A Survey on Developing Personalized Content Services in Museums

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Abstract

The personalized content services in museums are motivated by the need to enhance the visitors' experience through recommendations which consider the context of their visit, and by the need of curators to measure objectively the exhibition's impact. We survey the latest advancements in the fields of indoor localization, visitor profiling, content storage and presentation, as well as curator visualization tools, which are the main elements of such systems, and we highlight their strengths and weaknesses. We present an information architecture, which may offer useful insights to researchers and developers. Finally, we present the current challenges and the future trends.

Keywords: recommendations, museums, indoor localization, cultural heritage content, visualization, museum guides

1. Introduction

Museums are learning spaces that typically offer large amounts of information, including the exhibited artifacts, as well as the supplementary material that accompanies the artifacts. Typically, visitors have limited time, and therefore especially in large museums, they need to decide whether to allocate most of their time to a few prominent artifacts and the associated digital content, or to view more of them in a more superficial manner instead. Very often visitors are overwhelmed by the excessive amount of information; that situation results into an experience which is far below their expectations. Furthermore, curators wish to measure in a reliable and objective manner the impact of exhibitions. This is crucial to decide which artifacts attract the attention, and if the supplementary material makes them more interesting; this is an essential part of a constant feedback loop that may lead to exhibition optimization.

The *recommendation* (or *recommender*) *systems* (RSs) are interactive software systems that maintain information about the museum artifacts and their properties. They employ representations of users' preferences, and can use context observations to suggest targeted digital content, so that it matches their expectations. That content can have various forms such as multimedia presentations, virtual reality (VR), augmented reality (AR) or games. Such a system cannot really solve on its own the problems of a poorly designed exhibition; however the automated and objective acquisition of visitor patterns and preferences that it offers, can help curators redesign exhibitions to maximize the time efficiency and the knowledge transfer to different groups.

Guidance systems are available for most museums worldwide. However, recommendation options embedded in the guidance systems are less frequent, and even fewer options exist for real-time RSs that exploit sensor data. Some museums develop their own guiding applications alongside audio guide systems. The Met Museums application [1] allows for recommendations on what to see, from artworks to architecture based on user preferences, but there is no indication about real-time recommendation features. The Louvre Museum's official application [2] offers a custom visit based on the visitors available time, art interests, and accessibility issues. ArtLens App [3] seems to be more sophisticated as it uses image-recognition software, which recognizes a selection of two-dimensional artworks, and provides additional curatorial and interpretive content. It also employs a localization system based on Bluetooth that helps also creating a recommendation subsystem and a personalized tour among the artifacts, while enabling the creation of personal collections. On the other hand, there are museums that exhibit prototype recommendation and guidance systems in cooperation with research institutes. In Cooper Hewitt Design Museum, a smart pen is used for creating and saving virtual notes about artifacts, and contributes in the museums RS that is based on association rules and collaborative filtering techniques [4]. Finally, the Mnemosyne project [5] exploits visitors' profiles for gathering personalized multimedia content that is displayed on an interactive table towards the end of the visit. The system also provides recommendations to visitors based on knowledge-based and experience-based subsystems.

This work is motivated by the lack of a comprehensive survey on how to combine user profiling, indoor localization, and content visualization to develop personalized content services in museums. Researchers and developers in this field have to address several challenges, which are particular to the museum environment such as the non-intrusive sensor data acquisition, the limited infrastructure installation due to aesthetic concerns, location, and pose estimation in a dense environment where GPS is unavailable, recommendations that concern individuals as well as groups of visitors, accurate user profile acquisition and cold start, content representation in par with the artifacts and in real time, and use of mobile devices with limited processing capabilities.

This work is targeting researchers and developers working on personalized content services in museums, and its contribution is twofold: (a) It surveys personalized content services and the related infrastructure in museums, which can be developed around a proposed high-level architectural scheme. (b) It highlights some of the most promising research lines that may be pursued in the near future, and gives recommendations.

In the next section we present the related surveys, and explain the added value of the current one. In section 3 we briefly present the basic components and related methods for developing personalized content services in museums including localization, recommendation, content, and visualization for visitors and curators. In section 4 there is a discussion on challenges, recommendations, and future trends. Section 5 concludes this survey.

2. Related Surveys

This work is unique in the sense that it is the most up-to-date and the most targeted review on personalized content services in museums. Our target audience is the researchers and developers of such services. We survey the latest advancements in the fields of indoor localization, visitor profiling, content storage and presentation, as well as the visualization tools for curators. Several surveys have been presented in the past, which however, apart from referring older works, have only a partial overlap with our topic.

In [6] Ardissono et al gave an excellent overview of the research of that time on RSs in museums and cultural heritage sites. It mainly covered user profiling, knowledge representation, and filtering methods. However, there was less coverage of localization, and content visualization for visitors and curators. In [7] mobile services offered to museum visitors were surveyed from the perspective of user interface design considering mainly the context. In [8] mobile tourist guides were surveyed with more emphasis on the high-level design and architecture and less information about the lower level functions. Most of the surveyed systems were applicable in outdoor settings, and thus not that relevant to museums.

There is a corpus of works addressing RSs in tourism in general, such as Borras et al [9], which focused on the city tourism and included only a few museum systems, and Kabassi [10], which mentioned just a few museum systems as well. There are several surveys that examine different aspects of generic RSs. Among them [11], where RSs are classified according to their application fields and their data mining techniques; in [12] the most significant aspects of general RSs were examined, including the filtering algorithms, the bootstrapping problem, the similarity measures, and the social aspect. Another in-depth review in RS algorithms was presented in [13], which explained the macroscopic behavior of the popular RSs algorithms giving a physics perspective.

3. System Components

An architectural structure for personalized content services in museums is proposed in Fig. 1. The *Localization* subsystem uses sensors to locate the user or the artifact that is closer to the user or currently viewed by the user. The recommendation subsystem proposes content related to that artifact, and the relative pose of that artifact may be used for the projection of AR content on the user's screen. The *Recommendation* subsystem offers personalized content by using the visitor's profile, the available content, and the current context. The *Content* subsystem maintains digital material along with the associated descriptors, so that these can be matched to the user profiles. The *Visitor's Visualization* subsystem adapts the content for presentation on the mobile device. The *Curator's Visualization* subsystem presents graphically the exhibition statistics.

The overall workflow may look as follows: the user enters the museum after registration and initialization. The closest (or the viewed) artifact is located, and the user profile is matched with the most related content. Eventually sensors are used to capture the context, i.e., visitors' physiological state, focus of attention (FoA) etc. The matched content is retrieved from the content system, and then presented to the user's device after eventual adaptations, e.g., adaptation for AR projection. Asynchronously the curator may observe the statistics of the artifacts or supplementary material to decide on appropriate exhibition reconfiguration actions. In the following subsections we survey the latest developments concerning the subsystems displayed in Fig. 1.

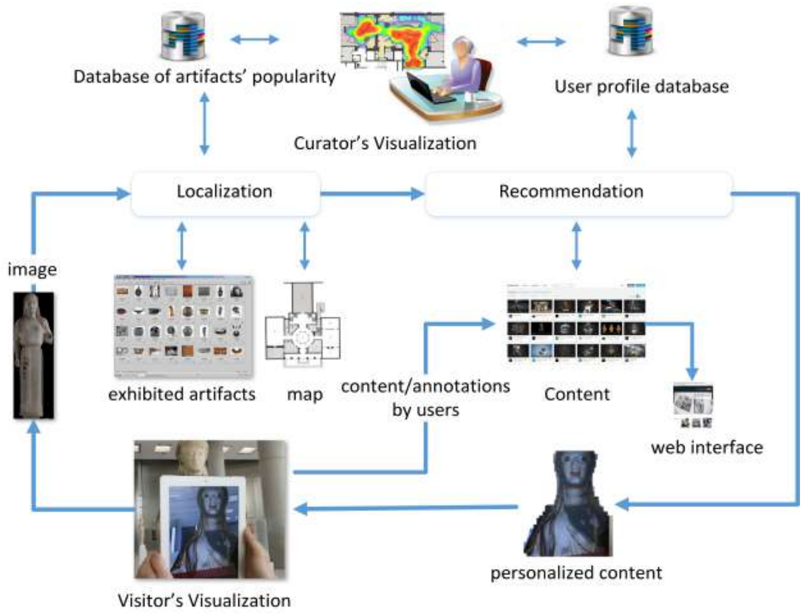

Figure 1: Proposed architectural scheme including the subsystems of localization, recommendation, content, visitor's visualization, and curator's visualization.

3.1. Localization

By having available the location, we can suggest artifacts based on their proximity or indirectly infer other elements of the context (previously seen artifacts, time in front of an artifact, etc). Further services can be realized using the visitor's pose, such as superposition of AR content. Indoor localization has been used in several other applications, such as navigation, tracking, emergency and safety, local news, location-based social networking, travel guidance, elderly assisted living, and pet/asset finding etc., with different requirements [14]. The localization problem is largely unsolved. The currently applied technology has achieved accuracy of a couple of meters. The challenge is how to increase this accuracy without having to resort to other technologies, which are not applicable in museums due to required infrastructure that harms museum aesthetics, and due to visitor obtrusion.

The basic localization approaches are: (a) the *proximity* determines the position of a device merely by its presence in a particular area within which operates a beacon of limited range; (b) *lateration* uses position data computed with redundancy from more than two distance measurements to nearby nodes; (c) *fingerprinting* the various RSS (receiver signal strength) tuples are measured in all meaningful positions offline, and then on-line the current measured RSS tuples are compared for the best agreement with a database; (d) *dead reckoning* is based upon previously determined positions and known or estimated speeds over the elapsed time, typically using inertial sensors; (e) *Kalman Filtering (KF)* and its nonlinear counterpart *Extended Kalman Filtering (EKF)* are typically used for fusing dead reckoning positions with absolute position updates to reduce accumulation errors.

The basic features of the localization technologies and their applicability in museums are given in Table 1. In Table 2 we summarize some of the most representative localization research in museums.

Manual localization is currently used in most museum guides, e.g., Sung et al [15]. The artifacts are numbered, and the user keys-in their number using a mobile device to view the associated content. **Barcode scanner** is faster and more usable. QR or HCCB codes [16], are very cheap to produce, and can be integrated well into mobile applications. Unfortunately, they are not preferable, since for small objects, they consume much space affecting their appearance, and for large objects, their location is often not obvious. **Infrared (IR) sensors** use the proximity, and has been used mainly by early systems. eacons emit infrared light, which includes unique codes. The emitted beams are highly directional, require line-of-sight, and many devices do not support IR. **Radio Frequency identification (RFID)** [17] does not require line-of-sight. The higher the frequency, the better the accuracy, but also the higher the attenuation. Active RFIDs are rather cumbersome with high energy consumption, while the passive ones are cheap and small and require no power source apart from the reading antenna, however antennas are undesirable in museums. Furthermore, metal or glass cases may result in undesired reflections. RFIDs require dedicated hardware. Typical approaches are: (a) proximity, e.g., in Wang et al, [18] , Ghiani et al [19], Hung et al [20]; (b) lateration, e.g., in Kanda et al [21] and in D'Amico et al [22]; and (c) fingerprinting, e.g., Phimmasean and Kanthavong [23]. **Near-Field Communication (NFC)** is a short-range technology, operating within a few

type	band	range	benefits	limitations	method
infrared	430THz 300GHz	10m	low power, highly directional	requires targeting the artifact (line of sight), many sensors for high accuracy	proximity
RFID	30-500KHz, 3-30MHz 433,865-930MHz	1-15m	no line of sight no power (passive devices)	infrastructure, reflections sparse setup	proximity, lateration fingerprinting
Zigbee	868Mhz,2.4GHz	20-30m	low power,very simple	interference	fingerprinting, proximity
Bluetooth	2.4-2.485 GHz	1-10m	simple, secure, low power supported by most devices	affected by museum crowd fingerprinting	proximity
NFC	13.56MHz	10cm	two way communication, supported by many devices	requires contact	proximity
WiFi	2.4GHz, 5GHz	30-50m	available in most museums and devices	affected by museum crowd	fingerprinting
Ultra Wide Band	3.1-10.6GHz	25m	high accuracy	too heavy infrastructure for museums unsupported by devices	lateration
Barcode reader	visual	a few cm	cheap, reliable available on most devices	aesthetically intrusive in museums	proximity
Wearable camera	visual	a few meters	natural interaction	complex processing, intrusive against policies of some museums	proximity
Camera on device	visual	a few meters	available on most devices	complex processing against policies of some museums	proximity
Ultrasonic audio	20-24KHz	10-15m	available on most devices	infrastructure required	proximity, fingerprinting

Table 1: Summary of typical features of indoor localization technologies, and the benefits and limitations of use in a museum setting.

Localization Method	References
RFID	Kanda et al [21], Wang et al [18] Ruotsalo et al [32] D'Amico et al [22], Ghiani et al [19], Hung et al [20]
Mobile camera	Ruf et al [33], Fockler et al [34]
Infrared beacons	Oppermann et al [35], Sparacino [36], Bombara et al [37], Rocci et al [38] , Petrelli et al [39], Kuflik et al [40]
Ultrasonic speaker	Bihler et al [41], Lazik and Rowe [42]
Manual	van Hage et al [43], Bohnert and Zukerman[44]
Barcode	Levialdi Ghiron et al [45], Wein [46], Ayala et al [47], Mason [48]
NFC	Angelaccio et al [49], Ceipidor et al [50], Ayala et al [47]
Zigbee	Kuflik et al [51], Lanir et al [52]
Bluetooth	Yoshimura et al [53], Martella et al [28], [54]
WiFi	Luyten et al [55], Pan et al [56], Kushki et al [57], Kaemarungsi et al [58], Chianese et al [59], Sark and Grass [60]
UWB	Dimitrova [61], Bueno et al [62], Gunes and Ibarra [63]

Table 2: Summary of representative localization methods in museums or other indoor settings.

centimeters allowing two-way communication [24]. The content can be stored in an NFC device following the Internet-of-Things paradigm. Several device manufacturers support it, but its limited range necessitates contact.

Zigbee is a standard for Wireless Personal Area Network (WPAN) operating in the ISM band [25]. It provides low power consumption and low data throughput. Distance estimation between two ZigBee nodes is usually carried out from RSS values. It operates in the unlicensed ISM bands, and is vulnerable to interference signals using the same frequency. **Bluetooth** (and **Bluetooth Low Energy (BLE)**) are also WPAN standards operating in the same band [26], [27]. Bluetooth is supported by most devices, it has low power consumption, and its protocol is simple but secure. It is typically used for proximity, e.g., [28] and fingerprinting, e.g., [29]. It can be affected by crowd, and often the RSS values are not easily accessible. **Ultra Wide Band (UWB)** is a radio technology for transmitting information by generating radio energy at specific time intervals [30]. It occupies a large bandwidth, thus enabling pulse-position or time modulation. It does not require a line-of-sight trajectory, and is less affected by the existence of other communication devices or external noise. In the Microsoft indoor competition of [31] UWB-based systems achieved up to a few cm accuracy. However, the requirement for expensive infrastructure is a serious limitation in museums.

WiFi is attractive, since its coverage is high, most mainstream devices have it, and most museums use it already [64]. WiFi doesn't require line-of-sight, and the range can be 50-100 meters. Lateration by measuring the RSS signals is not often used, due to reflections and occlusions [58], but is typically combined with fingerprinting, e.g., Luyten et al [55]. Machine learning methods are typically applied offline, e.g., kernel-based learning by Kushki et al [57], Canonical Correlation Analysis by Pan et al [56], Support Vector Machines by Sark and Grass [60]. WiFi is one the most popular options for avoiding heavy infrastructure [65].

