Improving museum visitors' Quality of Experience through intelligent recommendations: A visiting style-based approach

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Abstract This paper investigates the effect that smart routing and recommendations can have on improving the Quality of Experience of museum visitors. The novelty of our approach consists of taking into account not only user interests but also their visiting styles, as well as modeling the museum not as a sterile space but as a location where crowds meet and interact, impacting each visitor's Quality of Experience. The investigation is done by an empirical study on data gathered by a custom-made simulator tailored for the museum user routing problem. Results are promising and future potential and directions are discussed.

Keywords. Intelligent recommendations, Quality of Experience, agent-based modeling, visiting styles, crowd simulation

1. Introduction

Museums; places people visit for learning, socialization and entertainment purposes. Visitors want to leave the museum having purposefully spent their time there. In parallel, museums typically have a variety of items on exhibition. What each visitor is interested in seeing varies and it can be related to their interests, learning targets, available time, as well as on other factors such as the size of the museum.

A problem often faced by museum visitors is that they often do not fully profit from their visiting experience. That is, in the course of their visit, visitors may lose time viewing items that do not interest them and miss those that do, due to time restrictions or simply to the tiredness that inevitably occurs during visits.

Missing important exhibits and viewing items that the visitor is not so much interested in may significantly lower visitor's experience. Therefore, a need exists to improve the Quality of Experience (QoE) of museum visitors through intelligent recommendations that will route visitors inside the museum towards exhibits of interest, while, in parallel, minimizing the visitors' walking time within the museum. Such an approach would contribute towards shifting the museum from a static exhibition space to what we may call an Intelligent Environment, designed to assist and improve the overall experience of the visitor. Finally, it is also very important to examine the

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routing and recommendations given in the *context* of the museum, i.e. taking into account the particularities of the behavior of museum visitors, which are different than a generic crowd's behaviour.

1.1The Experimedia BLUE project

Experimedia BLUE[2], is a research project funded by the European Commission, to examine the above. Specifically, in Experimedia BLUE we are interested in augmenting museum visitor experience by designing intelligent recommendation algorithms that will offer a personalized visit to museum visitors according to their interests, the type of visitor that they are, but also to their personality. The experimentation setting of the project is the FHW[3] museum, a technological museum situated in Athens, Greece.

Briefly, the idea is as follows: visitors can play a Facebook game, prior to their visit, which allows us to identify, with different degrees of accuracy, their interests on the museum exhibition items and themes. During their visit, we provide visitors with handheld devices that allow us to deliver recommendations over which item to visit next, but also to monitor the visitors' movement within the physical space of the museum, thus detecting their visiting style. Visiting style is an important factor reflecting people's behavior when they are inside a museum and its detection can allow us to calibrate the recommendation algorithms specifically for the museum's context. After the visit, people can share their experiences through social media. Given that different museum visitors are expected to have different levels of interest for the exhibits, different walking patterns and visiting styles, and spend varying amounts of time on exhibitions, the first thing that we wish to explore in the BLUE project, prior to any experimentation with real users, is the degree to which intelligent recommendations can improve the visitors' QoE, considering all the parameters above.

1.2 Our contribution

In this paper we investigate the potential and limitations that intelligent recommendations have on the QoE of museum visitors, when designed to optimize the latter for interesting exhibit identification and walking time minimization. We design a smart recommendation algorithm and examine its expected performance for different levels of noise in the estimation of user interests. Most importantly, given that museum visitors are divided into visiting styles, we also examine the effect that such intelligent recommendations have on each visiting style, in order to identify possible approaches, and their context, for further QoE improvements, for the specific problem of museum visit augmentation.

The difference of the BLUE approach with current approaches that use intelligent recommendations to route crowds is that typically these focus on non-museum applications such as building evacuation plans. The approaches that focus on museums usually treat them as generic physical spaces and do not take into account the visiting styles of the visitors to optimize user routing. In addition the works on optimizing user routing inside museums(indicatively[12]) usually report few quantitative results, while they do not examine factors such as noise in visitor interest estimation.

