# EAI Endorsed Transactions

on Context-aware Systems and Applications

## **Essential Context-derived Reasons Formation from Context Information of Museum Ubiquitous Visitors**

Preeti Khanwalkar and Pallapa Venkataram\*

Protocol Engineering and Technology Unit, Department of Electrical Communication Engineering, Indian Institute of Science, Bangalore, India, 560012 *preetik@iisc.ac.in, pallapa@iisc.ac.in* 

### Abstract

INTRODUCTION: Recent advances in ubiquitous computing technologies have enabled anywhere, anytime personalized services to the museum ubiquitous visitors without any explicit requests. The system utilizes visitor, device, network, and other application related context information to provide required services to the museum ubiquitous visitors.

OBJECTIVES: In this work, we propose the formation of *Essential Context-derived Reasons (ECR)* from the context information of the museum ubiquitous visitors, which enables to provide required exhibit information museum services to the visitors.

METHODS: Context information of museum ubiquitous visitors is acquired and processed with multiple combinations to formulate into *Composite Context* which further leads to *ECR*. *ECR* provides an accurate understanding of museum ubiquitous visitor's requirements to provide the required services. We conducted simulation with relevant context information parameters and their percentage accuracy of acquisition and evaluates the accuracy of *ECR*.

RESULTS: Over 200 experiments, we found that for 90% context information available with high accuracy, the accuracy of *CC* ranges from 0.69 to 0.89, and the accuracy of *ECR* ranges from 0.77 to 0.95. This indicates that the effect of some of the inaccurately available context information of the museum ubiquitous visitors is proportionally mitigated by the other accurately available context information with their multiple combinations.

CONCLUSION: The simulation results show that the accuracy of *ECR* increases with the increase in reference structures of multiple combinations of accurately available context information of the museum ubiquitous visitors, which further enables to provide required exhibit information museum services to the visitors.

Received on 26 June 2020; accepted on 30 August 2020; published on 08 September 2020

**Keywords:** Museum Ubiquitous Visitors, Context Information, Essential Context-derived Reasons, Museum Services Copyright © 2020 Preeti Khanwalkar *et al.*, licensed to EAI. This is an open access article distributed under the terms of the Creative Commons Attribution license, which permits unlimited use, distribution and reproduction in any medium so long as the original work is properly cited.

doi:10.4108/eai.8-9-2020.166289

### 1. Introduction

The paradigm of providing museum services has especially changed from the perspectives of the ubiquitous visitors [1–7]. Museum ubiquitous visitors are the visitors who need museum services anywhere, anytime through any possible devices without explicit requests or interventions. For museum ubiquitous visitors, the traditional approach of requesting and receiving services through human guides have shifted to pro-actively filtering and providing required services through a technologically enriched environment. For providing such unobtrusive and adaptive services, it is essential to acquire context information of the museum ubiquitous visitors and to recognize the services that they required in the museum [8–11]. Context information is any information such as location, time, available devices, networks, professional qualifications, etc., which provides intelligence to the system to anticipate museum ubiquitous visitor's requirements



<sup>\*</sup>Corresponding author. Email: pallapa@iisc.ac.in

to provide the required services [9, 12-16]. The system utilizes context information to support museum ubiquitous visitors with their required services (e.g., exhibit information of interests, locations of next exhibits and few other facilities), thus to enhance the overall visiting experience [12, 14, 17, 18]. Even though, there exist multiple approaches in the literature, the new approach for processing the context information is still needed as providing exhibit information museum services to the ubiquitous visitors is a compelling future to enhance their museum visiting experience. The proposed approach exploits the combinations interdependencies, which proportionally mitigates the effect of lower percentage of inaccurately available context information with other accurately available context information with their multiple combinations. The multiple combinations of context information provides an accurate understanding of the ubiquitous visitor's requirements to provide the required exhibit information museum services and to improve their visiting experience.

