Cultural Location Touring Framework: A roadmap based on QoE modeling and visitor real-life behavioral choices

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Abstract. In our work and consideration cultural heritage spaces, and particularly museums, are considered as dynamic social systems, where visitor choices and decisions are interdependent and constrained. Under such a setting, and taking into account that each visitor aims at maximizing his own satisfaction, we initially formulate quantitative approaches and functions that capture and reflect visitor obtained Quality of Experience (QoE) from his touring experience, according to several socio-physical and behavioral factors. We further discuss and demonstrate how such a QoE modeling approach, can be used in order to improve and optimize various operation aspects of the cultural touring, both from visitor as well as museum operator points of view, while focusing on providing customized and personalized experience in visitor touring. In addition, we highlight how to treat the issue, that in practice visitors are not acting as neutral utility maximizers as commonly assumed, but often present risk seeking behaviors in their touring decisions. The latter affects significantly the various decisions making by the visitors and the corresponding obtained satisfaction, while provides useful guidelines for the museum operators with respect to their service offerings.

Keywords: Quality of Experience, risk-preferences, visitor behavior modeling, museum time management, congestion management, museum touring.

1 Introduction

Cultural heritage spaces, and in particular museums, are becoming dynamic environments in the service of the society aiming at reconnecting with the public and demonstrating their value and relevance in contemporary life. Several recent statistics [1-2] have made evident that museum exhibition draws the crowd, offering multiple experiences to the visitors. However new techniques are required towards actively engaging the museum visitors in a participatory manner towards improving their visiting experience. One of the most fundamental questions that arises in cultural spaces is: "Which is the most efficient methodology for enhancing cultural heritage spaces visiting experiences?"

In principle, in our consideration the evolving cultural heritage space environment is viewed as a Cyber Physical Social System, where visitors evolve in an environment that induces several constraints and interdependencies [3]. The visitor evolves in a physical or virtual space with others, where their behavior and decisions are constrained by the former, while influencing and being influenced by the latter [4]. The intuitive key principle followed in our consideration and work – considering visitor point of view - is simply stated as: “Making the most of your cultural heritage space visit”. Nevertheless, taking into account the cultural heritage space operator point of view, significant insights are obtained that can contribute to the following principle: “Knowing your visitors is an essential part of building your audience and better planning your services”.

In a museum, as opposed to other social environments, such as in a church or a school, the tempo of the experience is primarily controlled by the visitor himself, therefore a heavy burden regarding the visiting related decision making falls upon the visitor. More importantly, a specific visitor’s decisions with respect to several actions during his touring in the museum - ranging from determining which exhibit to visit up to optimizing the time to spend to each exhibit - are either explicitly or implicitly interdependent on the actions taken by other visitors that are present at the same time in the cultural heritage space.

Two different key research directions are identified towards addressing these major challenges, and offering an enhanced personalized museum visitor realistic experience. The first one refers to efforts associated with proper modeling of Quality of Experience (QoE), both qualitatively and quantitatively. Based on such QoE formal modeling, methodologies that improve the operation aspects of the cultural touring, both from visitor as well as museum operator points of view, are discussed. The second one deals with the critical aspect of properly using visitor behavioral insights, and more importantly incorporating behavioral factors into various operation processes and approaches, to examine and improve human cultural experiences. In the following we will introduce the challenges faced by each one of these directions, while providing insightful concepts, methodologies and our research approaches and designs, towards treating them, focusing primarily on the use case of museums.

2 Visitor Experience Modeling and Optimization

2.1 Quality of Experience Modeling

Visitor experience and satisfaction becomes a critical aspect of the effectiveness of various optimization approaches and decisions required through a visitor touring in a cultural space. Several research efforts have been devoted to the study of museum visitors’ perceived satisfaction [5-6]. These works argue that visitors’ satisfaction can be affected by several factors, both physical and cultural – either common or personalized, which may not influence visitor’s experience in the same manner and with equal weight. Visitor satisfaction, often referred to as QoE, is a subjective metric that refers to both the visitor personal style and characteristics, as well as the specific context under consideration. The proper treatment and formulation of those factors in well-structured expressions/functions reflecting museum visitors’ QoE is of high importance in order to understand, predict and optimize visitors’ QoE. The research works, presented in [7] through a qualitative analysis, and in [8] through a quantitative validation, identified four basic visiting styles in order to capture visitors' preferences and interests. Four animal metaphors, i.e., ant, butterfly, fish and grasshopper, have been respectively adopted to better demonstrate the corresponding visiting styles' attributes.