Ultrasonic audio requires the use of simple inaudible ultrasonic speakers. It is cheap, and can be easily integrated in many smart phones, which typically can sense audio of up to 24KHz. Speakers of known position emit their IDs, each in different frequency. Positioning can be done by proximity (e.g., Bihler et al [41]), lateration or fingerprinting (e.g., Lazik and Rowe [42]).

Cameras are attractive due to their rich information, and because they are embedded in most devices (e.g., Balakhontseva and Sieck [66], Bruns et al [67]). They can also be *wearable* or *statically mounted*. Content-based retrieval can be used for artifact recognition [68]. Taking photos is intuitive, makes tags and beacons redundant, and allows for classification of dense artifacts. However, taking photos is still not the most intuitive way of interaction, and often it is against museum policies. Furthermore, museums are complex environments, often exhibiting thousands of objects, which have to be classified from arbitrary perspectives, distances and under changing lighting conditions. *Wearable cameras*, e.g., on helmets or glasses, offer first-person views in a more intuitive way or can be part of an attention-tracking system; the intuitiveness is however balanced by the user obstruction. The integration into glasses gives the opportunity to view content directly onto them without attention switching, e.g., Mason [48] who used a QR scanner. Toyama et al [69] mounted a camera on a helmet as part of an eye-tracking system. The eye fixations (resting of the eyes) were employed to identify which was the currently viewed artifact. The image recognition results were used to label the frames of the video stream with the label of the recognized object. *Static cameras*, may offer some interaction capabilities, e.g., [70], however the requirement for visitor identification and tracking under occlusions and varying illumination, e.g., [71], and limited field of view, are quiet unattractive. Similarly, depth cameras like Kinect (e.g., [72]) are more robust to illumination variability, but still face similar issues. Mounting omnidirectional cameras on ceilings (e.g., [73]) may minimize occlusions, however still extensive infrastructure is required.

Combined sensor use. It becomes clear from the above, that no single technology is perfectly suited for a museum environment. Therefore, researchers have tried to tackle the different aspects of the localization problem by alternating between different sensors. Coarse localization methods are useful to scale down the computationally-intensive visual search in camera-acquired images, e.g., RFIDs by Wakkary and Hatala [74], bluetooth by Bimber et al [75] and Bruns et al [67]. The PIL project [51] employed three different kinds of devices: static RF beacons (in points of interest), fixed RF to TCP/IP gateways and wearable RF devices with audio sensors called "Blinds". The "Blinds" measured (a) proximity to beacons (location), (b) proximity to other "Blinds" (visitors), (c) short range voice level activity (engagement among visitors), (d) visitors orientation, using embedded magnetometers (engagement to artifacts and among visitors), and (e) motion using accelerometers (level of activity). However, carrying extra equipment may be considered obtrusive, increases maintenance costs and should be better avoided.

Sensor fusion tries to fuse the input from multiple sensors. This refers to the concurrent and unified use of sensor measurements, and is different from sensor combination which uses different sensors in different circumstances. Such a fusion involves the Inertial Measurement Unit (IMU), which is a module integrated into many smart phones and tablets, thus carried anyway by the majority of museum visitors; it uses several sensors (i.e., 3-axis accelerometer, gyroscope and digital compass), from which the approximate user position and orientation can be easily calculated. Several works used it e.g., [76] used mounted sensors on each foot (a rather obtrusive setting) in combination to extended Kalman filtering with accuracy of 2.5m. In Li et al [77], Ahmed et al [78] and Xiao et al [79] the WiFi fingerprinting was fused with data from the IMU unit and in Li et al [80] with magnetic signals for better accuracy. The mapping function between different sensor readings, and position is nonlinear and therefore machine learning methods were used to learn it, e.g., CRFs [79], neural networks [81], clustering and decision trees [78]. In [77] a magnetic sensor was used (along with WiFi and IMU) to detect magnetic anomalies, which are common inside buildings, e.g. due to power cables, electrical appliances or metal surfaces, to refine orientation. This is a promising research line, since the magnetic sensors are integrated into most mobile devices and the related processing is not too restrictive. Zhang et al [82] used lidar, IMU sensors and a fisheye camera; the reported accuracy was a few cm, but lidar sensors are far from portable and thus unusable by museum visitors.

3.2. Recommendation

The RSs are software systems that maintain a knowledge base about the *content* (supplementary digital material), the *users* (personal profile), and the *context* (the current state of the user and the museum environment). They also employ *filtering methods* (inference mechanisms) to make the best matching between users and content recommendations. In the following we briefly describe the basic elements of an RS, some of which may be automated by using sensors.

The *content* to be suggested refers to supplementary material associated with the artifacts. The following methods are typically used for content representation: (a) text descriptions and bag of words extracted manually or from related texts, synonyms or user tags e.g., in [44]; (b) semantic concepts defined in exhibition-specific ontologies, e.g., in [87]; (c) content-based representation methods of multimedia [68].

	RFID	IR	BT	WiFi	Zigbee	Camera	Acc	QR	IMU	audio	magn	lidar
Bay et al [83]			x			x						
Bimber et al [75]			x			x						
Bruns et al [67]			x			x						
Spasojevic et al [84]	x	x						x				
Wakkary & Hatala [74]	x					x						
Stock et al [85]	x	x		x								
Krueger et al [86]	x	x		x								
Kuflik et al [40]	x				x		x			x		
Li et al [81]				x					x			
Li et al [77]				x					x		x	
Ahmed et al [78]				x					x			
Xiao et al [79]				x					x			
Ju et al [76]									x			
Zhang et al [82]						x			x			x
Li et al [80]				x							x	

Table 3: Summary of typical fusion and combined localization methods (RFID, Infra Red, BlueTooth, WiFi, Zigbee, Camera, Accelerometer, QR code, Inertial Measurement Unit, Magnetic sensors). The works in the second half of the table, separated by the dashed line were not originally applied in museums, however are useful to mention.

The *user* model is typically associated to the content representation. It can have the following forms: (a) concepts represented in the domain ontology e.g., in [87]; (b) the same bag of words as the artifacts, e.g., in [44]; (c) demographic data such as age, nationality, education etc, e.g., in [88], which can be associated to preferences at a later stage; (d) list of items with their ratings, to be used in collaborative filtering, e.g., in [89]. Sensors can be used to infer the user's preferences (ratings) while the rest items are typically captured manually.

The *context* generally refers to the following information [90]: (a) user location (as extracted from location/surveillance sensors); (b) the user's emotional state; (c) the user's physiological state extracted from wearable sensors; (d) artifacts that have already been visited; (e) social environment, i.e., is the user alone or a member of a group (extracted implicitly from location/surveillance sensors); (e) available time in the exhibition defined by the museum opening hours or the visitor's schedule; (f) artifacts that are accessible; (g) museum layout. Sensors can be of use in acquiring the (a-e), while the rest are typically defined manually.

The *filtering methods* can be largely classified into the following: *Demographic filtering - DF* makes the assumption that individuals with certain common personal attributes (sex, age, country, etc.), which are captured during the registration process will also have common interests, e.g., [39]. *Content-based filtering - CBF* makes recommendations based on the semantics of the artifacts. The matching can be based on explicitly asking the users' preferences upon registration to map them to ontology concepts, or by implicit matching via a questionnaire, where representative artifacts have to be rated [87]. It can also be based on previous preferences by the users during the visit. The similarity can be based on (a) the ontology-based semantic attributes (b) the computational analysis of the supplementary text to extract meaning (c) from audio-visual analysis of related digital material. CBF will benefit from the standardization of the metadata for museum artifacts [91]. *Collaborative Filtering - CF* is based on the ratings provided by users of similar profile. The ratings can be acquired explicitly by direct asking or implicitly, acquired (e.g., access, time spent). *Hybrid filtering - HF* uses combinations between the aforementioned filtering techniques to achieve optimal performance to exploit merits of each one of them.

The filtering methods may also be classified as memory-based or model-based according to the method they employ. Memory-based methods operate over an entire database of ratings to make predictions. In contrast, model-based methods, like neural networks, learn a statistical model, and use that model to make predictions.

The RSs have reached a rather high level of maturity, and are now widely employed in mainstream web and mobile services [12]. However, the developers of museum content services still face several limitations and challenges in acquiring user's profiles, such as: (a) the cold start problems, i.e., how to initialize the profile of the users; (b) the non-invasive dynamic extraction of individual or group profiles; (c) the focus of attention for visitor profiling; (d) the physiological state of visitors for context extraction. These challenges are presented next.

3.2.1. Cold start

The cold-start problem occurs when it is not possible to make reliable recommendations due to an initial lack of ratings. It can be further classified into the sub-problems of "new community" (a new system with no ratings), "new item" (with no ratings, and thus not likely to be recommended), and "new user" (whose the profile has to be dynamically inferred) [12].

The "new community" problem can be tackled by creating an initial set of users-testers to initialize the system. Some extra motivation may be given to first users to use the system, e.g., free access to the service or to the

Work	cardinality	classes	features	classifier
Sparacino [36]	one	GBS	location, duration	Bayesian network
Hatala et al [97]	one	GBS	location	rules
Marti et al [98]	one	AFBG	motion, stop duration, trajectory	recurrent neur. network
Chittaro, Ieronutti [99]	one	AFBG	occupancy grid	visual observation
Sookhanaphibarn and Thawonmas [100]	one	AFBG	average/variance of observation time	probabilistic model
Zancanaro et al [101] and Kuflik et al [40]	one	unsupervised and AFBG	timing, exhibits visited, interaction, presentation viewing	k-means and neural network
Cuomo et al [102]	one	AFBG	objects viewed, timing, visiting sequence	k-means and rules
Martella et al [103]	one	unsupervised	trajectory, timing	agglomerative clustering
Kanda et al [21]	one	unsupervised	position	string matching
Shell et al [104]	one	unsupervised	position	Markov process
Bohnert et al [89]	one	unsupervised	position	fusion of probabilistic model & Markov process
Bohnert et al [105]	one	walking, hovering	position	SVM
Dim and Kuflik [106]	group	join/separate	mutual proximity/orientation, location and voice proximity	probabilistic
Dim and Kuflik [107]	pair	PGMPDL	orientation to exhibits, orientation correlation, velocity, time difference	dataflow

Table 4: Summary of profiling methods. "GBS" refers to greedy-busy-selective classes [36], while "AFBG" refers to ant-fish-butterfly-grasshopper [108] and PGMPDL refers to penguins-geese-meerkats-parrots-doves-lone wolves [107].

museum. The "new item" problem arises because the new artifacts entered in RS do not usually have initial ratings, and an item that is not recommended goes unnoticed. A common solution is to motivate users to rate new items. The "new user" problem is more challenging. New users have been only partially modeled, and have not yet provided any rating in the RS; thus they cannot receive meaningful personalized recommendations; therefore, new users may feel disappointed. The common strategy is to resort to demographic data, or short questionnaires to classify visitors into predefined classes and give more emphasis on DF than CF at the initial stages (e.g., [92]). The amount of such data must be carefully decided, since asking for more data impedes the visit experience, and raises privacy issues. Another approach is to ask for the user to rate some artifacts or content at the beginning of the visit or before the visit using a web interface, see e.g., [43]. This helps elicit the user's preferences in an intuitive way. However, it requires time and user awareness that such an option exists.

Recently there are have been some very interesting efforts to extract user engagement and emotion towards museums and cultural artifacts using social media analytics, e.g., Gerrard et al [93] and Chang et al [94]. Such methods may be used to approximate a profile. Furthermore, cross-platform based solutions like the ones proposed in [95], [96], may be of use in the future. Currently, there are too many issues to be resolved before these ideas can be of utility, such as the limited use of RSs by museums, the user privacy, the proprietary nature of the web RSs which prevents the implementation of roaming profiles, the uncertainty on how to translate a profile from one domain (e.g., video on-demand) to another (museum content). On the other hand, all these problems constitute an opportunity for ground-breaking research.

3.2.2. Dynamic extraction of individual or group profiles

Individual profiles: The extraction typically follows the supervised learning paradigm. Sparacino [36] defined three such typical profile types: (a) The *greedy*, who wants to know and see as much as possible; (b) the *busy* who just wants to get an overview of the exhibition; and (c) the *selective*, who wants to see and know in depth only about a few items. Then the path and length of stops were linked to a profile, which was estimated probabilistically by a Bayesian network. Time constraints were additionally considered. An extension of the Bayesian network suggested videos based on the content and the duration of the selected clips. The same profile types were used by Hatala and Wakkary [97] who used a knowledge-based (ontological) approach. The content selection was achieved by a rule-based system.

Earlier, Veron [108] had described some more detailed profile types: The *ant*, that follows specific paths, and observes almost all the exhibits; the *fish* who often moves in the room center without looking much at the exhibits; the *butterfly*, who doesn't follow a specific path, and stops frequently to observe; the *grasshopper*, visits only specific exhibits, and spends a lot of time observing them. These patterns became quiet popular, e.g., [99], [101], [100], [40], [102].

Chittaro and Ieronutti [99] identified the different visitor classes by using occupancy grids. Sookhanaphibarn [100] further explored that idea to create a measure using the visit time and the observation distance. Zancanaro et al [101] used supervised training of an artificial neural network and an unsupervised clustering method (k-means) with k=4, and found similarities between the two models. The observation features included the time spent at each point, the percentage of exhibits visited, and data describing the interaction with the guide application. Later an investigation was done on how profile prediction may change during a visit [40].

Cuomo et al [102] used the number of viewed artworks, the time spent interacting with them, and the visitor's path. A simple rule-based classifier was used, which was then compared to k-means, and was found to give similar results. Martella et al [28], used the paths and the visiting times. An agglomerative clustering method was used, which allowed for quite detailed profiles.

Very few works have exploited the concept of sequential patterns of behavior which can be sought in trajectories. Kanda et al [21] partitioned the museum space into areas using k-means clustering by sampling the trajectories of monitored visitors. The trajectories were then expressed as strings, and compared via string matching. Similarly, Shell et al [104] used a Markov process.

Bohnert et al. [89] predicted the location by means of: (a) the interest-based model, based on the interest in unseen exhibits (similar to CBF); (b) the transitional model, based on the trajectories of other visitors. A matrix involving all visitors and exhibits was calculated by using CF for missing items. The transition model was a Markov process which employed a weighted average of the two models. In the same line of research Bohnert et al [105] improved [89], to differentiate hovering from walking velocities and accelerations, along with an SVM.

The fusion of multi-sensory data along with the employment of state-of-the-art machine learning methods, like deep learning, have been employed successfully in other behavior recognition applications, e.g., in Jian and Yin [109]. Such a method is based on learning data representations in a hierarchical multilayer fashion. The first layers capture some elementary low-level signals in a similar fashion that the human brain does, while the next layers are able to capture patterns of increased complexity [110].

strategy is expected to offer significant benefits to the dynamic profile extraction in museums.

Group profiles: Most visitors in museums arrive in groups [111]. Despite its importance, the group modeling via group profile extraction is not so common due to (a) the difficulty to extract the profile of group members and (b) the difficulty to make appropriate recommendations to each group member according to the role of the person in the group.