The rest of this paper is organized as follows: Section 2 presents the related literature and positions the present work within it. Section 3 presents the modeling of

[2] Experimedia BLUE project, http://www.experimedia.eu/2012/10/01/blue/

[3] Foundation of the Hellenic World (FHW) museum, http://www.ime.gr/fhw/index.php?lg=2

the elements (museum, visitors, visiting styles, and recommendation algorithms) developed and used. Section 4 presents the experimental evaluation. Finally, section 5 discusses the obtained results, presents future work and concludes the paper.

2. Related Literature

2.1 Indoor localisation systems and location-based services

With the rise of GPS[6], localisation services have become very popular and seen a multitude of services, making good use of localisation systems, made readily available[14]. However, there is an inverse relation between the availability of the service and the need for the service as the structures we build create a shadow that cannot be penetrated by current GPS technology. Indoor localisation technologies have been developed to remedy the situation. They come in two categories: the first relies on the installation of an additional infrastructure [4; 9] while the second category aims at exploiting existing infrastructures[1; 16]. Indoor locations have since seen tailored services being developed[7]. In the scenario investigated in this paper, as well as in the BLUE project, indoor localisation technologies are to be used to capture museum visitor's positions, track their movement through a museum, and issue recommendations on their optimal path through the museum based on the visitors' personal preferences and interests.

2.2 Scenario-based user routing optimisation

In contrast to outdoor localisation systems which benefit from a very homogenous setting roads and paths are well defined and delimited clearly; indoor localisation is a bit trickier. Only part of the navigable space, notably corridors, is clearly defined. Therefore, indoor maps need to be enhanced, for example semantic information[5], to increase routing and navigation accuracy and flexibility. This will in turn enable indoor scenarios to take into account more diverse mobility types and develop specialised scenarios, e.g. for individuals with reduced mobility [8]. Due to its GPS-based scenario legacy, localisation systems focus on mobility scenarios given by physical mobility types and offer standard optimisation options (e.g. fastest, shortest) but do not account for individual's preferences, in regard to experience, to navigate spaces. However, Quality of Experience (QoE) is paramount when the objective is to experience an environment rather than merely navigating it.

Enhancing experiences through the use of technology is often proposed by using readily available, familiar, and easy to use devices. For example, the works of Andolina et al. [2]and Tesoriero et al. [15] make use of mobile devices to optimize cultural heritage visitor's experience by improvements to presentation, interaction, and integration. Unfortunately, they leave the potential for QoE improvement by interest-optimized visitor routing untapped. The work of van Hage et al. [3] approaches this problem by proposing to detect user preferences and compute a personalized visit, optimized by walking distance and the art objects that each visitor perceives as interesting. Roes et al. [11; 12] build upon the previous work by maintaining a dynamic user model and enriching the available palette of experiences by going online. However, the above works do not specify important elements such as the interest estimation accuracy and the effect that this has on the performance of the routing algorithm, nor do they take into account visitor's personalities, through their visiting styles, for the development of the recommendation and routing strategy. We think the latter are especially crucial, and complementary to interests, for providing relevant recommendations especially tailored for museum visitors.

In this paper we examine the effect that intelligent recommendations have on the Quality of Experience of museum visitors, for differentiated conditions of the involved visitor population (i.e. behavioral/movement patterns of the visitors, differentiated interests and crowd tolerance limits), and different noise levels of the input interest estimation algorithm.

3. Methodology

We use agent-based modeling to model the behaviour of the visitors inside the museum, as well as the museum's physical space. Below we describe the modeling performed, as well as the recommendation algorithm to be examined.

3.1 Basic Element Modeling

Museum

The museum is modeled as a set of nexhibits$= [e_1, e_2, \dots, e_n]$. Each exhibit represents one exhibit inside the museum. Each exhibit $\mathrm{e_i}$is modelled to have a:

- *Maximum crowd capacity* $\mathrm{M_i}$, which corresponds to the maximum number of people that can simultaneously visit the exhibit $\mathrm{e_i}$. For example, in the case of a painting, M would mean the maximum number of people that can gather around and see the exhibit, while in the case of an exhibit that is a video-projection room, M would mean the maximum number of seats available.