### 1.1. Proposed Idea

This work presents the Essential Context-derived Reasons (ECR) formation from the context information of the museum ubiquitous visitors. The context information of the museum ubiquitous visitors is acquired from the three categories, namely: Physical Environment Context Information, Visitor Activity Context Information, and Network Context Information, using the procedure of CI-Constructs. Further, context information is processed in two's, three's, and in higher combinations to formulate Composite Context (CC), which leads to Essential Context-derived Reasons (ECR). ECR of the ubiquitous visitors specifies that a particular exhibit information museum service is required and used to provide required services to the ubiquitous visitors. We present the case study with a variety of context information to provide different types of exhibit information museum services to the ubiquitous visitors. The simulation is conducted with relevant context information parameters and their percentage accuracy of acquisition, to evaluate the accuracy of ECR. Over 200 experiments, we found that for 90% context information available with high accuracy, the accuracy of CC ranges from 0.69 to 0.89, and the accuracy of ECR ranges from 0.77 to 0.95. The simulation results show that accuracy of ECR increases with the increase in reference structures of multiple combinations of accurately available context information of the museum ubiquitous visitors, which further enables to provide required exhibit information museum services to the visitors.

#### 1.2. Organization of the Paper

The rest of the paper is organized as follows. Section 2 discusses some of the related work. Section 3 defines the three types of context information of museum visitors. Section 4 explains the procedure of the acquisition of context information. Section 5 explains the formation of *Composite Context (CC)* of museum ubiquitous visitors. Section 6 describes the formation of *Essential Context-derived Reasons (ECR)* of museum ubiquitous visitors. Section 7 discusses the case study of the proposed scheme. Section 8 presents the simulation results, followed by the conclusion and future work in Section 9.

### 2. Related Work

The acquisition and processing of context information of museum ubiquitous visitors are explored from several perspectives in the literature [15, 19–25]. A systematic literature review of various types of context information and different context-aware architectures are discussed in [24, 26]. However, because of the complexity of a large number of available context information and their deduction methods, often application-specific context information is taken into consideration [27–29]. The potential of context information for providing museum services to the ubiquitous visitors is discussed in [17, 30–33].

Pallapa et al. [1, 17] have proposed the technique of *Context Information Constructs* (*CI-Constructs*) for the acquisition of context information. Different *CI-Constructs* [8] are defined as a multiway data structure to support the collection of a variety of context information from different sources. The acquired context information further formulated as observations and beliefs. Further, the formulated beliefs are utilized to provide the required museum services to the ubiquitous visitors.

The iMuseum system [33] acquires information about the visitor and surroundings, to recognize the visitor's purpose to support services in the museum. The system considers the context information such as visitor location, profile, surrounding environment, device capabilities, etc., through sensors, handheld devices, and applications. iMuseum has proposed ontologybased two sets three layers context model and the hierarchical model to process the acquired context information.

Zimmermann [9] has proposed the case-based reasoning to describe context information and to achieve context awareness of the system. Context information such as location, identity, time, and environment/visitor activity are considered, and described as cases to provide museum services. In [15], a theoretical framework is defined for the context-based design of mobile applications for the museum. Four context



dimensions such as the system, the infrastructure, the domain and the physical context are described which affect the interaction between the visitors and the museum.

iMuseumA [11] has utilized wireless sensor networks, visitor devices, and wireless communication infrastructure to provide context-based services to the visitors, guides, and the museum staff. The system has utilized a set of sensors, devices, that interacts with the visitor through the mobile application to decide the required services tailored to the locations and interests of the visitors. In another work, MyGuide [34] has utilized visitor's location, background knowledge, types of media, and preferred language to design a contextaware exhibit guide for the visitors.

Christopoulou et al. [35] have discussed contextawareness in the museum, and explained how different types of context information is used to improve the visitor's experience. For the indoor environment of the museum, applicable context parameters such as profiles of the visitors, visitor's location, the path followed by the visitors, device capabilities, etc., are considered. The authors have explained that effective usage of context information influences both the selection of relevant information contents for visitors and the selection of appropriate interaction methods.