The research field of computer-supported cooperative work and collaboration support has dealt with group modeling. Ardissono et al [112] studied how user and group interests evolve in time. Social behavior has been investigated in the emerging field of social signal processing (SSP) see, e.g., Pantic et al [113] and in pattern recognition, e.g., by Ibrahim et al [114]. How these fields intersect to make group recommendations remains an under-investigated area.

In a series of works by Dim and Kuflik [115], [107] profiles for groups of two people were defined: *penguins* who walk through exhibitions but do not pay attention to the exhibits; *geese* go together, but one visitor seems to lead; *meerkats* advance together and synchronized, paying attention to the exhibits ; *parrots* advance from one exhibit to another together, and interact while looking at the exhibits; *doves* stand face to face, ignoring the exhibits; *lone wolves* enter the museum together and then split. The features used were (a) mutual proximity, (b) mutual orientation while in mutual proximity, (c) orientation toward exhibits, (d) velocity, (e) time difference between the pair members, and (f) orientation correlation. A rule-based dataflow was used to classify group profiles. Meerkats and parrots have both mutual social interest and exhibit interest, and therefore shared presentations are recommended. Doves are already socially involved, and therefore no recommendation is made. Penguins show little interest in the exhibits, so anecdotes about museum exhibits may attract their attention. For geese, anecdotes are recommended to the leading person, who may invoke the interest of the follower as well. For lone wolves proposing a museum activity meeting point may invoke curiosity in the museum content.

3.2.3. Emotion recognition via physiological state monitoring

Several studies have shown that emotion can be an important cue for profiling, see, e.g., [116], and that measurable physiological changes co-occur with emotion, e.g., changes in heart rate, galvanic skin response, muscle tension, breathing rate and brain electrical activity [117]. By sensing these changes we can hope to recognize emotion of visitors, and adapt accordingly the provided content. Several types of wearable technologies can be used, like smart glasses, wrist/arm bands, smart watches, smart clothing, smart gloves, and Brain Computer Interfaces.

The *heart rate* variability has been an indicator of fear, panic, anger and appreciation [117]. It is measurable by an electrocardiogram (ECG), which can be captured from the surface of the skin through electrodes, or by photoplethysmographic (PPG) sensors; the latter may use optical input from the skin as in most smart watches

Work	sensors	classes	benefits	limitations
Sparacino [36]	skin conductance	level of excitement	non invasive	noisy signal classification
Damala et al [126]	heart rate skin conductance brainwave activity	level of excitement	highly informative signals	obtrusive
Du et al [127]	skin conductance	level of excitement	non invasive	noisy signal
Troendle and Tschacher [128]	skin conductance heart rate	Aesthetic quality, surprise, negativity, dominance, curative quality	informative signals, non invasive, rich emotions	hard classification
Abdelrahman et al [129]	EEG	level of engagement	informative signals	obtrusive

Table 5: Summary of works on physiological state monitoring for museum visitors, their benefits and limitations.

[118]. The *skin conductance*, (or galvanic skin response (GSR)), is another commonly used measure of affect. It is used to indirectly measure the amount of sweat in a person's sweat glands, since the skin is normally an insulator, and its conductivity primarily changes in response to ionic sweat filling the sweat glands. It varies linearly with the emotional aspect of arousal, and it has been used to differentiate between states such as anger and fear, and conflict and no conflict [117]. Several wearable devices have been presented to measure GSR such as watch-style sensor Bakker et al., [119], armband Dang et al., [120], wristband Hernandez et al., [121] etc. The *electrical activity of the brain* is triggered by firing neurons, and is measured through electroencephalograms (EEG) by placing electrodes on the surface of the head. Brain Computer Interfaces (BCI) simplify this task. They have been recently available as commercial and portable devices such as NeuroSky [122], and Emotiv [123], and have been used to gain insight about attentiveness/engagement, relaxation or creativity, e.g., in games [124] or in learning [125]. Table 5 gives a summary of representative works in a museum context.

One of the first such works was by Sparacino [36], where the GSR was used to identify the level of excitement. This was probabilistically evaluated with a Bayesian network. In the project ARtSENSE [126] heartbeat activity, GSR and brainwave activity were measured. However, no detailed experimental results were reported. Du et al [127] captured the affective responses using the GSR using a commercial wearable sensor on the arm. An experiment was conducted with fourty-six visitors viewing different paintings. The most extensive experiments so far were reported by Troendle and Tschacher [128]. Five hundred thirty-two visitors, used an electronic glove able to measure heart rate and GSR variability. Then they were associated to the emotions: Aesthetic Quality (artifact rated as pleasing, beautiful, emotionally moving, of high technique, composition and content, of artist or of importance in art history), Surprise/Humor (considered as surprising, funny), Negative Emotion (sadness, fear or anger), Dominance (dominant or stimulating), Curative Quality (artifact was staged and presented well or connected to other artworks).

BCI was tested in a museum context in [129], who conducted a pilot study with ten students by simulating a visit in a lab environment. Some correlation was found between measurement and engagement levels, however the results were at a preliminary level.

Physiological sensors face many challenges which explains why their use for personalized content services in museums is not widespread. They need to be non-invasive; there has been a lot of progress in that aspect, given the wide range of commercial products. However, high usability often impedes the signal quality, e.g., using optical sensors instead of electrodes may result into noisy and unstable signals. Ground truth data are difficult to produce: the data are difficult to label correctly due to subjective description of emotions, and the related equipment is often expensive and difficult to use in a museum context. Furthermore, there may be many other factors that can affect physiological signals that are totally unrelated to emotions.

3.2.4. Focus of attention extraction

The focus of attention (FoA) can be a significant cue, which may be associated to user's profile or context. Many position-based systems fail to answer whether the visitor is actually looking at an artifact or if s/he just happens to be in its proximity. The answer is trivial when the user explicitly asks for information using barcode identification, a camera etc., but is subtler when other localization methods are used. An outline of the works on FoA is presented in Table 6, and are described in more detail in the following.

Gaze trackers can give offer valuable information about FoA [138]. In contrast to other methods they can track not only which direction the person is looking at, but also where the eyes are fixated. The application of mobile eye tracking devices is still at its very infancy. Wearable gaze trackers have the potential to offer high quality data if used correctly. However, their common problem is their intrusiveness. After a few minutes the user does not feel comfortable, and this is a major issue. Furthermore, the timely calibration process is an additional negative factor which currently limits eye tracking systems to laboratory experiments.

Work	method	contribution
Wessel et al [130]	wearable eye-tracking	initial study of scanpaths in museum
Toyama et al [69]	wearable eye-tracking	fixations for artifact recognition
Mokatren et al [131]	wearable eye-tracking	fixation accuracy on paintings and other objects
Bachta et al [132] and Fantoni et al [133]	wearable eye-tracking	effect of visitor-specific calibration on accuracy
Eghbal Azar et al [134]	wearable eye-tracking	behavior classification by scan patterns
Damala et al [126]	wearable eye-tracking acoustic sensors	eye tracking and related content visualization implicit visitor attention from audio
Kuflik et al [51]	acoustic sensors	visitor engagement from audio
Calandra et al [135]	static eye/head-tracking	emotional arousal from pupil size
Brunelli et al [136]	static head/hand-tracking	stereo cameras for head pose and point actions
Kajinami et al [137]	static head-tracking	depth camera for head pose and point actions

Table 6: Summary of works on attention extraction methods for museum visitors.

Wessel et al [130] conducted an initial study on the eye tracking patterns of visitors in a museum. Later, the Museum Guide 2.0 [69], introduced a rather obtrusive head-mounted eye tracker acting as a personal guide; when it detected the user fixing his gaze on an artifact it would provide audio information on that specific object via earphones. Mokatren et al [131] reported promising results when the exhibits were on the same height, and had similar size (e.g., paintings); it was found to be far more challenging when viewing different objects on various spatial configurations. Eghbal-Azar and Widlok [134] identified several scan patterns that can be potentially used to characterize visitor behavior.

To visualize the provided AR content special eyeglasses were used by Damala et al [126]. The glasses had a see-through display which was capable of projecting information in the visitors field of view, as a virtual overlay. Additionally, the glasses had the ability to track the eye movements. To calculate the visitors gaze on an actual watched exhibit, an additional scene camera was attached to the eyeglasses. Fantoni et al [133] tested three different eye tracker applications. The overall evaluation showed that the trackers were generally received positively by visitors, although inaccurate without calibration to each specific user. On the other hand, the calibration process was time-consuming, and thus annoying for visitors. That confirmed the results presented by Bachta et al [132].

Recently Calandra et al [135] proposed a static non-invasive eye-tracking system. It extracted the points of gaze from eye movements and the head pose using the nose as an orientation landmark. Furthermore, the pupil size was measured, using infrared light for radius variations, which were associated to emotional arousal. The main problem with static systems is the very high cost of installing static cameras to cover large exhibition spaces.

Head tracking can give indications about the visitor's attention. In [139] a survey on appearance-based methods for head tracking was presented. Recently head pose was used for attention modeling, e.g., [140]. In a museum context Brunelli et al [136] used static stereoscopic cameras to detect the head pose, which approximately gave the FoA. The same stereoscopic system was able to extract the pointing gestures, which is another indication of attention. Similar results are attained by employing other sensors such as depth cameras as by Kajinami et al [137]. Unfortunately head tracking requires static cameras which, makes this technology applicable only at a small scale for museum guidance and personalized content services.

Acoustic sensors are an option to infer implicitly some information about the level of attention, since sounds can disturb the visitor, or speech signals may indicate engagement among the visitors. Therefore, it may be useful to know what is happening in the acoustic proximity. In [126] the acoustic events and background noises were captured using a set of omnidirectional condenser microphones and a multichannel audio data acquisition unit worn by the visitor. The system determined the level of disturbance, and if the visitor had turned towards the acoustic event. In [51] audio sensors were used on mobile devices to infer the level of engagement between pairs of visitors. Clearly, the acoustic sensors are attractive, especially given the fact that such sensors are embedded in mobile devices carried anyway by most visitors.

3.3. Content

In the following we provide an overview of the different types of content, information presented to the visitor, connection to artifacts, content organization, and presentation to the user.

The content that we most often see in museum guidance systems is multimedia-based, therefore it includes texts, sounds, images, videos, animation, narrations, virtual reality [141] and, lately, AR, as shown in [142] and [143]. Information that is presented to the visitor through guidance systems is usually based on artifacts, and includes descriptions, interpretations, observations of details, associations to other artifacts in the same museum, or artifacts in other museums, usability of objects, restoration information; it may also include descriptions of the broad historical or social context, and may follow the museum's room structure [144].

The most common interaction media in a museum guidance system are: (a) thematic guides based on classification criteria such as historical period, geographical area and type of artifacts, activity (e.g., music, daily routine, etc), (b) games, where the participants have to research, interpret, reveal and compete against other participants, e.g., a hidden treasure game, where the keys to finding objects have to be sought among the information provided for museum artifacts [145], (c) narration by historical or fictitious characters featuring daily life or historical events [146].

Typically, a content management system (CMS) provides a storing structure that supports the beforementioned interaction media types. It is usually a hierarchical structure of information objects about artifacts classified by thematic categories, geographical regions, and historical periods. The content also may include relations among artifacts, thesaurus, and keywords. Content organization in a CMS may be based on several standards. The International Committee for Documentation (CIDOC) of the International Council of Museums (ICOM) has led the development of the Conceptual Reference Model (CRM), providing perhaps the most complete model for describing concepts and relationships when documenting cultural heritage objects [147]. The CIDOC-CRM is intended to promote a shared understanding of cultural heritage information by providing a common and extensible semantic framework that any cultural heritage information can be mapped to. In this way, it can provide the semantic glue needed to mediate between different sources of cultural heritage information, such as that published by museums, libraries, and archives [148]. CIDOC-CRM is still employed by various cultural heritage content providers. CIDOC-CRM is structured as a hierarchical ontology.

On a broader level, Dublin Core provides metadata definitions for a wide range of multimedia content and physical objects that may include artifacts. Some efforts have been made for particularizing Dublin Core for cultural heritage such as the DCMI Cultural Heritage Metadata Task Group [149] and the proposal for the combination of CIDOC-CRM and Dublin Core [150]. Dublin Core is structured as metadata set of fifteen elements, each of which is characterized by name, label, definition and comment.

The Museum Documentation Association (MDA) in the UK has developed the SPECTRUM standard, that is a guide to good practice for documenting museum collections [147]. It has now reached version 5.0 [151]. It focuses on procedures taking place in a museum, such as loans that indirectly take into account artifacts.

Originated in the USA, Dublin Core is generic enough to describe digital resources (images, video and other multimedia files), and multimedia-related physical objects such as CDs, posters and artworks. Dublin Core metadata may also be used for combining metadata vocabularies of different metadata standards. On the other hand, SPECTRUM has been developed focusing on museum collections, artifacts and 21 transactional activities, such as moving objects around, and insurance coverage, which deal with museum artifacts or other objects that can be handled as artifacts. SPECTRUM is used by a set of museums in the UK, but in recent years the standard has been also adopted by other countries and translated into several languages, and became the collection management standard that is used around the world.

Another standard established by the Visual Resources Association Foundation (VRAF) is Cataloging Cultural Objects (CCO). VRAF continuously supports the future development, maintenance, web presence, and administrative structure of CCO, which is used in many cultural organizations ([152]). CCO is structured as a hierarchy of elements and rules among elements.

A standard which focuses on educational applications that may be used in museums is SCORM. It is used in Learning Management Systems (LMS) or in Learning Content Management Systems (LCMS) [153]. Authors incorporate SCORM in a CMS for virtual museums. SCORM is composed of three sub-specifications, the Content XML-based Packaging section that specifies how content should be packaged and described, the JavaScript -based run-time section that specifies how content should be launched and how it communicates with the LMS and the XML-based Sequencing section that specifies how the learner can navigate between parts of the course. A smart museum which incorporates Internet of Things technology is described in [154], where a proprietary CMS has been developed, and authors stress the need for standards in this type of museums as well.

Another standard is the Europeana Data Model (EDM), an XML-based data model which brings more meaningful links to Europe's cultural heritage data. Data from partners or external information resources with references to persons, places, subjects, etc., connect to other initiatives and institutions. This results in sharing enriched content, adding to it, and thereby generating more content in ways that no single provider could achieve alone. The EDM aims to translate into the richest resource discovery, and into improved display of more complex data [155].

Finally, we should mention Lightweight Information Describing Objects (LIDO), an XML harvesting schema, which is not intended to be used as a basis for a collection management system [156]. However, the schema is intended for delivering metadata, for use in a variety of online services, from an organization's online collections database to portals of aggregated resources, as well as exposing, sharing and connecting data on the web. The strength of LIDO lies in its ability to support the full range of descriptive information about museum objects. It can be used for all kinds of objects, e.g. art, architecture, cultural history, technology history, etc.

