacino as addressed in [12] for developing "The Museum Wearable project."

We describe the data set and its representation following the obtained findings with implications.

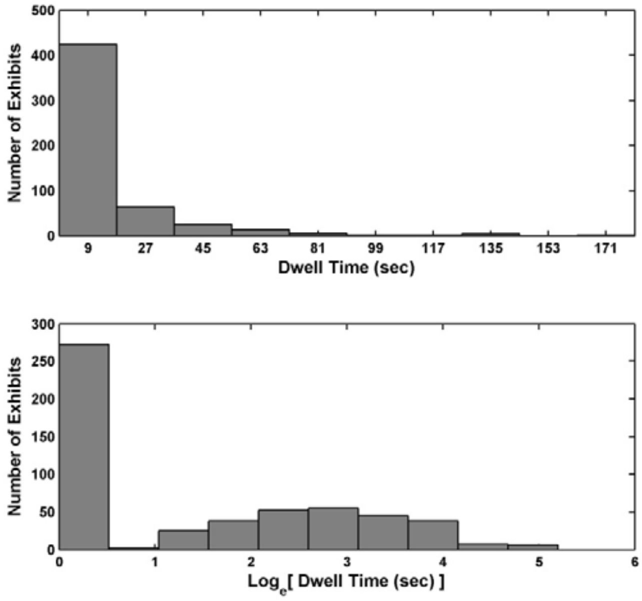


Figure 1. Histogram of visitor dwell time at a set of exhibits in the MIT museum.

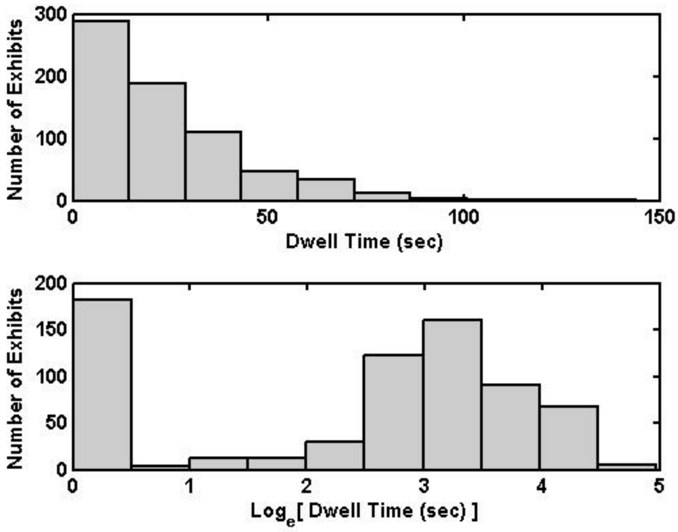


Figure 2. Histogram of visitor dwell time at a set of exhibits in the virtual Ritsumeikan gallery (RDAP).

4.1. Ritsumeikan Digital Archiving Pavilion (RDAP) in Second Life

We synthesized the visitor trajectories based on the metaphor of four animals -- Ant, Fish, Grasshopper, and Butterfly visiting styles-- as defined in [7]. These styles are as follows:

1. The ant visitors spend quite a long time to observe all exhibits and walk close to exhibits, but avoid empty spaces.
2. The fish visitors prefer to move to and stop over at empty spaces, but avoid areas near exhibits.
3. The grasshopper visitors spend a long time to see selected exhibits, but ignore the rest of exhibits.

4. The butterfly visitors observe almost all exhibits, but spend varied times to observe each exhibit.

The total number of synthesized trajectories is 36 where each visiting style has nine trajectories in the 3D virtual museum, named RDAP. RDAP, owned by the Global Center of Excellent in Digital Humanities Center for Japanese Arts and Cultures, of Ritsumeikan University, was created in Second Life. An objective of RDAP is to disseminate Japanese costumes, Kimonos, preserved them in a digital achieving system.

4.2. The MIT museum

We applied our approach to the visitor tracking information from 45 visitors. The visitor information is raw data, that is the number of seconds that visitors stayed in front of the corresponding objects. All these objects were visited in a linear sequence, that is one after the next, with no repetitions or change of path. The total number of objects is 12.