Cultural Heritage Information Presentation (CHIP) [16] is designed as a web application for providing personalized tours tailored to the visitor locations and interests. CHIP has considered location, temporal preferences, and art interests as visitor context. Both implicit and explicit mechanisms are used to collect a visitor context. In [36, 37], situation contexts and visitor profiles are combined to provide proactive services in a museum smart assistive environment.

The context-aware framework [38] is presented to assist museum visitors to enrich tour experience. The interests and knowledge of the museum visitors are obtained explicitly (through registration) and used to adapt the artwork information for children to senior researchers. The location of the visitor's device and the duration of the device at a particular location are considered as physical contexts. Likewise, interests and levels of understanding of the visitors are considered as a virtual context which is determined by analyzing information accessed by the visitors.

In [39], the usage of context-aware technology is discussed for the next-generation digital museum collections. The context-awareness is shown with three steps: (i) perception, (ii) analysis, and (iii) execution. The perception step is defined to gather information about visitors from sensors, devices, visitor modeling, or directly from visitor inputs. The analysis step is used to analyze previously collected data to provide intelligent museum services based upon analyzed results. The execution step is defined to recognize appropriate system behavior for the visitor based on the analysis of situation and environment. These three steps are considered to be essential to identify visitor needs, for example, to provide assistance by detecting visitor's behavior and movement path.

## 3. Types of Context Information of Museum Ubiquitous Visitors

The primitive set of Context Information (*CI*) according to the common characteristics of museum ubiquitous visitors and their surrounding environment is divided into three categories: *Physical Environment Context Information* (*PECI*), *Visitors Activity Context Information* (*VACI*), and *Network Context Information* (*NCI*). More specifically, the set of *CI* of museum ubiquitous visitors is defined as-

$$CI = \{PECI, VACI, NCI\}$$
(1)

We consider applicable context parameters from these three categories of context information, which are essential to provide the required museum services. With these three categories of context information, the system acquires and processes the complete set of information to perceive the museum ubiquitous visitor's requirements and to provide intuitive and unobtrusive museum services. These three categories of context information of museum ubiquitous visitors along with their examples and usages are described as follows.

#### 3.1. Physical Environment Context Information

*Physical Environment Context Information* specifies information related to the local surroundings of museum ubiquitous visitors. It comprises parameters corresponding to physical, spatial, and temporal features of the ubiquitous visitor surroundings which influence museum service requirements in different scenarios. We define physical environment context information *PECI* as a set of *j* parameters given by-

$$PECI = \{peci_1, peci_2, \cdots, peci_i\}$$
(2)

The examples of physical environment context information pertaining to the museum ubiquitous visitors are:  $peci_1 = visitor/device \ location, \ peci_2 = time$ , etc. This also includes other related parameters such as geographical coordinates (e.g.,  $12^{\circ}58'$  N,  $77^{\circ}38'$  E), geographical area, logical location (e.g. at the exhibit, cafeteria), relative distance from a particular exhibit, time of the day when museum service is used, the time duration of the museum service, number of times the museum service is used. *Physical environment context information* enables the system to determine the nearby exhibits, the shortest routes to the exhibits, or the



duration for which museum services are used by the ubiquitous visitors. Few examples of these parameters applicable to our work are: visitor is at exhibit, visitor is near to exhibit, visitor is spending a longer time, and visitor has used museum service for less time.