Standard	Description	Type	Pros	Cons
CIDOC-CRM	reference model for cultural heritage info	hierachical ontology	Focus on cultural heritage. detailed specification.	low support by commercial collections software
Dublin Core	USA-originated specification set for multimedia resources and physical objects	15 generic metadata elements for digital resources	Widespread use in many cultural institutions	too generic for artifacts description
SPECTRUM	UK-originated collection management standard for museums organized in procedures	metadata set and 21 procedures for museum-like artifacts	Standard in museum collections. embedded in collection software	focus on museum procedures, not on artifacts
CCO	content standard for cultural heritage	hierarchical metadata set	Structures context related to artifacts	Simple metadata structure.
SCORM	reference model for educational resources that defines sharable content objects	XML and JavaScript based	Support for educational activities in museums	only usable with another standard
EDM	data model for cultural artifacts	XML schema	Extensive documentation availability. Embedded validation rules	focuses only on European collections
LIDO	Delivering metadata schema for use in a variety of online services	XML harvesting schema	Focus on museum collections operations	Not intended to support commercial collections software

Table 7: Content structuring standards for museum content

Clearly there is a variety of options for structuring information about artifacts and collections. Developers should follow the most appropriate standard for their case, and build a database for storing the information by following the selected standards guidelines. To support maximum interoperability and portability among storage platforms, curator platforms, and devices running the personalized guidance system, open-source platforms are proposed to be employed. For example, in [154], developers employ Joomla as content management system, which combines MySQL, Apache and PHP, all open source platforms for database management, web serving, and scripting respectively with a friendlier interface. Employing proprietary platforms should be avoided due to difficulties to exchange information or to adapt it for newer mobile devices, and to support AR functionality or other virtual reality platforms.

Table 7 provides a summary of content structuring options for a museums artifacts that developers should follow in order to achieve broader compatibility with other content and applications including education and portability in various devices. The table also lists advantages and disadvantages of the various structuring options.

Finally, we should discuss the issue of privacy, as systems collect personal data of museum visitors. The lack of standards on privacy in museums has led developers of personalized service-providing systems to build their own specific models and store user data in proprietary formats [157]. In [6], authors state that personalization in cultural heritage creates a series of challenges that accompany lifelong user modeling in general: collecting evidence, remembering and forgetting (as users characteristics change), privacy and user controlwhat to disclose and what to keep private. Furthermore, recordings of activities and context-related information can expose personal information. Addressing privacy issues increases the acceptance of indoor navigation systems [158]. Some general approaches that can be suitable for museums too are presented in [159]: pseudonymous profiles and aggregation can be used when personalization information need not be tied to an identifiable user. Client-side profiles are useful when personalization services can be performed locally. User controls should always be considered on top of other technical approaches as they will likely make the personalized system more usable and trustworthy. In a Bluetooth-based guidance system in the Louvre Museum, the SHA algorithm was applied to each Bluetooth sensor where the MACID was converted to a unique identifier for avoiding invading visitor privacy [160]. In the system presented in [161], there was no need to maintain the identity of the visitors. Authors stated though that the identification might be beneficial for follow-up activities. Visitors may allow to be identified and contacted later if they are rewarded with benefits.

3.4. Visitor's visualization

The basic question in museology is how to improve the user experience and how to engage the visitor. In modern museology, museum visitors get in the center of attention during their engagement with artifacts and collections. They are associated with a more active role, especially with new technologies and social media with which they may express their preferences and produce multimedia material, which is displayed inside and outside of a museum and may influence future museum curators decisions regarding placement and overall visitor satisfaction. Toward this direction Falk and Dierking [162] proposed an interactive experience model and suggested that visitor experience is not a static state, but a dynamic process including experiences before, during and after the visit. Visitors prepare the museum material they are interested in before their visit to the museum. In this way, their visit gets more organized and they are able to gather related material, which they can assess further after their visit. A whole experience regarding a museum visit provides an emotionally, physically, intellectually and spiritually mixed feeling (Shaw and Ivens, [163]). This procedure is also backed by The Engaging Museum: Developing Museums for Visitor Involvement book [164] that guides museums on how to create the highest quality experience possible for their visitors. It is proved that creating an environment that supports visitor engagement with collections means examining every stage of the visit, from the initial impetus to go to a particular institution, to front-of-house management, interpretive approach and qualitative analysis afterwards.

Considering the capabilities of modern mobile devices, AR seems to be the optimal solution for engaging museum visitors while exploring artifacts [165]. The AR technology compared to the VR has the advantage of not isolating the user from the environment [166]. The replacement of simple information presentation with storytelling, including references to exhibits causes more personal engagement and better comprehension [167].

The AR applications are roughly classified into: (i) image-based applications in which an image triggers the reproduction of digital content related to that image and (ii) location-based, in which the proximity of the user to a specific point causes the content reproduction. Apple has introduced a new means for triggering AR with Face ID on iPhone X, which exploits a precise depth map of a face ([168]). This technology could be used for detecting specific artifacts, for which a depth map can be generated.

Several AR applications exist for museums [169], e.g., the MUSE [170] is a collaborative learning environment that may be used for designing gallery floor plans as well as for constructing descriptive captions for artifacts. ARLIS [171] and [172] are outdoor, location-based, educational AR systems based on situated learning theory and collaborative learning respectively, which apply AR and gaming. ARLIS uses an agent to determine which 3D objects and output voice files stored in the game story and learning process database should be sent to the AR presentation agent after recognizing a printed marker by a webcam. EcoMOBILE [173] combines AR via FreshAiR and environmental probeware during a field trip for students. REENACT [174] is an AR QR-code based Android application that employs immersive learning on Human History. Furthermore, CHESS [175], [167] aims to integrate interdisciplinary research in personalization and adaptivity, digital storytelling, interaction methodologies, and narrative-oriented mobile and mixed reality technologies, with a theoretical basis in museological, cognitive, and learning sciences. It aims to research, implement and evaluate both the experiencing of personalized interactive stories for visitors of cultural sites and their authoring by experts.

The tools for developing AR applications may vary (see Table 8). Simple tools are the FreshAIR for image-based and LayAR for location-based AR. More complex tools, which allow more flexibility to programmers though, are the open source AR Toolkit, and the commercial Vuforia. The most complete platform for mobile devices is the Unity 3D. By integrating plug-ins like those of Vuforia, Unity3D can support AR applications, in which the content can be 3D objects supporting interaction using the sensors of the mobile device. The platform can be extended by managed plug-ins and native plug-ins. The latter can access the operation system and other developers libraries. Therefore the combination of Vuforia with Unity 3D is attractive. However, location-based AR is not supported. The charging model is based on the number of modeled objects, which can incur high costs for large exhibitions. Vuforia has rather limited extensibility through plug-ins, and apart from the camera it does not exploit other sensors.

Other indicative platforms for application development are the Android Studio, which is specific for the Android OS and Xcode for iOS. The Ionic framework is oriented for hybrid (mobile and desktop) web-based applications, whereas Sencha targets HTML applications Phone Gap is supported by Adobe and Appcelerator, is based on JavaScript. However, these platforms can support 3D representations for objects, only through extensions.

Regarding the active engagement of visitors with artifacts, authors in Anderson, and Rowley (2008) as cited in [176] indicated that with development of multimedia techniques, the boundaries between different museum trips, such as historic museums, historic parks and life museums have become insignificant. They also refer to edutainment, which allow visitors to have active and passive experiences. In [177], authors examine new services offered by museums for their visitors, which include visitors perceptions of novelty and interactive communication and interpretation. Authors cite that interactive communication can bring benefits to a social relationship such as feelings of familiarity, friendship, and social support and trust between exchange partners and aligned perceptions and expectations. Overall, these techniques are found to enhance the visitor experience and intention to make repeat visits. Authors in [178] evaluate the contribution of new media and other items that engage and activate visitors through their visit on a cultural site in order to succeed in repeat visits as a result of their overall satisfaction. Using interactive panels and guided tours are measured to have the strongest influence on engagement, followed by using social interaction space and videos and audios. In [179], authors also support that the museum experience may be enhanced by resources that support visitors in producing experiences for others, such as labels and text-panels as well as touch-screen systems and hand-held computers, may be designed to facilitate collaborative engagement

Platform	Type	Features (Pros/Cons)	URL
LayAR	Image-based AR	Wizard-based / commercial, limited free version	www.playfreshair.com
FreshAiR	Location-based AR	Wizard-based / commercial, limited functionality in free version	www.layar.com
ARToolkit	Image-based AR	Open source / programming skills required	artoolkit.org
Vuforia	Location-based AR	Extensions supported, scripting capabilities, inter-operability / commercial, limited free version limited support, poor handling of various screen sizes	www.vuforia.com
Unity3D	3D mobile applications	Extensions, scripting, support material and case studies /commercial, limited free version	unity3d.com
Android Studio	Mobile apps for Android	multilanguage scripting / slow IDE, platform dependent	developer.android.com
XCode	Mobile apps for iOS	multilanguage scripting / expensive, platform dependent	developer.apple.com
Ionic	Mobile apps	Framework, cross platform / debug and performance issues	ionicframework.com
Sancha	Mobile apps	HTML-based, focus on interface / limited scripting	www.sencha.com
Phone Gap	Mobile apps	Hybrid apps / debug and performance issues	phonegap.com
Appcelerator	Mobile apps	JavaScript-based / cross platform issues	www.appcelerator.com

Table 8: Augmented reality and mobile applications development platforms

with exhibits. Concerning museums use of social media in order to increase participant engagement toward relationship maintenance, authors in [180] collected 315 online surveys among American museums and conducted nine in-depth interviews with professionals currently working with social media. Results indicate that American museum professionals believe becoming involved with social media is important. There is some evidence suggested by the authors that museums are trying to increase their use of social media for multi-way communication strategies.

An early implementation that features some of the above interactivity and visitor engagement is Points of Departure [181], an exhibition in which artworks and educational media were seamlessly integrated. Four multimedia prototypes were developed and deployed in the galleries: interactive smart tables featuring curatorial video introductions to each of the six exhibition themes; handheld iPAQ Gallery Explorer PDAs displaying video clips of featured artists; a Flash-based Make Your Own Gallery activity in which visitors were invited to curate their own exhibition and comment on. Similar interactive features are found in most modern museum applications that have been presented. ArtLens [3], enhances the visitors museum experience by providing the option to design individual tours, offering tools to better understand artwork through augmented reality, and guiding users with interactive real-time maps. All visitors favorite artworks can be used to create personalized tours, find specific artworks in the museum or share on social media. The Met App [1] can save visitors favorite art, events, and exhibitions, and add them to their calendar. As already mentioned, The Pen [4] allows the visitor to participate in the immersion room and process lab, both spaces in which a visitor can draw or sketch out their own designs as they are inspired by the collection around them. Additionally, the visitor can take their experience beyond the museum walls by accessing their visit online after they have left. Creators of The Pen state that this interactive participation is in stark contrast to the typical passive experience. Finally, the metaphor proposed for the user interface of Mnemosyne [5] engages mostly the participation of a visitor as it is based on the idea of a hidden museum waiting to be unveiled, starting from the top (the physical artworks) and moving deeper towards additional resources such as explanations and relations between one artwork and others. During this exploration, which is visitor controlled, a vertical animation starts when the user touches an artwork item, in order to move the point of view under the current space and reveal the level including the related resources to this artwork. Related resources include similar artworks according to the experience recommendation system using the visitor profile.

Regardless of the technologies used, a personalized guidance system should offer visitors the following interaction features: (a) Activation by recommendation: The guidance system proposes the visitor certain artifacts and/or visit routes based on user profile or context (i.e., individual or group visit, type of movement in the exhibition, purpose of visit, time availability). (b) Automatic artifacts presentation: When a visitor is idle in a room long enough, the presentation of randomly selected artifacts around the visitors viewing area is triggered. The visitor may then control the playback, and choose where to focus. (c) Conditional activation: The visitor chooses explicitly an artifact for which a presentation is activated.

Based on the previous discussion, to further enhance visitor engagement, as shown in Figure 1, the system should also allow visitors to search a museums database before their visit via a web interface in order to detect their prepared artifacts. During the visit, users may interact with a digital representation of an artifact on their mobile device and be able to save and project their edits. After their visit, users should be able to save and further reuse their experience. A detailed user scenario about this engagement is presented in Section 4.5.

Finally, regarding the content appearance, after the deprecation of technologies such as Adobe Flash, developers are proposed to employ technologies that allow seamless presentation in devices of various sizes, hardware and operating systems. These technologies include Scalable Vector Graphics (SVG), which is a markup language for describing 2D graphics applications and images, and a set of related graphics script interfaces ([182]), and Cascading Styles Sheets 3 (CSS), the latest version of which added rich interactive and animation features ([183]). The use of such technologies in coordination with web scripting languages eliminates the need for installing new software on visitors' devices. To this end, appropriate design paradigms, such as responsive design, are also required ([184]).

3.5. Curator's visualization

A curator's visualization system can be developed on top of the personalized content infrastructure, and offer online monitoring and data analytics of an exhibition on a per-artifact base, which is a major requirement for museum curators [52] for better presentation. The curator's visualization subsystem should calculate and present statistics, such as the number of activations of the artifacts presentations per visitor, the duration that visitors devote for every presentation, most visited museum rooms or artifacts, popularity of supplementary material. It can also provide reports, such as popularity per age group or profile type, per week day, season or daytime.

Developers should employ similar technologies as the visitor's visualization subsystem for platform independence. Open-source databases such as MySQL along with web scripting technologies are proposed. For content visualization per se, modern web technologies are proposed to be employed for presenting statistics, content, and for extracting various data views. [185] describes the use of web technologies such as SVG for interactive data visualization, statistical diagrams (e.g., bar and pie charts), and data trends. Alternatively, Python and JavaScript may be employed for browser-based visualizations [186].

If curators already use a museum management system, its functionality could be extended to cover the statistical analysis of the personalized guidance system. It is feasible, as most modern museum management systems employ web technologies and standard database management systems. Argus [187] is a popular web-based Collections Management Solution (CMS) used for managing and presenting artifacts and objects, and for engaging visitors. The retail-based RetailPro [188] supports responsive design, portable content, reports, transformation of content parameters, reorganization of collections and organization of virtual collections; it also supports fundraising, membership, ticketing, sales, events and programs. The Museum System [189] is a CMS that supports planning and managing of exhibitions, and generates reports; it contains a digital asset management module, and offers administrative support. MuseumPlus [190] supports managing collections and exhibitions, and is in use in over 900 museum sites worldwide. It manages loans and exhibitions, and automates workflows and procedures. CollectiveAccess [191] is a web-based open source CMS that embraces Dublin Core. Finally, Museum Anywhere [192] offers collection management and presentation through mobile devices, and supports integrating content from other museum management software.

4. Discussion

The progress made towards personalized content services in museums is evident, however most of such systems still remain at an experimental stage. The challenges described in section 1 have been only partially addressed. The main questions the developers have to answer are related to: (a) the available devices: can the available sensors (and software) on mainstream devices capture location/emotion/profile data? are they really usable in a museum context? is their performance sufficient and able to cover the whole duration of a visit? who should provide the devices? and (b) the content type: how can we build adaptable content? can we extract the user preferences for individuals and groups? These are discussed in the following.

4.1. Devices provided by museum vs "Bring Your Own Device"

The provision of personalized content services is based on the existence of mobile devices capable of doing the tasks of localization, data retrieval, profile extraction and content visualization. Clearly it is preferable to avoid the use of dedicated hardware, which is expensive to buy and maintain [41]. The smart phones and tablets offer themselves as a very attractive option for a variety of reasons. They have become a commodity so they are affordable and popular. They come equipped with a variety of sensors and network receivers, that can be directly used by applications, i.e., camera, bluetooth, WiFi, IMU unit (able to measure force, angular rate, or sometimes magnetic field, using a combination of accelerometers and gyroscopes, or magnetometers).