Each exhibit also belongs to one museum *room*. Therefore exhibits can either be co-located in the same room or they can be located in different rooms. Each exhibit is "connected", i.e. accessible via walking, to all the exhibits of the same room. Also, in this specific modeling, each room has one exhibit connected to the museum *entrance*, as this is the case for FHW (all exhibition rooms are accessible directly from the entrance without the need to pass from other rooms first). A room may be connected, always through exactly one exhibit, to another room. To model the above, we define:

- An $|\mathrm{E}| \times |\mathrm{E}|$exhibit positioning matrix$\mathrm{P} = [\mathrm{p_{11}}, \dots, \mathrm{p_{|E||E|}}]$. Each element$\mathrm{p_{ik}}$ of the positioning matrix P can be defined as follows:

$$\mathrm{p_{ik}} = \begin{cases} 2, \text{ if } \mathrm{e_i} \text{ and } \mathrm{e_k} \text{ connect two different rooms} \\ 1, \text{if } \mathrm{e_i} \text{ in the same room with } \mathrm{e_k} \\ 0, \text{none of t}he\text{ above} \end{cases} \quad (1)$$

- An$|\mathrm{E}| \times |\mathrm{E}|$exhibit distance matrix$\mathrm{D} = [\mathrm{d_{11}}, \dots, \mathrm{d_{|E||E|}}]$. Each element $\mathrm{d_{ik}}$ of the positioning matrix D can be defined as follows:

$$\mathrm{d_{ik}} = \begin{cases} -1, \quad \text{if } \mathrm{p_{ik}} = 0 \\ \mathrm{d}, \text{ if } \mathrm{p_{ik}} = 1, \quad \text{with } \mathrm{d_{min}} \le \mathrm{d} \le \mathrm{d_{max}} \\ \mathrm{d_R}, \text{ if } \mathrm{p_{ik}} = 2, \quad \text{with } \mathrm{d_{Rmin}} \le \mathrm{d_R} \le \mathrm{d_{Rmax}} \end{cases} \quad (2),$$

where d is the distance of exhibits within the same room, and $\mathrm{d_R}$ is the distance between rooms, which is taken as the distance between the two exhibits connectingthe rooms. Finally, for each room we also define inside each room a pseudo-exhibit, which serves as the room's center and will be used for the modeling of the movement of certain visitor types (detailed in section 3.2).

The positioning matrix is used to find the connections between items of the same room and between rooms and the distance matrix is used to calculate the path distances. These two matrices can be given, if we want to experiment on a specific museum setting, or they can be generated using the following four parameters: 1) min and max exhibits distances for the exhibits of the same room, 2) min and max room distances 3) number of total rooms in museum and 4) number of exhibits per room. The simulation described here use the above 4 parameters to generate museum settings.

Visitor

Visitors are modeled to arrive to the museum with an inter-arrival rateμ, randomly distributed between two time parameters: $\mu_{min} \leq \mu \leq \mu_{max}$.

Each visitor *j* has the following characteristics:

- *Interest per Exhibit*$I_{e_{ij}}$, $0 \leq I_{e_{ij}} \leq 1$, where $I_{e_{ij}}$is a Real number and the bounds 0 and 1 mean respectively no interest or perfect interest for exhibit *i*.
- *Crowd Tolerance*C_i. The number of other people that the visitor can handle around the exhibit, without a decrease of his satisfaction from the visit. It is modeled per exhibit, as a percentage of the maximum crowd capacity of the exhibit, i.e.:$C_i = p \cdot M_i$, where M_i is the maximum capacity of exhibit i.
- *Maximum available Time*T_j, where$t_{min} \leq T_j \leq t_{max}$, and 1 time unit simulates 1 minute. The time that the user can spend inside the museum. It starts counting the moment the visitor enters. Once it is over, the visitor exits the museum.
- *Walking speed*S_j, simulated in meters/second. Will be used to calculate the time needed to go to an exhibit, in the QoE function.
- *Time spent per Exhibit*$t_{e_{ij}}$. We assume that the time each user will spend seeing each exhibit is directly proportional to their interest for that exhibit:

$$t_{e_{ij}} = f(I_{e_{ij}})$$

  , where$f$is defined separately for each visitor type, and described in detail in section 3.2. Regarding time, each visitor also has a $maxExhibitTime$ and $minExhibitTime$ correspond respectively to the overall maximum and minimum times that the user can spend on one exhibit.