4.3. Results and their implications

We found that the segmentation of the exhibit space of MIT and RDAP can be achieved with four eigenvectors when the significance score was initially set to 78.08% and 93.48%, respectively. Four eigenvectors of the associated matrix of the MIT and RDAP exhibitions are shown in Figures 3 and 4, respectively. Basically, the first eigenvector cannot be used for partition because its components are all negative (even or all positive). When increasing the size of set V', we can obtain more number of cluster where the size of clusters will be smaller. The resulting segmentation of exhibit space according to both MIT and RDAP is shown in Figures 5 and 6, respectively.

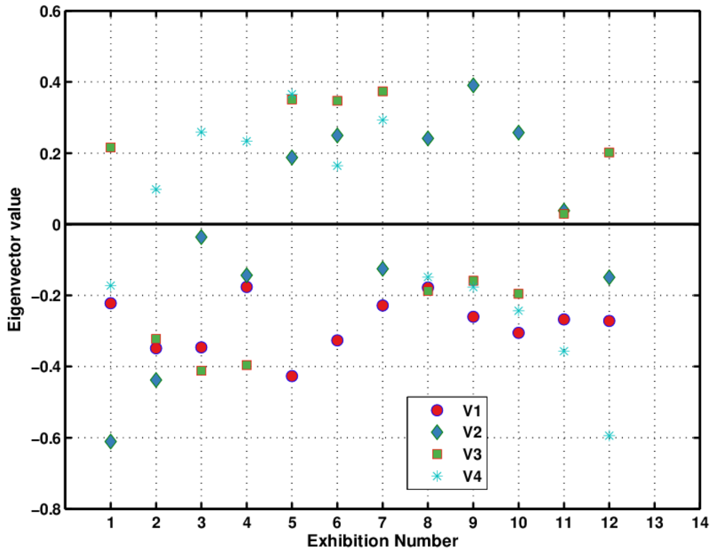


Figure 3. Eigenvectors of the exhibit space in the MIT museum of 12 exhibits where the four symbols (dot, diamond, square shape and asterisk) are used to represent v_1, v_2, v_3, and v_4.

For the MIT exhibition space, the following implications will be beneficial for the designers and curators. There are some groups of exhibits [1,12], [2,4], [8,9,10] with the strong relevance as shown by their scores of greater than 84.18%. In some situations such as the re-arrangement of exhibits, the designers should not disperse groups [2,4] or [8,9,10], but replace a group of them with another. The resulting segmentation also reveals that the first and last exhibits as analogous to the introduction and conclusion parts because the group [1,12] has the strong relevance.

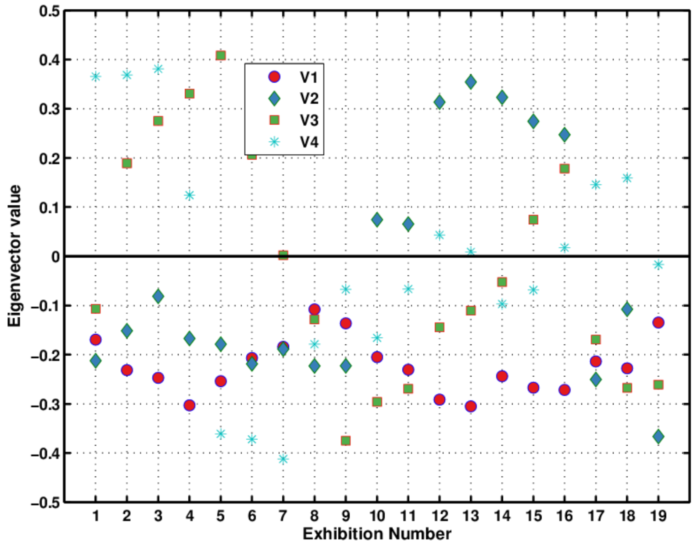


Figure 4. Eigenvectors of the exhibit space in the RDAP of 19 exhibits where the four symbols (dot, diamond, square shape and asterisk) are used to represent v_1, v_2, v_3, and v_4.