There are currently two basic options (a) provision of devices by the museum (b) the visitors use their own devices (Bring Your Own Device - BYOD). For many years the museums have been offering their visitors mobile audio guides, while the use of other devices was considered disruptive, and was forbidden. The advent of smart mobile phones and tablets has challenged this policy. In the meantime, the benefits from BYOD were demonstrated, e.g., [193], [194], [195]. Therefore many museums have revised their policy, and seek ways to exploit this reality. By adopting BYOD, museums do not have to rent or purchase equipment, dedicate space for its storage, keep the equipment charged and in good shape, update and maintain content and software, and train and pay staff to support it and secure it. The visitors are more familiar with their personal device; some of the groups with special needs have them optimized for accessibility. It appears that all the museum needs to do is produce good content and market the programs availability, however, this apparent convenience actually brings a more complex set of challenges.

The visitor should be aware of the availability of a BYOD program, and therefore advertizing it is critical. The museum should still have to provide access to headsets and power. Furthermore, a significant issue is compatibility of the devices with the provided content, by offering either a platform-specific application or Web apps. The platform-specific application creates much higher development and maintenance costs, and has to be installed by users but can use more easily the device's resources. On the other hand, web applications require only a browser, and are based around Web standards shared among different mobile operating systems, making them widely compatible. From the visitor's perspective, accessing a Web application is as simple as clicking on a link, rather than going to the additional step of downloading and installing an app. However, web apps are reliant on an active network connection for full function, and they may have limitations in accessing device-specific hardware such as Bluetooth, IMU sensors, integrated cameras etc. Furthermore, it is not clear in advance whether the device will be able to cope with the required processing power, and if their battery will be enough for a use that may extend to a few hours. Furthermore, there are still many people who do not own smart devices. Therefore, a mixed policy which would balance the BYOD with the availability of a limited number of museum-owned devices could possibly combine the advantages of both approaches.

In the mid-term the focus of research and development will probably be on how to make the applications and AR content more compatible and portable to mobile devices, how to be able to capitalize on higher processing power, and how to employ different sensors, like the 3D cameras on the iPhone 8 [196]. However, in the long term we believe that users will look for more intuitive means of interaction. Smartphones and tablets though affordable, may still not give the desired level of accuracy regarding position or artifact retrieval (see next subsection). They may also distract the visitors from the exhibition. Users prefer more natural ways of interaction, such as using camera-equipped glasses, which are able to provide audio and visual information on the glass, e.g., [48]. Indeed, smart glasses do allow for an immersive experience without the need to carry a device and without the need to switch focus between the device and the exhibition. Moreover, they can integrate cameras and other sensors. In [197], smart glasses are described as the "logical extension of BYOD" (Bringing Your Own Device), which can offer curators new opportunities for museum interpretation that are not offered by hand-held technology. Unfortunately, the currently available solutions are far from mature, e.g., in [198] the Google Glass and Vuzix M100 were compared; among the problems were the low usability due to obstruction of the user's view, the rather short battery life, the battery overheating, and the difficult communication with the device. Despite the technical challenges such solutions are expected to become more attractive in the future.

4.2. Pose accuracy vs minimal space modification and non-intrusiveness

The available solutions for localization in a museum environment vary from visual to radio-frequency, mechanical, audio and visual. Clearly the indoor localization problem has attracted the interest of researchers from many disciplines. The abundance of different approaches reveals the fact that the research community has not converged to a single, widely acceptable solution that can achieve the desired accuracy at a reasonable cost. Indeed, despite the great deal of progress made in the last decade, most current solutions cannot easily achieve an acceptable performance level. The requirements for the museum environment typically include accuracy better than 1m (depending on the density of artifacts), absence of coverage gaps, immunity to crowd and moving furniture, minimal installation costs, and minimal aesthetic clutter. Most systems are ad-hoc designed in non-realistic environments. Apart from low position accuracy and coverage problems, the need for extensive node deployment and maintenance turns out to be a serious problem.

The yearly Microsoft indoor localization competition reflects the amount of progress made the last years in this field [65]. The most successful such methods that use UWB signals, or lidar sensors are not applicable in museums due to heavy infrastructure and heavy client devices. Similarly, solutions that require the user to mount sensors on their feet for pedestrian dead reckoning, are obtrusive, and thus not acceptable. On the other hand, methods based on WiFi and IMU, which do not require heavy infrastructure achieved a localization of up to a couple of meters. Similar approaches that rely on WiFi signals experienced an additional error of 3m, due to the furniture setup changes and due to the moving crowd [65]. A very common approach for infrastructure-free approaches is the fingerprinting; however, it requires a time-consuming measurement process of the RSS values in many different positions, which can be a real problem in large museums. The issue is even bigger in exhibitions that may change frequently. Solution to this long and arduous task can be given by autonomous robots as proposed by Li et al [80]; such robots will be able to move in the exhibition and take thousands of measurements in space and time, and simulate the effects of human presence. If combined with some state-of-the-art learning methods such as deep learning (e.g., [199]) fingerprinting can probably give even better results.

Unfortunately, the location information is typically not enough; to suggest focused content, and to display AR aligned with the artifacts we also need the pose of the user or of the device relative to the artifact in case that accurate registration is needed (a simpler AR approach would do just a superposition without registration). This can be possible by image-based approaches, which seems to necessitate the use of cameras on the portable devices (see e.g., [200]). A visual map, which can be learnt offline could provide additional information about the geometrical relations between artifacts (metric maps) or could provide more conceptual graph-based information (topological maps) to scale down artifact search. A lot of such work has been done in the mobile robotics literature for solving the so-called SLAM (Simultaneous Localization And Mapping) problem [201]. The integration of new sensors on mobile devices such as the depth camera (see e.g., [196]) brings a set of new opportunities and challenges. For example how will this rich information be exploited, given the rather limited computational resources (by balancing with calculations in the cloud? what can be scheduled onboard to avoid network latency?) or how will the map be updated when the exhibition changes (online learning or crowdsourcing?). Such questions need further attention in the years to come.

4.3. Accurate cultural engagement vs. available wearable technology

There seems to be a connection between physiological measurements and engagement [128], as well as between emotion and user preferences [116], which may be used for recommendations in museums, however this goal has been elusive so far. Despite the large amount of wearable sensors available, their applicability is still limited due to high noise levels and due to other factors not related to engagement that may affect the output. Currently, the most reliable measure seems to be the amount of time spent in front of an artifact or the time viewing digital items; however, the visitor's attention may be focused somewhere else. Furthermore, only a gross estimation of user's interest can be extracted, while more precise states/emotions are often required. Major restrictions are posed by the high amount of noise and the obtrusiveness of the currently available sensors. A significant gap is the lack of reliable public datasets on cultural engagement. Research towards mitigating these issues is expected to have a great impact.

The wearable gaze trackers, as part of smart glasses, seem to be a promising technology for extracting FoA in real time. However, currently the adoption this technology is undermined by its extreme cost (in the order of 10K USD per set). Another serious technical issue is the need for visitor-specific calibration, which consumes time, and can be annoying. Still, after calibration the accuracy of the extracted focus is not guaranteed, especially for targets of variable shape [131]. Typically users can stand such glasses only for a few minutes because they seriously limit the visitor's field of view. There is plenty of room for research on how to alleviate these issues and make such systems more usable, less obtrusive, and more affordable. The research and development of more compact sensors for gaze tracking is expected to help gaze tracking to find its way to the consumer market, and become an asset for museum recommendation systems.

4.4. Recommendations for individuals and groups

Non-intrusive behavior recognition via sensors aspires to be part of an effective user profile acquisition process by simply classifying the user to one of the known categories, and then use CF to extract the profile. The case of a single user has attracted significantly larger amount of research than the case of people visiting in pairs or groups.

For single user profiles the supervised learning approaches are quiet popular, e.g., the metaphor of Veron [108]. The metaphor may be useful as a conceptual model, or as a baseline approach, however, the profiles can be significantly more complex, which largely depends on the exhibition and visitors' demographic data. The heavily researched trajectory data are useful, but in most cases they do not capture how the visitor behaves while being in the same location (e.g., standing still, moving, rotating, communicating etc). Much less work has been done on group profiling, mainly by the pioneering work of [107]; it has partially addressed the problem by studying pairs of visitors, and by making recommendations for them. In groups the challenge is to identify the overall group behavior, as well as the individual needs of the group members based on their role in the group. The complexity of supervised learning approaches in such settings is expected to increase exponentially with the group size; big effort is required to define (a) profile types, (b) features from from different sensors, and (c) group / individual recommendations, which explains why research in this direction is limited, despite its high commercial interest.

We believe that the unsupervised learning methods like deep learning, (e.g., [202], [109], [114]) can be useful in group profiling for the following reasons: (a) they can cope with large amounts of heterogeneous data like the ones produced by different sensors and define the optimal feature representations (b) they can be used to do clustering of behaviors following an agnostic approach about meaningful profile types and their characteristics.

Indeed the deep learning framework seems to fit well the application setting, since there is abundance of information from sensors on mobile devices, physiological sensors, and static sensors. Furthermore, it is very hard to know the subtleties of the various emotions and profiles in advance based on these data.

4.5. Content and visualization

Based on content structuring systems presented in Section 3.3, it gets clear that content developers should base their implementations on the variety of available standards. More specifically, content developers: (a) should choose a standard based on the type and quantity of artifacts along with their structure and presentation needs, (b) should take into account supplementary operations needed for their content such as educational activities, lending operations, maintenance, creation of temporary and virtual exhibitions and cooperative exhibitions with other museums as long as these operations influence the guidance systems operation, (c) are proposed to choose a storage format that fully supports the selected standard, and that can import and export content based on that standard, massively or on a per artifact basis, (d) should ensure high speeds during content retrieval, so that to avoid any lag in the mobile guidance system operation, (e) should handle the storage process of multimedia content related to artifacts so that to ensure fast retrieval, and avoid huge storage needs, and (f) should favor open source technologies for content storing, web serving and scripting, which enhances interoperability.

Regarding content management and visualization, a lot of systems are available, open source and proprietary, as shown in Section 3.5. In some museums, a management system for artifacts and collections among other operations may already be available. Other museums would be obliged to install such systems, if they want to support a mobile guidance system. In any case, content administrators are proposed to (a) favor the choice of an open source system or provide content export options according to some standard if they already use a proprietary system, (b) support multiple export options standards for their content, which will enhance interoperability, (c) implement uniform interactivity among multiple devices and operating systems, (d) provide multiple interaction schemes for supporting interaction on either single artifacts or complete collections, (e) provide multiple report generating options for focusing on needed maintenance options, (f) embrace dynamic and vector-based content visualization techniques to avoid the installation of specialized plug-ins and software, and (g) examine options for real-time monitoring and displaying visitors routes in the museum.

Based on the discussion about active user engagement, as part of the personalized content services structure, visitors should be offered services that let them control their visit to a museum and contribute their experience to provide a basis for future visits. This engagement is illustrated in the following scenario: (a) Potential visitors of a museum may access and search the artifacts database and prepare a set of artifacts that they would be interested in and store them in their mobile device. (b) Upon arrival at the museum, an optimal route is designed based on the preselected artifacts and the recommendation subsystem (c) While following a route, visitors may focus on certain information from the visualization subsystem and store it or link it in their device (d) Through their devices and by use of augmented reality as described in the visualization subsystem, visitors may interact with the artifacts, according to their kind and perform, e.g., game-like actions in a painting (e.g. by distorting a painting, a visitor may understand better the painters rationale and style [203] or by decomposing interactively an archaeological artifact in order to focus on its architecture, e.g., [204]). Similar actions may be implemented on a per artifact basis as extra services in the visualization subsystem (e) Visitors may compose their own presentations based on the stored content and project it in their devices or wirelessly at large displays at certain areas in the museum, in case larger groups are involved and even build educational activities around them by exploiting customized interaction activities per artifact as the previously mentioned. (f) After their visit, visitors may find the stored content in their devices and share part of it along with their comments through social media applications in order to encourage future visits.

Most of the presented platforms, support many of the aforementioned features. For example, [154] embraces open source technologies such as Apache, MySQL and PHP for building a custom CMS. Similarly, Museum Anywhere relies one open source technologies for building a generic CMS for artifact collections. Other research projects such as [153] employ DCMI for describing cultural information and SCORM for educational content, and they build their own CMS for content management. Lucidea and RetailPro manage museum collections, and focus on lending and exhibition issues. On the other hand, MuseumPlus and the Museum system are museum management systems that excel in offering multiple ways for fast searching through the systems material, and generating reports, whereas conforming to standards such as SPECTRUM and MDA. MuseumPlus has also the advantage of many successful installations in heterogeneous museums all over the world and of the inclusion of a multimedia module for handling accordingly the import and reuse of multimedia content. Finally, RetailPro and Museum Anywhere support responsive design dynamic interfaces and uniform appearance in mobile devices respectively. However, a deeper integration is needed among visualization techniques and mobile devices towards the support of open standards for content structuring, uniform appearance in various devices and multiple interaction schemes that engage visitors.

4.6. High performance vs low processing power

The issue of power consumption in mobile devices has been extensively discussed in literature. Obviously, higher performance leads to higher processing power needs that lead to quicker battery drain. As shown below, battery consumption depends mainly on network usage, display time, and CPU and memory operations. Researchers came up with proprietary systems that reduce power consumptions and guidelines for limiting this issue.

In [205], it is shown that JPEG is the best image format for the Android browser. The authors' experiments propose that using links instead of JavaScript greatly reduces the rendering energy for the page. Moreover, Google Analytics forces web pages to reload, which increases network load. Authors cite that sites that position elements using CSS need far more energy to render. TailEnder [206] is a tool that aggressively prefetches data, although this may include useless data, and developers have proved that this technique reduces the overall energy consumed. In [207], authors have shown that the most energy consuming parts of a mobile phone are the wireless technologies and not the display or the CPU, as this is the case for laptops. For the short-range communication, authors suggest that Bluetooth should be used in case only a few data needs to be exchanged. If more data needs to be transmitted, WiFi should be used. Authors cite that "It does not cost much to have BT always on, and that this creates opportunities for new services which combine the local communication with cellular communications". In [208], authors have discovered that high-power consumption is due to opening webpages with rich dynamic content based on scripting and multimedia. They propose Virtual-Machine based Proxy (VMP), which shifts the computing from smartphones to the VMP. Authors in [209] propose webpage-aware scheduling for high-performance and energy-efficient mobile web browsing. They apply regression modeling to predict webpage load time and energy consumption, through detailed characterization of webpage variance. Authors prove that such predictive models allow the scheduler to identify the ideal core and frequency configurations for webpages to minimize the energy consumption under latency cut-off constraints. [210] shows that the majority of power consumption can be attributed to the GSM module and the display, including the LCD panel and touchscreen, the graphics accelerator/driver, and the backlight. Finally, WattsOn [211] is a system that allows a developer to estimate the energy consumed by her app in the development environment itself. WattsOn can (i) identify energy hungry segments during the app run, and (ii) determine which component (display, network or CPU) consumes the most energy.

Additionally, a better balancing of the tasks to be done onboard and those to be done on the cloud would certainly help. User profiling can be better done on the cloud since there the user and content data can be easily stored, and dynamically updated. The supplementary material can be partially stored on the device depending on the storage capacity, otherwise it has to be retrieved from the network. Image registration is better done onboard to avoid network latency, using some lightweight algorithms or utilizing the IMU sensors for approximate matching. Heavier tasks such as image matching to a map or database are more efficiently performed on the cloud.