- *QoE*. Each user has a Quality of Experience metric. This measures how satisfied the user is from his visit inside the museum. We can intuitively assume that for each item the user visits, his QoE is proportional to the user's interest on the item, and inversely proportional to the time it took him to reach the exhibit. Therefore, for a userj that is currently at exhibit e_k and he is going to exhibit e_i, we model QoE_{ij}as follows:

$$QoE_{ij} = w_1 \cdot I_{e_{ij}} + w_1 \cdot \left({}^{1}\!/_{walkTime_{ij}} \right) \quad (3)$$

  , where$0 \leq w_1, w_2 \leq 1$ are calibration weights and$walkTime_{ij} = \frac{d_{ik}}{S_j}$ and d_{ik} is the distance between the current exhibit e_k and exhibit e_i . For the simulations, $I_{e_{ij}}$ and $\left(1/_{\text{walkTime}_{ij}}\right)$ are also normalised in the [0,1] range. Finally, the total Quality of Experience QoE_j at the end of the visitor's visit is:

$$QoE_{ij} = \sum_{i=1}^{n} QoE_{e_{ij}} \qquad (4)$$

3.2 Visiting styles modeling

Apart from the above basic characteristics, each museum visitor belongs to one of 4 distinct visiting styles described using animal metaphors (ant, butterfly, fish or grasshopper).Each visiting style corresponds to a specific movement pattern of the visitor inside the physical space of the museum. Including the visiting styles into the modeling renders the simulations more tailored to the specific context of museum visit applications and further supports its reliability in supporting decision-making based on the simulation results. For the modeling of the visiting styles we use two literature studies. The first, the work of Veron and Levasseur[10] describes visiting styles from a behavioral perspective. The second, work of Sookhanaphibarn and Thawonmas[13], is among the few who perform a mathematical modeling of each visiting style, limited however only to one exhibition room and using x, y coordinates instead of a graph-based model that we employ. In the following we extend the aforementioned modeling to fit the graph-based model that we use.

Ant

Ant visitors move linearly, visiting almost all exhibits, showing interest in the detail, avoiding empty spaces and following a clear path and the curator’s suggestions. In modeling terms, the ant visitor visits the exhibits of each room sequentially, choosing the each time closest not-visited exhibit until all exhibits of the room have been visited. The ant’s interest $I_{e_{ij}}$, with i the exhibit and j the visitor, is given by a normal distribution, in the [0,10] range and mean equal to 5. Also, the ant has very low interest for room centers, meaning that Ant visitors do not frequently pass from these points but they rather visit exhibits in a linear fashion. The time spent per exhibit is $t_{e_{ij}} = f\left(I_{e_{ij}}\right) = I_{e_{ij}} \cdot e^{-\rho\left(\frac{C_i}{M_i}\right)}$, where j is the visitor, C_i is the current crowd around the exhibit i, M_i is the maximum crowd capacity of the exhibit and ρ is a weighted constant used as defined in [13].

Fish

Fish visitors move in the center of rooms, seeking to see the “larger” picture, not approaching most exhibits and not stopping very frequently. Their interest $I_{e_{ij}}$ is modeled the same as that of ants, with the difference that a Fish visitor has also very high interest for room centers. This means that Fish visitors will spend a lot of their time and pass often from room centers and then, visit certain exhibits according to their interest. Fish also are modeled to return to the center after each exhibit visit and after exiting a room, they choose not to visit the centers of rooms that they have visited, to avoid eternal loops in their movement pattern (induced by their high interest for centers rather than for any other exhibit in each room). The time spent per exhibit for the Fish is $t_{e_{ij}} = f\left(I_{e_{ij}}\right) = I_{e_{ij}} \cdot e^{-\rho\left(1-\left(\frac{C_i}{M_i}\right)\right)}$, where i, j, ρ, C_i, M_i are defined as in the previous.