Furthermore, several additional works emphasizing on the sociocultural aspect of museum visitors' QoE, have been presented in the literature, including [9] where museum visitors' behavior is studied towards evaluating the impact of exhibitions on visitors' satisfaction, and [10] that relates visitors' emotions with the corresponding QoE. A first attempt to formulate museum visitors' QoE in mathematical functions was proposed in [11] considering visitor's distance from the exhibit and his / her stop over time to the exhibit. Furthermore, the authors in [12] studied the effect of smart routing and intelligent recommendations on improving museums visitors' QoE.

In our work in [13-14] a holistic approach to the formulation and optimization of QoE functions of the visitors was introduced, identifying the most influential parameters that affect the QoE notion. Towards relating the physical parameters to visitors' perceived QoE five main parameters have been identified as detailed and documented in the literature [7, 11-12]. The five main parameters are: distance between exhibit and visitor, distance between two sequential exhibits, crowd density, time spent with facilitator providing useful information to the visitors about the exhibits, exhibition size. Taking into account that the aforementioned parameters do not influence visitor's QoE in the same manner, we have developed a questionnaire [15] addressed to experts (e.g. archeologists, museum and gallery directors, etc.) towards determining the importance of each parameter, as well as obtaining some critical values of these parameters in order to design at a second step the formal QoE functions. Based on this, a human-in-the-loop approach was proposed in [14] towards determining a physical, personal and interest-aware museum touring methodology that maximizes visitor's QoE. Furthermore, a self-organizing mechanism for forming museum visitor communities was introduced [16], which exploits the visitors' personal characteristics and social interactions, and which aims at enhancing visiting experience based on a participatory action research process.

2.2 QoE-Based Recommendation Selection and Time Management

However, the aforementioned efforts have focused on quantifying and optimizing visitors' perceived QoE, mainly expressed via physical context parameters (e.g., museum's size, placement of the exhibits, etc.). They do not properly consider the impact of the visitor's choice, in selecting among a set of recommendation services made available to him/her by the museum, as well as determining his/her optimal visit time, in view of the available services. Therefore, we propose to address this problem in a formal and unified manner.

Specifically, we rely on the iterative design and adoption of: i) a machine learning framework to treat the problem of intelligent recommendation selection, and ii) a game theoretic approach to determine museum visitors' optimal visiting time, driven by the visitors' QoE optimization in the museum. The latter consideration is motivated on one hand by the distributed nature of the optimization problem under treatment and the selfish behavior of the visitors in terms of maximizing their own perceived QoE, and on the other hand by the fact that decisions of the various visitors are interrelated. The visitors are modeled as learning automata, adopting a machine learning mechanism and using a learning process to select the most appropriate recommendation to perform their museum touring. Each type of recommendation available to the visitors offers different levels of QoE, for example from offering them a simple map for a self-guided tour to a guided visit in their own language. The visitors are able to intelligently sense their environment (e.g., actions of other visitors) while keeping a history of their own decisions in order to make more educated and advantageous actions in the future, as time evolves, and finally, converge and select the type of recommendation that will improve their perceived QoE. Given the museum visitors' actions in terms of recommendation selection, each museum visitor aims at determining his/her optimal visiting time in order to maximize his/her perceived QoE. This is formulated as a distributed maximization problem of each museum visitor's combined QoE function with respect to his/her visiting time. Considering the distributed nature of the optimization problem and the selfish behavior of the visitors in terms of optimizing their own perceived QoE, a game theoretic approach is adopted towards determining its solution.

This overall process is an iterative one, where the output of the visiting time management problem feeds the learning system in a recursive manner (Fig. 1) in order to build knowledge and conclude to the optimal recommendation selection, even if changes apply to the system as it evolves. The necessary information in order to take their decision is their visiting time, the corresponding perceived combined QoE values at the previous time slot of the machine learning framework, and the penetration of each recommendation within the visitors' pool. The latter (i.e. reward probability) is expressed via the ratio of the total QoE achieved by visitors who selected a specific recommendation, over the total QoE achieved by all museum visitors who are present inside the museum at the examined timeslot.