Based on the above, some guidelines could include the following: (a) Prefer Bluetooth for small portions of content (e.g., location data, user selections) or use WiFi otherwise (multimedia); (b) prefetch more content on the mobile device than perform successive transports, which is an argument in favor of application installation vs web-based applications; (c) adjust screen brightness to the current lighting conditions; (d) adjust content quality based on the devices quality; (e) lower performance and content quality when battery level is under a certain threshold; (f) employ responsive design that is adapted optimally on a device; (g) choose content prefetch versus incremental web page loading based on the amount of content and the devices capabilities; (h) choose content interactivity and appearance (e.g. CSS, SVG, JavaScript) vs load speed (e.g. with plain HTML and images) depending on the needed functionality of a specific part of the application; (i) exploit techniques of mobile devices for lower power consumption (e.g., dim display, turn off network on idle time periods, and use IMU sensors to decide on inactivity); (j) efficient balancing between onboard tasks and tasks on the cloud.

5. Conclusion

In this work we have surveyed the state of the art in the key technical areas that are involved in developing personalized content services for museum visitors. We reported some of the most representative current methods and tools for location extraction, recommendation, content maintenance, visitors' and curators' visualization. We described the basic strengths and weaknesses of each approach, and we gave suggestions and recommendations to developers who wish to implement such services and to researchers, who wish to advance the state of the art.

Personalized content services in museums have a great potential, however many challenges have not been addressed, which has prevented their wide adoption. These challenges mainly regard methods for localization with minimal infrastructure, non intrusive devices and methods to measure cultural engagement. Furthermore, it is still unclear how group profiling can be modeled, and how recommendations to the individual group members can be made. This is of particular importance given the large amount of people visiting museums in groups.

The development of recommendation systems that are able to dynamically adapt to context is in the intersection of several disciplines, such as content management, mobile and pervasive computing, computer vision, pattern recognition, and user interfaces. A field connecting horizontally these disciplines is the machine learning; indeed, it can be employed to address some key issues like localization, content modeling and retrieval, dynamic profile extraction and cold start, attention modeling and emotion recognition. The advancements in the above fields are expected to contribute towards more versatile, technically mature, and commercially exploitable systems.

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References

[1] Metropolitan Museum, The metropolitan museum of art (2018).
URL https://metmuseum.org/visit/met-app

[2] The Louvre Museum, New app: My visit to the louvre (2018).
URL http://www.louvre.fr/en/new-app

[3] Cleveland Museum of Art, Artlens app (2018).
URL http://clevelandart.org/artlens-gallery/artlens-app

[4] B. Kanpetch, Building a recommendation system for the Cooper Hewitt design museum (2016).
URL https://blog.nycdatascience.com/student-works/building-recommendation-system-cooper-hewitt-design-museum/

[5] M. Integration, C. Center, The mnemosyne project (2015).
URL http://www.micc.unifi.it/projects/Mnemosyne/

[6] L. Ardissono, T. Kuflik, D. Petrelli, Personalization in cultural heritage: the road travelled and the one ahead, User Modeling and User-Adapted Interaction 22 (1) (2012) 73–99.

[7] D. Raptis, N. Tselios, N. Avouris, Context-based design of mobile applications for museums: A survey of existing practices, in: Int. Conf. on HCI with Mobile Devices and Services, ACM, 2005, pp. 153–160.

[8] M. Kenteris, D. Gavalas, D. Economou, Electr. mobile guides:A survey, Pers. Ubiq. Comp. 15 (1) (2011) 97–111.

[9] J. Borras, A. Moreno, A. Valls, Review: Intelligent tourism recommender systems: A survey, Expert Syst. Appl. 41 (16) (2014) 7370–7389.

[10] K. Kabassi, Personalisation Systems for Cultural Tourism, Springer, Heidelberg, 2013, pp. 101–111.

[11] D. H. Park, H. K. Kim, I. Y. Choi, J. K. Kim, A literature review and classification of recommender systems research, Expert Systems with Applications 39 (11) (2012) 10059 – 10072.

[12] J. Bobadilla, F. Ortega, A. Hernando, A. Gutirrez, Recommender systems survey, Knowledge-Based Systems 46 (2013) 109 – 132.

[13] L. Lu, M. Medo, C. H. Yeung, Y.-C. Zhang, Z.-K. Zhang, T. Zhou, Recommender systems, Physics Reports 519 (1) (2012) 1 – 49.

[14] A. Basiri, E. S. Lohan, T. Moore, A. Winstanley, P. Peltola, C. Hill, P. Amirian, P. F. e Silva, Indoor location based services challenges, requirements and usability of current solutions, Computer Science Review 24 (2017) 1 – 12.

[15] Y.-T. Sung, K.-E. Chang, H.-T. Hou, P.-F. Chen, Designing an electronic guidebook for learning engagement in a museum of history, Comput. Hum. Behav. 26 (1) (2010) 74–83.

[16] Denso ADC, (2011).
URL http://www.nacs.org/LinkClick.aspx?fileticket=D1FpVAvvJuo%3D&tabid=1426&mid=4802

[17] S. A. Weis, Rfid (radio frequency identification): Principles and applications (2007).
URL http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.182.5224&rep=rep1&type=pdf

[18] Y. Wang, N. Stash, L. Aroyo, P. Gorgels, L. Rutledge, G. Schreiber, Recommendations based on semantically enriched museum collections, Web Semantics: Science, Services and Agents on the WWW 6 (4) (2008) 283–290.

[19] G. Ghiani, F. Patern, C. Santoro, L. D. Spano, Ubicicero: A location-aware, multi-device museum guide., Interacting with Computers 21 (4) (2009) 288–303.

[20] J. C. Hung, J.-D. Weng, Y.-H. Chen, A recommendation system based on mining human portfolio for museum navigation, Evolving Systems 7 (2) (2016) 145–158.

[21] T. Kanda, M. Shiomi, L. Perrin, T. Nomura, H. Ishiguro, N. Hagita, Analysis of people trajectories with ubiquitous sensors in a science museum, in: IEEE Int. Conf. on Robotics and Automation, 2007, pp. 4846–4853.

[22] G. D'Amico, A. D. Bimbo, A. Ferracani, L. Landucci, D. Pezzatini, L. Santi, RFID-based solutions for user profiling in interactive exhibits, in: 2011 IEEE International Symposium on Multimedia, 2011, pp. 216–221.

[23] S. Phimmasean, Sisongkham; Kanthavong, Smart tracking system applied for laos museum using rfid technology based on fingerprint technique, in: Int. Conf. on El. Eng./Electronics, Computer, Telecomm. and Inf. Techn., 2016.

[24] NFC Forum, Nfc forum (2018).
URL https://nfc-forum.org/

[25] Zigbee Alliance, Zigbee alliance (2018).
URL http://www.zigbee.org

[26] Bluetooth, Bluetooth technology website (2018).
URL https://www.bluetooth.com/what-is-bluetooth-technology/how-it-works

[27] R. Bruno, M. Conti, E. Gregori, Bluetooth: Architecture, protocols and scheduling algorithms, Cluster Comp. 5 (2) (2002) 117–131.

[28] C. Martella, A. Miraglia, J. Frost, M. Cattani, M. van Steen, Visualizing, clustering, and predicting the behavior of museum visitors, Pervasive and Mobile Computing 38 (2) (2017) 430–443.

[29] D. G. Luca, M. Alberto, From proximity to accurate indoor localization for context awareness in mobile museum guides, in: Int. Conf. on HCI with Mobile Devices and Services Adjunct, ACM, 2016, pp. 1002–1009.

[30] R. S. Kshetrimayum, An introduction to uwb communication systems, IEEE Potentials 28 (2) (2009) 9–13.

[31] Microsoft, Microsoft indoor localization competition IPSN (2017).
URL `https://www.microsoft.com/en-us/research/event/microsoft-indoor-localization-competition-ipsn-2017/`

[32] T. Ruotsalo, K. Haav, A. Stoyanov, S. Roche, E. Fani, R. Deliai, E. MäKelä, T. Kauppinen, E. HyvöNen, Smartmuseum: A mobile recommender system for the web of data, Web Semant. 20 (2013) 50–67.

[33] B. Ruf, E. Kokiopoulou, M. Detyniecki, Mobile museum guide based on fast sift recognition, in: Int. Conf. on Adapt. Multimedia Retr.l: Identifying, Summarizing, and Recommending Image and Music, 2008, pp. 170–183.

[34] P. Föckler, T. Zeidler, B. Brombach, E. Bruns, O. Bimber, Phoneguide: Museum guidance supported by on-device object recognition on mobile phones, in: Proceedings of the 4th International Conference on Mobile and Ubiquitous Multimedia, MUM '05, ACM, New York, NY, USA, 2005, pp. 3–10.

[35] R. Oppermann, M. Specht, A nomadic information system for adaptive exhibition guidance, Archives and Museum Informatics 13 (2) (1999) 127–138.

[36] F. Sparacino, The Museum Wearable: real-time sensor-driven understanding of visitors' interests for personalized visually-augmented museum experiences, in: Proc. of Museums and the Web, 2002, pp. 17–20.

[37] M. Bombara, D. Cal, C. Santoro, Kore: a multi-agent system to assist museum visitors, in: in Proceedings of the Workshop on Objects and Agents, 2003, pp. 175–178.

[38] C. Rocchi, O. Stock, M. Zancanaro, M. Kruppa, A. Krüger, The museum visit: Generating seamless personalized presentations on multiple devices, in: Int. Conf. on Intelligent User Interfaces, ACM, 2004, pp. 316–318.

[39] D. Petrelli, E. Not, User-centred design of flexible hypermedia for a mobile guide: Reflections on the hyperaudio experience, User Modeling and User-Adapted Interaction 15 (3-4) (2005) 303–338.

[40] T. Kuflik, Z. Boger, M. Zancanaro, Analysis and Prediction of Museum Visitors' Behavioral Pattern Types, Springer Berlin Heidelberg, Berlin, Heidelberg, 2012, pp. 161–176.

[41] P. Bihler, P. Imhoff, A. B. Cremers, Smartguide a smartphone museum guide with ultrasound control, Procedia Computer Science 5 (2011) 586 – 592.

[42] P. Lazik, A. Rowe, Indoor pseudo-ranging of mobile devices using ultrasonic chirps, in: ACM Conference on Embedded Network Sensor Systems, ACM, 2012, pp. 99–112.

[43] W. R. Van Hage, N. Stash, Y. Wang, L. Aroyo, Finding your way through the Rijksmuseum with an adaptive mobile museum guide, in: Int. Conf. on The Semantic Web: Research and Applic., Vol. Part I, 2010, pp. 46–59.

[44] F. Bohnert, I. Zukerman, Personalised viewing-time prediction in museums, User Modeling and User-Adapted Interaction 24 (4) (2014) 263–314.

[45] S. Levialdi Ghiron, C. M. Medaglia, A. Perrone, "Art-sonomy": Social Bookmarking of Real Artworks via Mobile Applications with Visual Tags, Springer Berlin Heidelberg, Berlin, Heidelberg, 2009, pp. 375–384.

[46] L. Wein, Visual recognition in museum guide apps: Do visitors want it?, in: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, CHI '14, ACM, New York, NY, USA, 2014, pp. 635–638.

[47] I. Ayala, M. Amor, M. Pinto, L. Fuentes, N. Gmez, imuseuma: An agent-based context-aware intelligent museum system, Sensors 14 (11) (2014) 21213.

[48] M. Mason, The mit museum glassware prototype: Visitor experience exploration for designing smart glasses, J. Comput. Cult. Herit. 9 (3) (2016) 12:1–12:28.

[49] M. Angelaccio, A. Basili, B. Buttarazzi, W. Liguori, Smart and mobile access to cultural heritage resources: A case study on ancient italian renaissance villas., IEEE ComSoc, 2012, pp. 310–314.

[50] U. B. Ceipidor, C. M. Medaglia, V. Volpi, A. Moroni, S. Sposato, M. Carboni, A. Caridi, Nfc technology applied to touristic-cultural field: A case study on an italian museum, in: 5th Int. Workshop on NFC, 2013, pp. 1–6.

[51] T. Kuflik, J. Lanir, E. Dim, A. Wecker, M. Corra, M. Zancanaro, O. Stock, Indoor positioning in cultural heritage: Challenges and a solution, in: 2012 IEEE 27th Conv. of Electr. and Electronics Eng. in Israel, 2012, pp. 1–5.

[52] J. Lanir, T. Kuflik, J. Sheidin, N. Yavin, K. Leiderman, M. Segal, Visualizing museum visitors' behavior: Where do they go and what do they do there?, Personal and Ubiquitous Computing (2016) 1–14.

[53] Y. Yoshimura, F. Girardin, J. P. Carrascal, C. Ratti, J. a. Blat, New tools for studying visitor behaviours in museums: A case study at the Louvre, in: Inf. and Comm. Technologies in Tourism 2012, 2012, pp. 391–402.

[54] K. Kikuchi, R. Tazawa, N. Honma, H. Minamizawa, A. Miura, DOD-based indoor loc. using BLE beac. (2017).
URL `https://www.microsoft.com/en-us/research/wp-content/uploads/2016/11/Naoki_Honma.pdf`

[55] K. Luyten, H. Van Loon, D. Teunkens, K. Gabrils, K. Coninx, E. Manshoven, Archie: Disclosing a museum by a socially-aware mobile guide, in: The 7th Int. Symp. on Virtual Reality, Archaeology and Cultural Heritage, 2006.

[56] J. J. Pan, J. T. Kwok, Q. Yang, Y. Chen, Multidimensional vector regression for accurate and low-cost location estimation in pervasive computing, IEEE Trans. on Knowl. and Data Eng. 18 (9) (2006) 1181–1193.

[57] A. Kushki, K. N. Plataniotis, A. N. Venetsanopoulos, Kernel-based positioning in wireless local area networks, IEEE Transactions on Mobile Computing 6 (6) (2007) 689–705.

[58] K. Kaemarungsi, P. Krishnamurthy, Analysis of wlan's received signal strength indication for indoor location fingerprinting, Pervasive Mob. Comput. 8 (2) (2012) 292–316.

[59] A. Chianese, F. Marulli, V. Moscato, F. Piccialli, Smartweet: A location-based smart application for exhibits and museums, in: 2013 Int. Conf. on Signal-Image Technology Internet-Based Systems, 2013, pp. 408–415.

[60] V. Sark, E. Grass, Software defined radio for time of flight based ranging and localization, Tech. rep., Microsoft Indoor Localization Competition (2014).

[61] R. Dimitrova, Sensor application for museum guidance, in: Proceedings of the 2nd Workshop on Positioning, Navigation and Communication (WPNC05) and 1st Ultra-Wideband Expert Talk (UET'05), 2005, pp. 75–79.

[62] D. R. Bueno, E. Viruete, L. Montano, An autonomous tour guide robot in a next generation smart museum,, in: Int. Symp. on Ubiquitous Computing and Ambient Intelligence, 2011.

[63] E. Gunes, G. Ibarra, Intranav low-cost indoor localiz. syst. & IoT platform for ind. and cons. markets (2017).
URL `https://www.microsoft.com/en-us/research/wp-content/uploads/2016/11/Quantitec.pdf`

[64] Wi-Fi Alliance, Discover wi-fi: Specifications (2018).