Grasshopper

Grasshopper visitors are persons of particular interests, they only approach certain exhibits, cross empty spaces and spend a significant amount of time in front of items of interest. To model those exhibits that are of interest for the Grasshopper, we use a Beta PDF distribution with $\gamma = 1$ and $\beta = 5$, as in [13]. Then applying a threshold L, we select the exhibits that the Grasshopper will be interested in. For these exhibits, we model an interest $I_{e_{ij}}$, given by a Gaussian distribution but with a mean very close to 1, to model the very high interest that the Grasshopper has on these exhibits. For the rest of the exhibits, the Grasshopper has 0 interest. The time that the Grasshopper spends per exhibit is also affected by the above-selected exhibits as follows:

$$t_{e_{ij}} = \begin{cases} I_{e_{ij}} \cdot e^{-\rho\left(\frac{C_i}{M_i}\right)}, if I_{e_{ij}} > L \\ 0, if I_{e_{ij}} < L \end{cases} \tag{5}$$

, where L is the threshold on the Beta distribution, and the rest of the parameters are defined as in the previous.

Butterfly

Butterfly visitors move nonlinearly, they do not follow the curator's suggestions, they often change the direction of their movement, approach exhibits, are interested in the detail and are affected by environmental affordances, such as the accessibility of the exhibit. The Butterfly visitor is modeled to also present a selective exhibit probability, like the case of the Grasshopper, but on the inverse, i.e. a Butterfly is interested in most of the exhibits. To model the exhibits of interest for the Butterfly we use a Beta PDF distribution with $\gamma = 5$ and $\beta = 1$, as in [13]. Again placing a threshold L, low this time, we define the exhibits that the Butterfly has interest in. The exhibits underneath this threshold present a 0 interest for the Butterfly. For the selected exhibits we use a Gaussian distribution with mean equal to 7. The time that the Butterfly spends per exhibit is defined to be similar to that of the ant for those exhibits with $I_{e_{ij}} > L$ and 0 otherwise.

3.3 Modeled Systems

We model two systems implementing two kinds of visitor behaviour in the museum:

- *Simple visit*. Visitors enter the museum and select exhibits to see, according to their visiting style. For each visitor, if the exhibit he/she selects has reached its maximum crowd capacity M_i, or it has more visitors than the crowd tolerance limit of the specific visitor, then he/she moves to another exhibit. For going from one exhibit to the other, visitors always take the shortest path. The resulting simulated system, with its 4 subsystems (one for each visiting style) is referred to as the "no recommendation" system and serves as the benchmark.
- *Recommendation-based visit*. Visitors in this system are given exhibit recommendations, through a recommendation algorithm (described later on). In case the algorithm recommends them an exhibit for which their estimated interest is above 7 (in a scale of 10): $I_{e_{ij}} > 7$, then they follow the recommendation. Otherwise they behave like in the random system, i.e. they randomly select an exhibit. It should be noted that the algorithms makes its

recommendations based on the estimated interest of the user, which is modeled as the real interest of the user plus noise. The noise, which basically models the approximation error that the algorithm will have in reality, is set by the "noise "parameter of the simulator (also depicted in the GUI of figure 8), as a range between two numbers, each in the scale of [0,10], since interest is also measured in this scale. Then before each recommendation, the algorithm selects a random number in the range set for the noise and adds/subtracts it from the real user interest. This estimated value is the one used for the recommendation decisions of the algorithm. Example: Assume we set noise to be in the [1,2] range and a user with real interest 7/10. This means that the best possible approximation of this user's interest is 7 ± 1 and the worst possible is 7 ± 2. Therefore the algorithm estimates the user's interest as a random number in the [5,6] or in the [8,9] ranges. The recommendation algorithm used in the specific paper is as follows:

- *“Smart” algorithm*. The algorithm optimizes for the QoE function, as given in eq. (4). This is the classical content-based recommendation scheme where the recommender takes into account user interests and walking time to try to maximize the user satisfaction.