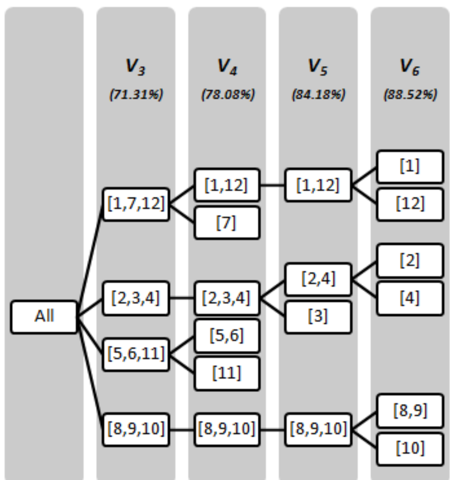


Figure 5. Cluster tree of exhibits in the MIT.

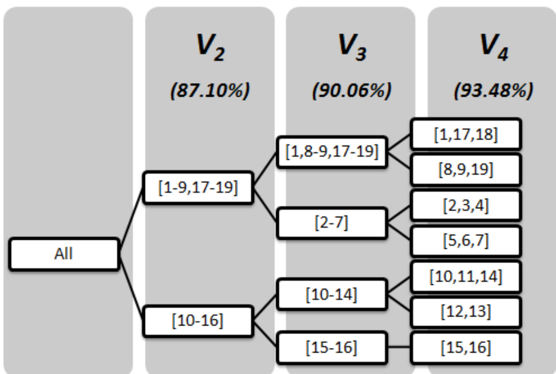
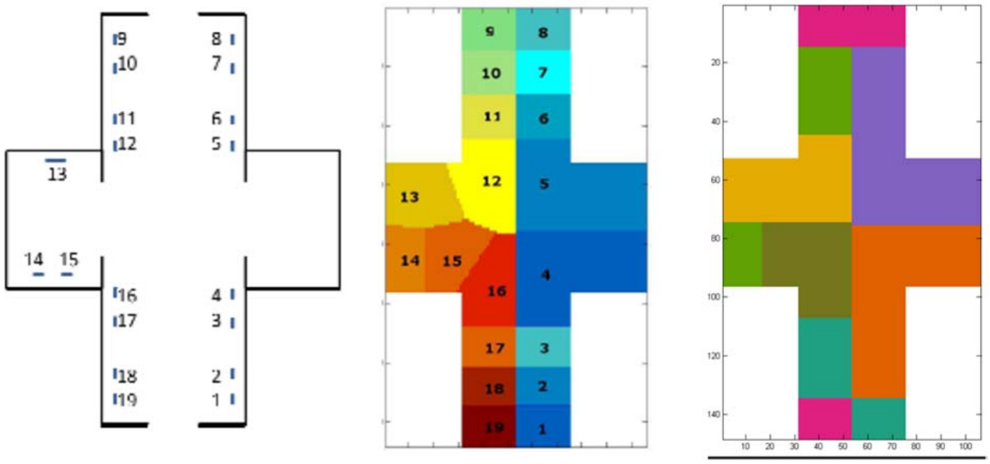


Figure 6. Cluster tree of exhibits in the RDAP.



(a) Exhibition space (b) Item boundary (c) Grouping items

Figure 7. Resulting segmentation of RDAP: (a) Gallery layout of exhibits in the RDAP, (b) Boundary of the voronoi cells (items), and (c) Segmentation of the exhibit space by using $V' = \{ v_1, v_2, v_3, v_4\}$ in the RDAP museum of 19 exhibits where areas with the same color belong to the same cluster.