URL https://www.wi-fi.org/discover-wi-fi/specifications
[65] D. Lymberopoulos, J. Liu, The microsoft indoor localization competition: Experiences and lessons learned, IEEE Signal Processing Magazine 34 (5) (2017) 125–140. doi:10.1109/MSP.2017.2713817.
[66] H. Balakhontseva, J. Sieck, Web-server application for fast and robust recognition of exhibits in the museum, International Journal of Computing 13 (3) (2014) 176–182.
[67] E. Bruns, B. Brombach, T. Zeidler, O. Bimber, Enabling mobile phones to support large-scale museum guidance, IEEE MultiMedia 14 (2) (2007) 16–25.
[68] O. Marques, Visual information retrieval: The state of the art, IT Professional 18 (4) (2016) 7–9.
[69] T. Toyama, T. Kieninger, F. Shafait, A. Dengel, Museum guide 2.0 - an eye-tracking based pers. assistant for museums and exhibits, in: Re-Thinking Techn. in Museums 2011: Emerging Experiences, Un. of Limerick, 2011.
[70] X. Zabulis, D. Grammenos, T. Sarmis, K. Tzevanidis, P. Padeleris, P. Koutlemanis, A. A. Argyros, Multicamera human detection and tracking supporting natural interaction with large-scale displays, Machine Vision and Applications 24 (2) (2013) 319–336.
[71] D. I. Kosmopoulos, A. D. Doulamis, A. Makris, N. D. Doulamis, S. Chatzis, S. E. Middleton, Vision-based production of personalized video, Sig. Proc.: Image Comm. 24 (3) (2009) 158–176.
[72] C.-S. Wang, D.-J. Chiang, Y.-C. Wei, Intuitional 3D Museum Navigation System Using Kinect, Springer, 2013, pp. 587–596.
[73] C. Gamallo, C. V. Regueiro, P. Quintía, M. Mucientes, Omnivision-based kld-monte carlo localization, Robot. Auton. Syst. 58 (3) (2010) 295–305.
[74] R. Wakkary, M. Hatala, Situated play in a tangible interface and adaptive audio museum guide, Personal Ubiquitous Comput. 11 (3) (2007) 171–191.
[75] O. Bimber, E. Bruns, B. Brombach, Mobile phone-enabled museum guidance with adaptive classification, IEEE Computer Graphics and Applications 28 (2008) 98–102.
[76] H. Ju, S. Y. Park, C. G. Park, Pedestrian dead reck. syst. consid. actual condition of the foot-mounted IM (2017).
URL https://www.microsoft.com/en-us/research/wp-content/uploads/2016/11/Ju_SoyoungPark.pdf
[77] L. Li, C. Zhao, G. Shen, F. Zhao, Indoor localization with multi-modalities, Tech. rep., Microsoft Indoor Localization Competition (2014).
[78] N. Ahmed, A. Ghose, C. Agrawal, A. K.and Bhaumik, V. Chandel, A. Kumar, Smartevactrak: A people counting and coarse-level localization solution for efficient evacuation of large buildings, in: IEEE Int. Conf. on Perv. Comp. and Comm. Work., 2015, pp. 372–377.
[79] Z. Xiao, H. Wen, A. Markham, N. Trigoni, Lightweight map matching for indoor localisation using conditional random fields, in: International Symp. on Inf. Processing in Sensor Networks, IPSN '14, 2014, pp. 131–142.
[80] C. Li, F. Cristian, G. Zhe, X. Qiang, R. Z., Robot-assisted fingerprint-based indoor localization (2017).
URL https://www.microsoft.com/en-us/research/wp-content/uploads/2016/11/McMaster_ZhengRong.pdf
[81] C.-L. Li, C. Laoudias, G. Larkou, Y.-K. Tsai, D. Zeinalipour-Yazti, C. G. Panayiotou, Indoor geolocation on multi-sensor smartphones, in: Int. Conf. on Mobile Systems, Applications, and Services, ACM, 2013, pp. 503–504.
[82] J. Zhang, S. Huber, D. Duggins, K. Dowling, S. Singh, Compact, real-time localization without reliance on infrastructures (2017).
URL https://www.microsoft.com/en-us/research/wp-content/uploads/2016/11/Kaarta_RealEarth.pdf
[83] H. Bay, B. Fasel, L. V. Gool, Interactive museum guide: Fast and robust recognition of museum objects, in: In Proc. Int. Workshop on Mobile Vision, 2006.
[84] M. Spasojevic, T. Kindberg, A study of an augmented museum experience, Tech. rep., Hewlett Packard (2001).
[85] O. Stock, M. Zancanaro, P. Busetta, C. Callaway, A. Krüger, M. Kruppa, T. Kuflik, E. Not, C. Rocchi, Adaptive, intelligent presentation of information for the museum visitor in peach, User Modeling and User-Adapted Interaction 17 (3) (2007) 257–304.
[86] A. Krüger, M. Kruppa, C. Rocchi, Integration of Mobile and Stationary Presentation Devices PEACH - Intelligent Interfaces for Museum Visits, Cognitive Technologies, Springer, 2007, Ch. 7, pp. 147–164.
[87] Y. Wang, S. Wang, N. Stash, L. Aroyo, G. Schreiber, Enhancing content-based recommendation with the task model of classification., Vol. 6317 of LNCS, Springer, 2010, pp. 431–440.
[88] W. A. Eardley, D. E. Ashe, B. D. Fletcher, An ontology engineering approach to user profiling for virtual tours of museums and galleries, International Journal of Knowledge Engineering 2 (2) (2016) 85–91.
[89] F. Bohnert, I. Zukerman, S. Berkovsky, T. Baldwin, L. Sonenberg, Using interest and transition models to predict visitor locations in museums, AI Commun. 21 (2-3) (2008) 195–202.
[90] A. Krüger, J. Baus, D. Heckmann, M. Kruppa, R. Wasinger, The adaptive web, Springer-Verlag, Berlin, Heidelberg, 2007, Ch. Adaptive Mobile Guides, pp. 521–549.
[91] C.-H. Yu, J. Hunter, Documenting and sharing comparative analyses of 3d digital museum artifacts through semantic web annotations, J. Comput. Cult. Herit. 6 (4) (2013) 18:1–18:20.
[92] D. Luh, T. Yang, Museum recommendation system based on lifestyles, in: 2008 9th International Conference on Computer-Aided Industrial Design and Conceptual Design, 2008, pp. 884–889. doi:10.1109/CAIDCD.2008.4730703.
[93] D. Gerrard, M. Sykora, T. Jackson, Social media analytics in museums: extracting expressions of inspiration, Museum Management and Curatorship 32 (3) (2017) 232–250. doi:10.1080/09647775.2017.1302815.
[94] S.-K. Chang, L. Greco, A. De Santo, Sentiment Detection in Social Networks Using Semantic Analysis: A Tool for Sentiment Analysis and Its Application in Cultural Heritage Realm, Springer International Publishing, Cham, 2015, pp. 183–193.
[95] W. Min, B. Bao, C. Xu, M. S. Hossain, Cross-platform multi-modal topic modeling for personalized inter-platform recommendation, IEEE Trans. Multimedia 17 (10) (2015) 1787–1801.
[96] M. Yan, J. Sang, C. Xu, M. S. Hossain, A unified video recommendation by cross-network user modeling, ACM Trans. Multimedia Comput. Commun. Appl. 12 (4) (2016) 53:1–53:24.
[97] M. Hatala, R. Wakkary, Ontology-based user modeling in an augmented audio reality system for museums, User Modeling and User-Adapted Interaction 15 (3) (2005) 339–380.
[98] P. Marti, A. Rizzo, L. Petroni, G. Tozzi, M. Diligenti, Adapting the museum: a non-intrusive user modeling approach, Springer Vienna, Vienna, 1999, pp. 311–313.
[99] L. Chittaro, L. Ieronutti, A visual tool for tracing users' behavior in virtual environments, in: Proceedings of the Working Conference on Advanced Visual Interfaces, AVI '04, ACM, New York, NY, USA, 2004, pp. 40–47.
[100] K. Sookhanaphibarn, R. Thawonmas, A Movement Data Analysis and Synthesis Tool for Museum Visitors' Behaviors, Springer Berlin Heidelberg, Berlin, Heidelberg, 2009, pp. 144–154.
[101] M. Zancanaro, T. Kuflik, Z. Boger, D. Goren-Bar, D. Goldwasser, Analyzing Museum Visitors' Behavior Patterns, Springer Berlin

Heidelberg, Berlin, Heidelberg, 2007, pp. 238–246.
[102] S. Cuomo, P. De Michele, A. Galletti, G. Ponti, Classify Visitor Behaviours in a Cultural Heritage Exhibition, Springer International Publishing, Cham, 2016, pp. 17–28.
[103] C. Martella, A. Miraglia, M. Cattani, v. S. Maarten, Leveraging proximity sensing to mine the behavior of museum visitors, in: IEEE Int. Conf. on Pervasive Computing and Communications, 2016, pp. 1–9.
[104] D. Shell, S. Viswanathan, J. Huang, R. Ghosh, J. Huang, M. Matarić, K. Lerman, R. Sekuler, Spatial behavior of indiv. and groups: Preliminary findings from a museum scenario, in: IROS Work. on Spat. Beh. Modeling, 2007.
[105] F. Bohnert, I. Zukerman, D. W. Albrecht, Realistic Simulation of Museum Visitors' Movements as a Tool for Assessing Sensor-Based User Models, Springer Berlin Heidelberg, Berlin, Heidelberg, 2012, pp. 14–25.
[106] E. Dim, T. Kuflik, Group situational awareness: Being together, in: D. Cheng, Kinshuk, A. Kobsa, K. Partridge, Z. Yu (Eds.), Work. on Personalization in Mobile and Pervasive Computing, Vol. 478, CEUR-WS.org, 2009.
[107] E. Dim, T. Kuflik, Automatic detection of social behavior of museum visitor pairs, ACM Trans. Interact. Intell. Syst. 4 (4) (2015) 17:1–17:30.
[108] E. Veron, M. Levasseur, Ethnographie de lExposition, Bibliothque publique dInformation, Centre Georges Pompidou, Paris, 1983.
[109] W. Jiang, Z. Yin, Human activity recognition using wearable sensors by deep convolutional neural networks, in: ACM Int. Conf. on Multimedia, ACM, 2015, pp. 1307–1310.
[110] I. Goodfellow, Y. Bengio, A. Courville, Deep Learning, MIT Press, 2016.
[111] S. Bitgood, Environmental psychology in museums, zoos, and other exhibition centers, in: Handbook of environmental Psychology, 2002, pp. 461–480.
[112] L. Ardissono, G. Bosio, A. Goy, G. Petrone, M. Segnan, F. Torretta, Collaboration support for activity management in a personal cloud environment, Int. J. Distrib. Syst. Technol. 2 (4) (2011) 30–43.
[113] M. Pantic, R. Cowie, F. D'Errico, D. Heylen, M. Mehu, C. Pelachaud, I. Poggi, M. Schroeder, A. Vinciarelli, Social Signal Processing: The Research Agenda, Springer London, London, 2011, pp. 511–538.
[114] M. S. Ibrahim, S. Muralidharan, Z. Deng, A. Vahdat, G. Mori, A hierarchical deep temporal model for group activity recognition, in: IEEE Conference on Comp. Vis. and Pat. Rec., 2016, pp. 1971–1980.
[115] E. Dim, T. Kuflik, Early detection of museum visitors identities by using a museum triage, in: Conf. on User Modeling, Adaptation, and Personalization, Montreal, Canada,, Vol. 872, CEUR-WS.org, 2012.
[116] G. D. Chiappa, L. Andreu, M. G. Gallarza, Emotions and visitors satisfaction at a museum, International Journal of Culture, Tourism and Hospitality Research 8 (4) (2014) 420–431.
[117] J. Healey, Physiological sensing of emotion (2015).
URL `http://www.oxfordhandbooks.com/10.1093/oxfordhb/9780199942237.001.0001/oxfordhb-9780199942237-e-023`
[118] J. Stables, Best heart rate monitor: Top watches, chest straps and bands (2017).
URL `https://www.wareable.com/fitness-trackers/best-heart-rate-monitor-and-watches`
[119] J. Bakker, M. Pechenizkiy, N. Sidorova, What's your current stress level? detection of stress patterns from gsr sensor data, in: Int. Conf. on Data Mining Workshops, 2011, pp. 573–580.
[120] T. L. Dang, S. K. Liu, S. Fels, Zentrader, an emotion-reactive interface, in: Int. Conf. on Entertainment Computing, Springer-Verlag, Berlin, Heidelberg, 2011, pp. 294–299.
[121] J. Hernandez, R. R. Morris, R. W. Picard, Call center stress recognition with person-specific models, in: Int. Conf. on Affective Computing and Intelligent Interaction - Volume Part I, 2011, pp. 125–134.
[122] NeuroSky Inc., EEG-ECG Biosensors (2018).
URL `http://www.neurosky.com`
[123] EMOTIV Inc., Emotiv (2018).
URL `http://www.emotiv.com`
[124] M.-S. Yoh, J. Kwon, S. Kim, Neurowander: A bci game in the form of interactive fairy tale, in: ACM Int. Conf. Adjunct Papers on Ubiquitous Computing, ACM, 2010, pp. 389–390.
[125] J. Huang, C. Yu, Y. Wang, Y. Zhao, S. Liu, C. Mo, J. Liu, L. Zhang, Y. Shi, Focus: Enhancing children's engag. in read. by using context. BCI train. sessions, in: Conf. on Hum. Fact. in Comp. Syst., ACM, 2014, pp. 1905–1908.
[126] A. Damala, N. Stojanovic, T. Schuchert, J. Moragues, A. Cabrera, K. Gilleade, Adaptive Augmented Reality for Cultural Heritage: ARtSENSE Project, Springer Berlin Heidelberg, Berlin, Heidelberg, 2012, pp. 746–755.
[127] S. Du, E. Shu, F. Tong, Y. Ge, L. Li, J. Qiu, P. Guillotel, J. Fleureau, F. Danieau, D. Muller, Visualizing the emotional journey of a museum, in: EmoVis Conf. on Emotion and Visualiz., Linkoping Univ., 2016, pp. 7–14.
[128] M. Troendle, W. Tschacher, The physiology of phenomenology: The effects of artworks, Emp. Studies of the Arts 30 (1) (2012) 75–113.
[129] Y. Abdelrahman, M. Hassib, M. G. Marquez, M. Funk, A. Schmidt, Implicit engagement detection for inter. museums using bci, in: Int. Conf. on HCI with Mobile Devices and Serv. Adjunct, ACM, 2015, pp. 838–845.
[130] D. Wessel, E. Mayr, K. Knipfer, Re-viewing the museum visitors view, in: The 7th International Symposium on Virtual Reality, Archaeology and Cultural Heritage, 2007.
[131] M. Mokatren, T. Kuflik, I. Shimshoni, Using eye-tracking for enhancing the museum visit experience, in: Proc. of the Int. Working Conf. on Advanced Visual Interfaces, ACM, New York, NY, 2016, pp. 330–331.
[132] E. Bachta, R. J. Stein, S. Filippini-Fantoni, T. Leason, Evaluating the practical applications of eye tracking in museums, in: Museums and the Web, 2012.
[133] S. F. Fantoni, K. Jaebker, D. Bauer, K. Stofer, Capturing visitors gazes: Three eye tracking studies in museums, in: MW2013: Museums and the Web 2013, 2013.
[134] K. Eghbal-Azar, T. Widlok, Potentials and limitations of mobile eye tracking in visitor studies: Evidence from field research at two museum exhibitions in germany, Social Science Computer Review 31 (1) (2013) 103–118.
[135] D. M. Calandra, D. Di Mauro, D. D'Auria, F. Cutugno, E.Y.E. C. U.: an Emotional eYe trackEr for Cultural heritage sUpport, Springer International Publishing, Cham, 2016, pp. 161–172.
[136] R. Brunelli, A. Albertini, C. Andreatta, P. Chippendale, M. Ruocco, O. Stock, F. Tobia, M. Zancanaro, Detecting Focus of Attention, Springer Berlin Heidelberg, Berlin, Heidelberg, 2007, pp. 45–70.
[137] T. Kajinami, T. Narumi, T. Tanikawa, M. Hirose, Digital Display Case Using Non-contact Head Tracking, Springer Berlin Heidelberg, Berlin, Heidelberg, 2011, pp. 250–259.
[138] O. Ferhat, F. Vilario, Low cost eye tracking: The current panorama, Comput. Intelligence and Neuroscience 2016.
[139] E. Murphy-Chutorian, M. M. Trivedi, Head pose estimation in computer vision: A survey, IEEE Transactions on Pattern Analysis and