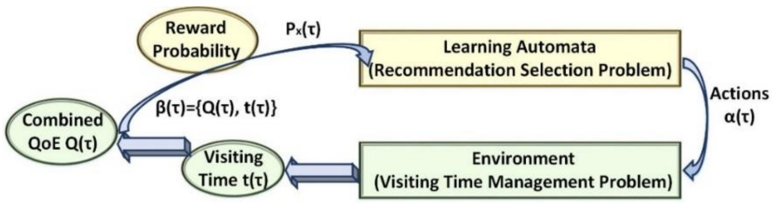

Fig. 1. QoE-based joint recommendation selection and visiting time management

3 Incorporating Visitor Behavioral Factors and Real Life Choices in Decision Making

As mentioned before, cultural heritage sites, such as museums, are reflections of society as they are repositories of historical, precious and significant objects and artifacts [17]. Therefore, observation of the behavior of visitors within a cultural heritage space area makes it possible to identify some particularly important issues and phenomena that occur during a touring experience.

In particular, with respect to congestion and popularity, museum exhibits can be classified in two main groups: a) safe exhibits, that typically correspond to less congested ones, where the visitors are assumed to receive guaranteed satisfaction proportional to the effort (e.g. time) investing in them, and b) common pool of resources (CPR) exhibits, which are the most popular ones with possibly increased congestion and uncertain outcome in terms of visitor satisfaction. CPRs belong to a broad class of goods that share two common characteristics [18]. They are non-excludable, thus it is impossible to exclude someone from benefiting or accessing the good and they are subtractable meaning that the consumption by one user reduces the ability of being used by another. With reference to the latter, it is absolutely true that it is not feasible to prevent a visitor from observing an exhibit, and the more time a visitor spends observing an exhibit, the less available this exhibit becomes to the rest of the visitors. Therefore, an exhibit constitutes a resource that experiences negative externalities and its extensive "usage" may lead to the "failure" of the exhibit.

Respecting the need for distributed, autonomous and scalable solutions and algorithms, the focus has been placed on the study of non-cooperative paradigms (e.g. game theory as described above) where decisions are taken autonomously by the visitors, which though may not directly interact or explicitly cooperate with each other, they become interdependent. The majority of existing approaches have relied on the principles of Expected Utility Maximization, where visitors aim at selfishly maximizing their own degree of satisfaction (i.e. QoE), as expressed through various forms of utility functions. Nevertheless all the methodologies and approaches used so far, have not managed to properly address the fact that individuals in real life do not necessarily behave as neutral expected utility maximizers, but they tend to exhibit risk-seeking or loss aversion behavior especially under uncertainty.

To deal with this challenge, we exploit Prospect Theory [18-23] in order to integrate risk preferences in the involved utility function, depicting deviations in decision making due to risk seeking or loss aversion that traditional models fail to capture. Following the aforementioned exhibit classification, in our work Prospect Theory is adopted and applied to determine visitor optimal visiting time in museum exhibits and evaluate the achieved QoE. Prospect Theory is one of the most widely accepted behavioral models of user decision-making under probabilistic uncertainty. It is the most accepted description of how people assess probabilities and utilities at outcomes and how people combine these two in gambles or competitions [20]. Visitor losses or gains are measured with respect to a reference point, which is defined as the ground truth based on the common sense of human behavior, while are possibly rated differently and not linearly. Furthermore, overconsumption of a resource in many cases has regularly been associated with a subsequent failure of the resource (i.e. CPR exhibits), with the investors eventually receiving negative returns from their initial investment. Prospect theoretic solutions will be formulated via a utility function (Fig. 2) associated with visitors´ returns or satisfaction by investing in a resource according to the following equation:

$$U(z) = \begin{cases} (z - z_0)^a, z \geq z_0 \\ -k(z - z_0)^\beta, z < z_0 \end{cases} \tag{1}$$

where $z \in \mathbb{R}^n, n \in \mathbb{N}$ is user's perceived utility and $z_0 \in \mathbb{R}^n$ is a reference point, which acts as the ground truth for each visitor. The parameter $k, k \in \mathbb{R}$ represents the idea that the loss curve is usually steeper than the gains curve, thus quantifies visitor sensitivity to losses as compared to gains, while by properly tuning parameters $a, \beta \in \mathbb{R}$ we can determine the extent of the non-linearity in the corresponding utility curves, illustrating the relative sensitivity to gains and losses of small magnitude compared to those of large magnitude. It is highlighted that parameters a, β, k can be visitor specific satisfaction related parameters and characterize in a unique and personalized manner each visitor $i, i \in N$, i.e. a_i, β_i, k_i, and thus can be exploited towards providing the possibility for a more personalized visitor' satisfaction treatment.