4. Experimental evaluation

In the following we present certain preliminary results, derived from simulating an environment that features the modeling presented above. The modeling parameters chosen for the specific experimental evaluation, and for the purposes of the BLUE project, are illustrated in Table 2.

Table 1. The parameters used in the scenario evaluation

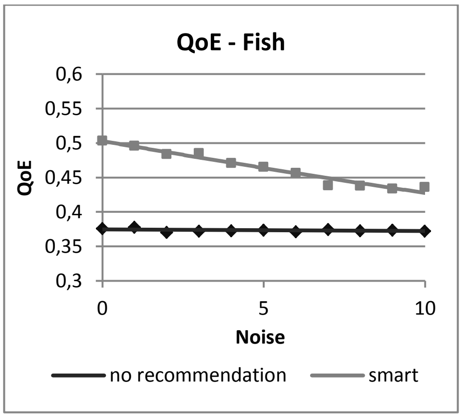
Parameter	Value
General Parameters	
Runs per result	20
Noise input to recommender	0-10/10
Total simulation time	18,000 units
Visitor parameters	
Maximum available Time	**[1800, 5400]**
Walking speed	[0.83,1.83]
Time spent per Exhibit	[60,500]
Visitor inter-arrival rate	120
Crowd tolerance	[0.7, 1]
Museum parameters	
Exhibit distance (in the same room)	[2,5]
Room distance	[100,500]
Exhibit crowd limit	[4,10]
Number of rooms	5
Exhibits per room	6

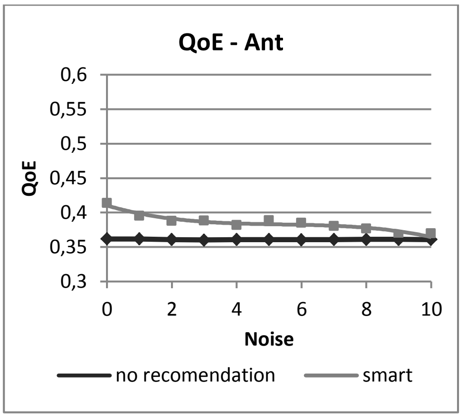
4.1Results

First we measure the QoE between the simple and smart systems, for different levels of recommendation noise (i.e. the error between an ideal recommendation and the one actually provided by the system). This first scenario answers the basic question of whether a QoE-based recommendation increases the QoE of the visitors and, if so, by how much. The recommendation algorithm being deployed in the FHW museum will inevitably have an approximation error (regarding its estimation of user interest per exhibit). Therefore, this scenario mirrors the QoE improvements that we expect when accounting for the algorithm's approximation error.

As we can see in Figure 1, the recommendation noise directly affects the level of visitor QoE, for all 4 types of visitors, since it affects the accuracy of the recommendation algorithm. In other words, the more inaccurate the algorithm's estimations, the lower its final average visitor QoE, This is expected as QoE is computed from the fulfillment of user interests. The very high levels of noise, for example above7, of the Figure correspond to the "worst case scenario" accuracy error that may be encountered for visitors that have not used the Facebook game and, therefore, their profiles are unknown to the algorithm when they first enter the museum. As they gradually move and respond to recommendations, we can expect that the recommendation algorithm's accuracy error will drop. However, in both cases (for high and low noise) we observe that the visitor's QoE is higher than the previously established baseline, where visitors move based only on their visiting type without any recommendations.