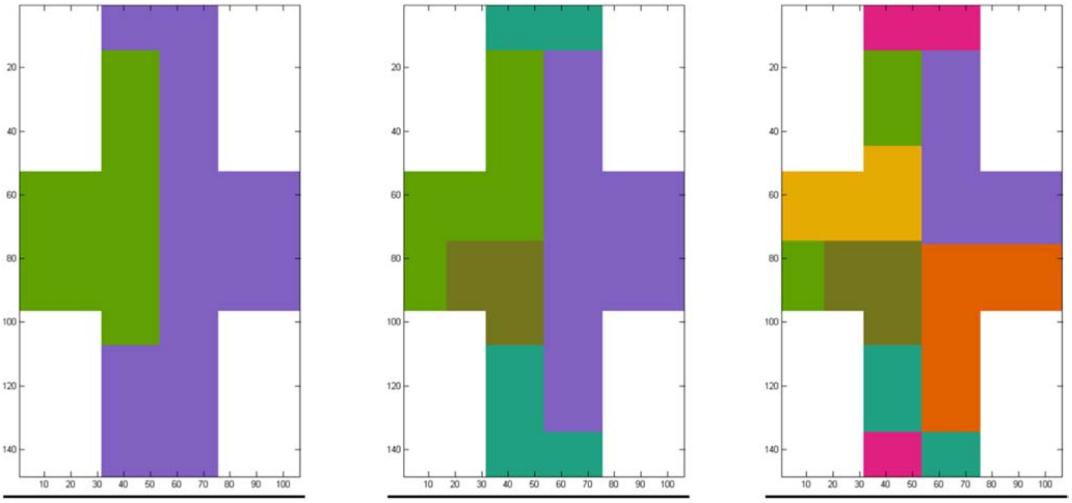
Since we used the synthesized data set of visitors in the RDAP exhibition space, the clusters would be rather related to the four visiting styles (ant, fish, grasshopper, and butterfly). To understand the implications, we must interpret the result based on the visiting styles as well as the gallery layout and the segmenting space. They are as shown in Figure 7. The findings are summarized below.

1. By $V' = \{v_1, v_2\}$, two clusters [1-9,17-19] and [10-16] correspond to the common visited items and the rarely visited items, respectively. This results from the butterfly visitors who likely skip only a few.
2. By $V' = \{v_1, v_2, v_3\}$, two interesting clusters are [1,8-9,17-19] and [15-16].
   (a) The former is fragmented from the common visited items because they are arranged at the entrance of hallway and the end. This group of [1,8-9,17-19] has received more attention than group of [2-7]. Although the fish visitors preferred to observe the atmosphere, they often stopped near the entrance of hallway and the end. This is a reason of segmenting [1,8-9,17-19] into [1,8-9,17-19] and [2-7].
   (b) The latter is fragmented from the rarely visited items because they are placed near T-junction that a small number of visitors would stop at them. If they stopped at 15, they would be stop at 16 but not further continue 13, 14. This might causes from the butterfly and grasshopper visitors.

5. Conclusions and future works

This paper introduces how to use eigenvectors with theory of graph spectra as potentially valuable applications for designing exhibition space and arranging exhibit items. The dwell time during their trip in exhibition is used for identifying a degree of visitor attention and exhibit interesting. To validate our approach, two use cases shows that our approach is practical for a real application in both real and virtual worlds. The implication of segmenting space has the meaning related to the accepted fact of visitor circulation in the exhibition space.

The proposed technique adopt the paradigm of divide and conquer into breaking down the space into two partitions, until these become basic units. The top-down segmentation will allow users to decide the level of segmentation in order to meet their satisfaction. The meaning of three levels of segmentation (example of RDAP) is shown as Figure 8. For our future works, we will design and develop an user system interaction for segmenting exhibition space because the user interaction will help the system to determine the hierarchical level of segmentation. Then, we will conduct the system evaluation in user domain. The user evaluation includes both quantitative and qualitative methods.



(a) (b) (c)

Figure 8. Our proposed segmentation approach with divide and conquer approach: (a) Result from the butterfly visitors who likely skip only a few (b) Result from the fish visitors who preferred to observe the atmosphere, they often stopped near the entrance of hallway (Bottom) and the end (Top), and (c) Result from all types of visitors as described in Figure 7.

6. References

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