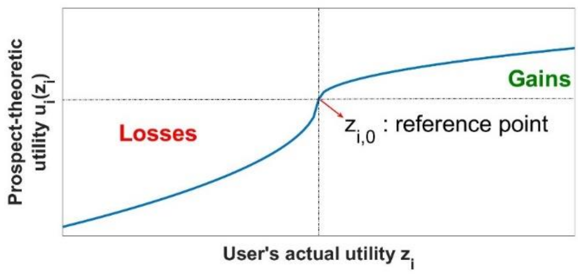

Fig. 2. Prospect Theoretic Utility

In a museum, the visitor will be able to invest time either in a safe resource, characterized by fixed gain or to a common pool of resource (CPR), characterized by low cost and higher than the safe resource – usually less predictable - gain. The CPR rate of gain return decreases in the total investment of the resource. The above model can be formulated and solved as a common pool resource (CPR) game where users select to invest between a common (shared) and a safe (standard) resource, with different returns from each resource type. Following this example, the equation below summarizes the choices of safe resource and CPR, and it will be combined with equation (1) to formulate the visitor-centric QoS-aware distributed resource management problems:

$$U_i(\boldsymbol{x}) = \begin{cases} \mathrm{g} \cdot \mathrm{e}, & \text{if } x_i = 0 \\ \mathrm{g} \cdot (\mathrm{e} - x_i) + x_i \cdot \mathrm{r}(x_T), & \text{if } x_i \neq 0 \end{cases} \tag{2}$$

where g is the gain per time unit investment received from investing in the safe resource. The visitor has a total available budget of time e and invests x_i to the CPR, which is characterized by $\mathrm{r}(x_T)$ rate of return, which is decreasing with respect to the total investment by all the visitors, i.e., $\mathrm{r}(x_T) = \sum_{i=1}^{|N|} x_i$, where $|N|$ is the total number of visitors. It should be highlighted that if the visitor invests a lot of time in the CPR exhibit, then the CPR's failure probability increases. In the case of CPR failure, the visitor receives no return from it.

4 Open Issues and Future Steps

As mentioned before, part of our current and future work focuses on studying the behavior of museum visitors in terms of recommendation selection and improving their perceived QoE, under the risk averse and risk seeking aspect of their decision-making process. As current models do not properly address the fact that individuals in real life do not necessarily behave as neutral expected utility maximizers especially under uncertainty, integrating risk preferences in the involved utility function depicting such deviations in decision making is of high research and practical importance.

Under this perspective, the concept of announcing different pricing policies per recommendation will be examined as an incentive mechanism provided by the museum to the visitors, in order to deal with the congestion control, the routing of the visitors within the museum, and the overall planning of the visiting traffic and touring. Additionally, innovative intrinsic and extrinsic motivation mechanisms will be devised and paired with the aforementioned incentive mechanism to improve the word of mouth reputation of the museum, increase the revisit and engagement of the visitors and support the smooth operation of the museum and increase of its profits.

It is also of high practical significance to investigate how framing effects can influence or even drive visitor route and overall touring decisions, by appropriately and intelligently providing people with options within the context of a specific frame, while at the same time enable cultural heritage site operators to properly plan the visiting traffic within the cultural heritage site.

Finally, our future plans include the execution of real experimentation with actual museum visitors in order to validate the proposed framework and its applicability under realistic conditions. Context-awareness and the Internet of Things (IoT) infrastructure and intelligence offer tools that can significantly promote our proposed research framework to the actual market. For example, specific measurements regarding visitors' behavior can be acquired and considered in our methodology, via the support of cameras and video processing techniques. As a result, the integration of the overall proposed museum touring framework with real-time information obtained through an IoT infrastructure will allow the dynamic adaptation of the proposed approaches to the actual museum conditions, towards realizing an IoT-based smart museum for a new interactive cultural experience.

Acknowledgements. This research effort is supported by ICCS Research Award under Grant Number 65020601.

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