Other interesting results can be observed when examining the gain in QoE for each visiting style on its own. As we have observed, the type of visitor that can be expected to receive the highest improvement of experience is the Fish (Fig. 1a), followed by the Ant (Fig. 1b). Butterfly type visitors (Fig.1d) and Grasshoppers in particular (Fig. 1c), only show a slight, to almost no improvement in QoE when a recommendation algorithm is used. This can be explained by the fact that Fish, typically moving in the center of the exhibition rooms, may accidentally "miss" many exhibition items. Hence, directing them towards specific items of interest significantly improves their overall QoE. The same goes for Ants and Butterflies, although to a lesser extent, as these visitors show, inherently, a more uniform distribution of interest for items inside the museum. Finally Grasshoppers, being visitors that have a very high interest in very specific exhibits, will visit these exhibits regardless of the external conditions of the museum space (e.g. other visitors) or interest-based recommendations.





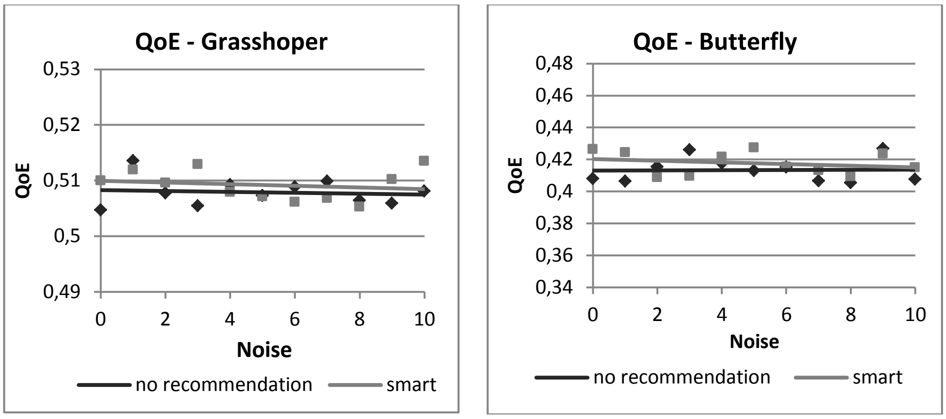
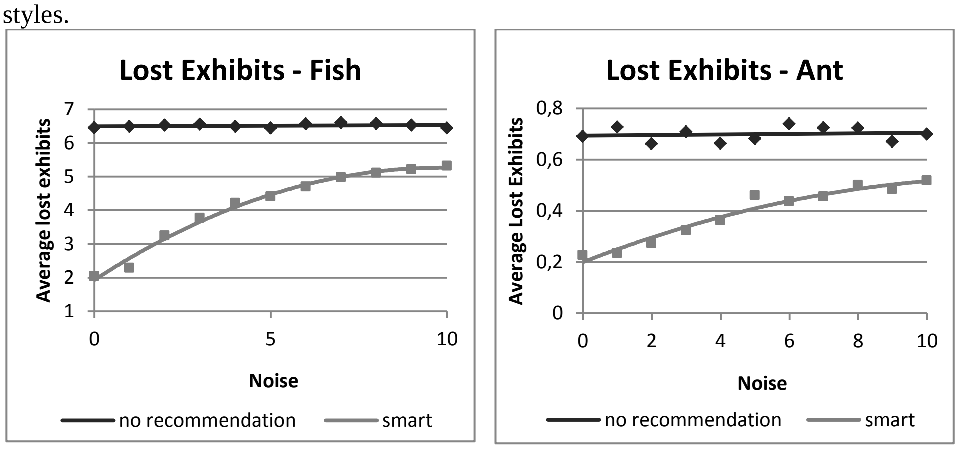


Figure 1. Quality of Experience achieved with and without recommendations

Figure 2 depicts the number of missed exhibits for different ranges of noise in the recommendation algorithm's estimations. Missed exhibits are those that the visitor is very interested in (internal interest > 7 on a scale of10) but that he does not see because they are not recommended by the algorithm due to high estimation noise. As expected, the higher the noise, the higher the number of lost exhibits. However, we also observe that, at all noise levels, the recommendation-based system does not result in a significantly lower number of missed exhibits, thus the loss of QoE for visitors, even at high levels of approximation error, is acceptable.