Machine Intelligence 31 (4) (2009) 607–626.
[140] A. Riener, A. Sippl, Head-pose-based attention recogn. on large public displays, IEEE Comp. Graphics & Appl. 34 (1) (2014) 32–41.
[141] G. Conti, S. Piffer, G. Girardi, R. De Amicis, G. Ucelli, Dentrotrento: A virtual walk across history, in: Proc.s of the Working Conf. on Advanced Visual Interfaces, AVI '06, ACM, New York, NY, USA, 2006, pp. 318–321.
[142] C.-Y. Chen, B. R. Chang, P.-S. Huang, Multimedia augmented reality information system for museum guidance, Personal and Ubiquitous Computing 18 (2) (2014) 315–322.
[143] R. Hammady, M. Ma, N. Temple, Augmented Reality and Gamification in Heritage Museums, Springer International Publishing, Cham, 2016, pp. 181–187.
[144] S. Valtolina, P. Mazzoleni, S. Franzoni, E. Bertino, A semantic approach to build personalized interfaces in the cultural heritage domain, in: Working Conference on Advanced Visual Interfaces, ACM, 2006, pp. 306–309.
[145] L. L. Scarlatos, Y. Dushkina, S. Landy, Ticle: A tangible interface for collaborative learning environments, in: CHI '99 Extended Abstracts on Human Factors in Computing Systems, ACM, New York, NY, 1999, pp. 260–261.
[146] S. H. Owsley, K. J. Hammond, D. A. Shamma, S. Sood, Buzz: Telling compelling stories, in: Proceedings of the 14th ACM International Conference on Multimedia, MM '06, ACM, New York, NY, USA, 2006, pp. 261–268.
[147] P. F. Marty, W. B. Rayward, M. B. Twidale, Museum informatics, Ann. Review of Inf. Science and Technology 37 (1) (2003) 259–294.
[148] CIDOC Documentation Standards Working Group, CIDOC - CRM (2017).
URL http://www.cidoc-crm.org/
[149] DCMI Cultural Heritage Metadata Task Group, DCMI Cultural Heritage Metadata Task Group (2013).
URL https://github.com/dcmi/archive/blob/master/mediawiki_wiki/Cultural_Heritage_Metadata_Task_Group.md
[150] L. Carrasco, S. Vidotti, Dublin core and CIDOC CRM harmonization, Int. Conf. on Dublin Core and Metadata Appl. (2015) 198–200.
URL http://dcpapers.dublincore.org/pubs/article/view/3779
[151] Europeana, Spectrum 5.0 consultation draft (2018).
URL http://collectionstrust.org.uk/spectrum/spectrum-5/
[152] Visual Resources Association Foundation, CCO - Cataloging Cultural Objects (2017).
URL http://cco.vrafoundation.org/index.php/aboutindex/who_is_using_cco/
[153] J. I. Rojas-Sola, M. Castro-Garcia, M. del Pilar Carranza-Cacadas, Content management system incorporated in a virtual museum hosting, Journal of Cultural Heritage 12 (1) (2011) 74 – 81.
[154] A. Chianese, F. Piccialli, Designing a smart museum: When cultural heritage joins IoT, in: 2014 Eighth International Conference on Next Generation Mobile Apps, Services and Technologies, 2014, pp. 300–306.
[155] Europeana Foundation, The Europeana data model for cultural heritage (2017).
URL http://pro.europeana.eu/files/Europeana_Professional/Share_your_data/Technical_requirements/EDM_Documentation/EDM_Factsheet.pdf
[156] E. Coburn, R. Light, G. McKenna, R. Stein, A. Vitzthum, Lido v1.0 - lightweight inf. describing objects (2010).
URL http://www.lido-schema.org/schema/v1.0/lido-v1.0-specification.pdf
[157] T. Kuflik, O. Stock, M. Zancanaro, A. Gorfinkel, S. Jbara, S. Kats, J. Sheidin, N. Kashtan, A visitor's guide in an active museum: Presentations, communications, and reflection, J. Comput. Cult. Herit. 3 (3) (2011) 11:1–11:25.
[158] C. Barberis, B. Andrea, M. Giovanni, M. Paolo, Experiencing indoor navigation on mobile devices, IT Professional 16 (1) (2014) 50–57.
[159] E. Toch, Y. Wang, L. F. Cranor, Personalization and privacy: a survey of privacy risks and remedies in personalization-based systems, User Modeling and User-Adapted Interaction 22 (1) (2012) 203–220.
[160] Y. Yoshimura, S. Sobolevsky, C. Ratti, F. Girardin, J. P. Carrascal, J. Blat, R. Sinatra, An analysis of visitors' behavior in the louvre museum: A study using bluetooth data, Environment and Planning B: Planning and Design 41 (6) (2014) 1113–1131.
[161] J. Lanir, T. Kuflik, J. Sheidin, N. Yavin, K. Leiderman, M. Segal, Visualizing museum visitors' behavior: Where do they go and what do they do there?, Personal and Ubiquitous Computing 21 (2) (2017) 313–326. doi:10.1007/s00779-016-0994-9.
URL https://doi.org/10.1007/s00779-016-0994-9
[162] J. H. J. H. Falk, . Dierking, Lynn D. (Lynn Diane), . Falk, John H. (John Howard), The museum experience, Washington, D.C. : Whalesback Books, 1992, includes bibliographical references.
[163] C. Shaw, J. Ivens, Building Great Customer Experiences, Beyond philosophy, Palgrave Macmillan, 2002.
[164] G. Black, The Engaging Museum: Developing Museums for Visitor Involvement, Heritage (Routledge), Routledge, 2005.
URL https://books.google.gr/books?id=qqbHvoeDupMC
[165] M. Dunleavy, C. Dede, Augmented Reality Teaching and Learning, Springer, 2014, pp. 735–745.
[166] G. Liestøl, O. Smørdal, O. Erstad, Stem learning by means of mobile ar. exploring the potential of augmenting classroom learn. with situated simulations and practical activities on location, Int. Conf. on Educ. and New Learn. Tech., IATED, 2015, pp. 6515–6522.
[167] A. M. McNamara, Enhancing art history education through mobile augmented reality, in: Proc. of the 10th Int. Conf. on Virtual Reality Continuum and Its Applications in Industry, ACM, New York, NY, 2011, pp. 507–512.
[168] Apple, iPhone X (2018).
URL https://www.apple.com/iphone-x/
[169] G. Koutromanos, G. Styliaras, "the buildings speak about our city": A location based augmented reality game, in: 2015 6th International Conference on Information, Intelligence, Systems and Applications (IISA), 2015, pp. 1–6.
[170] C. M. L. Ho, M. E. Nelson, W. Müeller-Wittig, Design and implem. of a student-generated virt. museum in a lang. curriculum to enhance collaborative multimodal meaning-making, Comp. Educ. 57 (1) (2011) 1083–1097.
[171] C.-M. Chen, Y.-N. Tsai, Interactive augmented reality system for enhancing library instruction in elementary schools, Computers & Education 59 (2) (2012) 638–652.
[172] E. Klopfer, J. Perry, K. Squire, M.-F. Jan, Collaborative learning through augmented reality role playing, in: Conf. on Computer Support for Collaborative Learning: Learning 2005: The Next 10 Years!, 2005, pp. 311–315.
[173] A. M. Kamarainen, S. Metcalf, T. Grotzer, A. Browne, D. Mazzuca, M. S. Tutwiler, C. Dede, Ecomobile: Integrating ar and probeware with environmental education field trips, Comput. Educ. 68 (2013) 545–556.
[174] Y. Blanco-Fernandez, M. Lopez-Nores, J. J. Pazos-Arias, A. Gil-Solla, M. Ramos-Cabrer, J. Garcia-Duque, Reenact: A step forward in immersive learning about human history by AR, role playing and soc. net., Exp. Syst. with App. 41 (10) (2014) 4811 – 4828.
[175] Chess Consortium, The Chess Project (2017).
URL http://www.chessexperience.eu/
[176] S. ChiehWen, M. Shen, M. Chen, Special interest tour preferences and voluntary simplicity lifestyle, International Journal of Culture,

Tourism and Hospitality Research 2 (4) (2008) 389–409.
[177] N. Y.-M. Siu, T. J.-F. Zhang, P. Dong, H.-Y. Kwan, New service bonds and customer value in customer relationship management: The case of museum visitors, Tourism Management 36 (2013) 293 – 303.
[178] B. Taheri, A. Jafari, K. O'Gorman, Keeping your audience: Presenting a visitor engagement scale, Tourism Management 42 (2014) 321 – 329.
[179] D. vom Lehn, Embodying experience: A videobased examination of visitors' conduct and interaction in museums, European Journal of Marketing 40 (11/12) (2006) 1340–1359.
[180] A. Fletcher, M. J. Lee, Current social media uses and evaluations in american museums, Museum Management and Curatorship 27 (5) (2012) 505–521.
[181] P. Samis, Points of departure: Curators and educators collaborate to prototype a museum of the future, David Bearman and Franca Garzotto (editors). International Cultural Heritage Informatics Meeting: Proceedings from ICHIM01 1 (2001) 623–637.
[182] W3C, Scalable vector graphics (2017).
URL https://www.w3.org/Graphics/SVG/
[183] W3C, Cascading style sheets (2018).
URL https://www.w3.org/Style/CSS/Overview.en.html
[184] W3C, Standards for web applications on mobile: current state and roadmap (2018).
URL https://www.w3.org/Mobile/mobile-web-app-state/
[185] S. Murray, Interactive Data Visualization for the Web, O'Reilly Media, Inc., 2013.
[186] K. Dale, Data Visualization with Python and JavaScript: Scrape, Clean, Explore & Transform Your Data, O'Reilly Media, 2016.
[187] Lucidea, Argus, make your collection more visible and accessible than ever before (2018).
URL https://lucidea.com/argus/
[188] RetailPro, Retailpro (2018).
URL http://www.retailpro.com/
[189] GallerySystems, Collection management software, museum and art collections (2018).
URL https://www.gallerysystems.com/products-and-services/tms-suite/tms/
[190] Zetcom, Museum plus (2018).
URL http://www.zetcom.com/en/products_en/
[191] CollectiveAccess, Collective access (2018).
URL http://www.collectiveaccess.org/
[192] MuseumAnywhere, Museum anywhere (2018).
URL http://museumanywhere.com/
[193] S. Sayre, Bring it on: Ensuring the success of BYOD programming in the museum environment, museums and the web 2015 (2015).
URL http://mw2015.museumsandtheweb.com/paper/bring-it-on-ensuring-the-success-of-byod-programming-in-the-museum-environment/
[194] T. Moussouri, G. Roussos, Mobile sensing, byod and big data analytics: New technologies for audience research in museums, Participations, Journal of Audience and Reception Studies 11 (1) (2014) 270–285.
[195] T. Moussouri, G. Roussos, Conducting visitor studies using smartphone-based location sensing, J. Comput. Cult. Herit. 8 (3) (2015) 12:1–12:16.
[196] R. Hacket, Apple iphone 8 and iphone xs 3d cameras look like game changers (2017).
URL http://fortune.com/2017/09/12/apple-iphone-8-iphone-x-3d-camera/
[197] E. Merrit, Trendswatch 2015. in Center for the Future of Museums (2015).
URL http://www.aamus.org/resources/center-for-the-future-of-museums/projects-and-reports/trendswatch/trendswatch2015
[198] T. Brusie, T. Fijal, A. Keller, C. Lauff, K. Barker, J. Schwinck, J. F. Calland, S. Guerlain, Usability evaluation of two smart glass systems, in: 2015 Systems and Information Engineering Design Symposium, 2015, pp. 336–341.
[199] G. Flix, M. Siller, E. N. lvarez, A fingerprinting indoor localization algorithm based deep learning, in: 2016 Eighth International Conference on Ubiquitous and Future Networks (ICUFN), 2016, pp. 1006–1011.
[200] Z. Huang, P. Hui, C. Peylo, D. Chatzopoulos, Mobile AR survey: a bottom-up approach., CoRR abs/1309.4413.
URL http://dblp.uni-trier.de/db/journals/corr/corr1309.html#HuangHPC13
[201] T. Taketomi, H. Uchiyama, S. Ikeda, Visual slam algorithms: a survey from 2010 to 2016, IPSJ Transactions on Computer Vision and Applications 9 (1) (2017) 16.
[202] L. Deng, D. Yu, Deep learning: Methods and applications, Found. Trends Signal Process. 7 (3-4) (2014) 197–387.
[203] Dedo Comunicazione, Starry night of Vincent Van Gogh - interactive animation by Petros Vrellis (2012).
URL https://www.youtube.com/watch?v=XtNXuMo-DrY
[204] Wikimedia Commons, Trajans column (2018).
URL https://upload.wikimedia.org/wikipedia/commons/6/6c/Trajans-Column-lower-animated.svg
[205] N. Thiagarajan, G. Aggarwal, A. Nicoara, D. Boneh, J. P. Singh, Who killed my battery?: Analyzing mobile browser energy consumption, in: Int. Conf on World Wide Web, ACM, New York, NY, 2012, pp. 41–50.
[206] N. Balasubramanian, A. Balasubramanian, A. Venkataramani, Energy consumption in mobile phones: A meas. study and implications for net. app., in: SIGCOMM Conf. on Internet Measurement, ACM, 2009, pp. 280–293.
[207] G. P. Perrucci, F. H. P. Fitzek, J. Widmer, Survey on energy consumption entities on the smartphone platform, in: 2011 IEEE 73rd Vehicular Technology Conference (VTC Spring), 2011, pp. 1–6.
[208] B. Zhao, B. C. Tak, G. Cao, Reducing the delay and power consumption of web browsing on smartphones in 3g networks, in: 2011 31st International Conference on Distributed Computing Systems, 2011, pp. 413–422.
[209] Y. Zhu, V. J. Reddi, High-performance and energy-efficient mobile web browsing on big/little systems, in: 2013 IEEE 19th International Symposium on High Performance Computer Architecture (HPCA), 2013, pp. 13–24.
[210] A. Carroll, G. Heiser, An analysis of power consumption in a smartphone, in: Proc. of the USENIX Annual Technical Conference, USENIXATC'10, USENIX Association, Berkeley, CA, USA, 2010, pp. 21–21.
[211] R. Mittal, A. Kansal, R. Chandra, Empowering developers to estimate app energy consumption, in: Int. Conf. on Mobile Computing and Networking, Mobicom '12, ACM, 2012, pp. 317–328.