Analyzing the results per visitor type we witness the same pattern as before,, i.e. that Fish are expected to benefit the most from the recommendation of exhibits by the smart algorithm, while Grasshoppers benefit the least. Ants and Butterflies innately miss very few exhibits, with Ants seeming to benefit the most, among the two visiting styles.



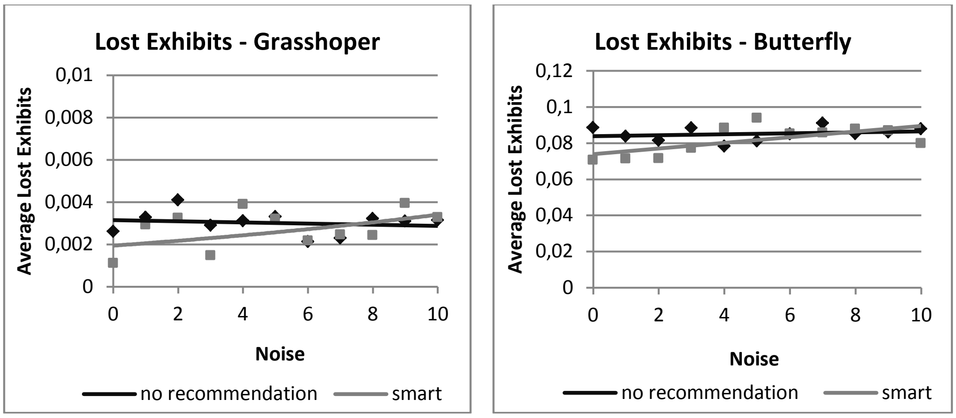


Figure 2. Average number of missed exhibits with and without recommendations

5. Discussion, Future Work and Conclusion

In this paper we examine the effect that intelligent recommendations (designed to improve QoE and reduce walking time) have on the QoE of visitors belonging to the 4 prevalent behavioral and movement patterns that literature gives us for museum visitors. To do so, we model in detail the museum setting, the behavioral and movement patterns of museum visitors, including their visiting styles, as well as the recommendation algorithm. We then examine, through simulation evaluation, the effect of the algorithm on the QoE on the visitors. Experimental results show that Fish is the type of visitors that can benefit the most, since their QoE considerably improves after receiving interest-based routing recommendations. Ants and Butterflies can also be helped although not as extensively as the Fish. The Grasshopper is the type expected to profit the least from such an algorithm, mainly because Grasshoppers know a priori which exhibits they would like to see, regardless of interest estimation or distance. The noise in the estimation of visitor interests was found to play an important role in the efficiency of visitor routing, further supporting the need for accurate a priori interest estimations like the one we use in the BLUE project through the Facebook game visitors can play before visiting. Noise, however, even at very high levels, was not found to worsen QoE when compared to giving no recommendations. This is positive, as it can provide more flexibility in experimentation with various recommendation strategies.

Having a good base for the modeling and simulation of the 4 different visitor's types, in the future we would like to develop and examine recommendation algorithms that are tailored and adapted to each style separately. Perhaps in this way we may achieve further improvement on visiting types like the Butterfly or the Grasshopper that seem to experience a low benefit from the generic interest-based recommendation algorithm used in this paper. Another interesting data point would be to measure the QoE not per visitor but per exhibit to examine the distribution of user "satisfaction" with each exhibit. This could allow museum curators to optimize their exhibitions by potentially re-arranging exhibit items within the physical space of the museum, according to the visitor types that the museum most often hosts. We also plan to examine visitors' response to recommendations when museums of different size and exhibit density are concerned. Furthermore, we intend to extend the present work to mixed crowd scenarios (populations of different visiting styles, or populations where some visitors receive recommendations and others do not), as well as on visitor groups (such as families of school classes) rather only on individual visitors. Validation with real users in a selected museum scenario is also envisaged.

Finally, it would be interesting to observe the effect that crowd congestion has on the QoE of the different visiting styles. We are currently examining the algorithm's response in relation to different congestion levels inside the museum, in order to come up with intelligent routing algorithms that optimize the visitors' QoE for congestion as well.

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