### 3.2. Visitor Activity Context Information

*Visitor Activity Context Information* refers to information specific to a particular ubiquitous visitor and his/her museum related activities. We define visitor activity context information *VACI* as a set of *k* parameters given by-

$$VACI = \{vaci_1, vaci_2, \cdots, vaci_k\}$$
(3)

The examples of visitor activity context information are  $vaci_1 = visitor activities$ ,  $vaci_2 = educational$ qualifications, etc. For a museum ubiquitous visitors, visitor activities include related context parameters such as standing or sitting; educational qualifications include context parameters such as professionals, college students, school kids, etc. Visitor activity context information such as standing at exhibit enables the system to determine the need of exhibit information museum service. From professional qualifications, the system determines the understanding level of museum ubiquitous visitor to provide exhibit information at a certain level of detail. Few examples of these parameters applicable to our work are: visitor is standing, visitor is sitting, visitor is a professional, visitor is a school kid.

#### 3.3. Network Context Information

*Network Context Information* provides information regarding networks, devices, or any other resources through which ubiquitous visitors avail museum services. *Network context information* enables the system to decide the formats and features of the contents of museum services that needs to be provided. We define network context information *NCI* as a set of *l* parameters given by-

$$NCI = \{nci_1, nci_2, \cdots, nci_l\}$$
(4)

The examples of network context information are  $nci_1 = type$  of devices,  $nci_2 = device$  capabilities,  $nci_3 = type$  of networks,  $nci_4 = network$  delay, etc. It includes hardware and software capabilities of devices, and network characteristics used to avail the museum services. Network context information, for instance, device capabilities enable the system to decide the format of the museum services (e.g., Mpeg for laptop and 3gp for smartphones). Similarly, the low bandwidth network connection enables the system to decide summarized exhibit information instead of a large amount of

exhibit information. Few examples of these parameters applicable to our work are: visitor has a smart phone, visitor has a low battery smart phone, visitor has a laptop, and visitor has 8 Mbps WiFi connectivity.

## 4. Context Information Acquisition of Museum Ubiquitous Visitors

Context information acquisition refers to the collection of context information of museum ubiquitous visitors from varied available sources [39–42]. To efficiently collect context information, a systematic procedure is needed that uniformly handles different context information and provide them as requested. In our work, we use the procedure of *Context Information Constructs (CI-Constructs)* [8] to acquire the three categories of context information. The procedure of *CI-Constructs* is described in detail as follows.

### 4.1. Context Information Constructs

*Context Information Constructs (CI-Constructs)* represent a multiway data structure, where each construct is designed to acquire the related pre-defined context parameters. The construct structure provides the flexibility to expand, organize, and manage any type of context information with uniform abstraction. Individual *CI-construct* is designed to acquire a particular category of context information, which further extends to include related context parameters as shown below.

- *What*: collects information related to the museum ubiquitous visitor activities (e.g., standing, sitting), capabilities of devices and networks such as device battery power, network bandwidth, etc.
- *When*: acquires information regarding time, day, particular time instant, duration of exhibit information museum services used.
- *Where*: obtains information about geographical location or place of a museum ubiquitous visitor, visitor distance (near or far) from a particular exhibit.
- *Who*: acquires information specific to a museum ubiquitous visitor or a group of museum ubiquitous visitors such as educational qualifications professionals, college students, and school kids.
- *Which*: collects information about the type of devices (e.g., laptop, smartphone) or networks (e.g., WiFi, Cellular) that are used to avail the
- **Horseuncquives**esinformation about the way or manner, the format of the museum services such as MPEG, 3GP, etc., which needs to be provided.

These *CI-Constructs* in their modified form offers flexibility to acquire different context information. For the acquisition of context information partly



filled construct structures are designed. During the acquisition process depending on the sophisticated system design, the required fields are filled with sensed, visitor supplied information, or any other sources of context information such as embedded devices, system APIs, databases, and authorized persons.

The acquisition of context information of the museum ubiquitous visitors, practically not possible to get accurate as specified [43], hence, we compute CC with the available context information as an intermediate step before computing the ECR. We process different combinations of context information as CC and further as ECR which provides more significant and comprehensively useful information about the requirements of the ubiquitous visitors [44]. The multiple combinations provide a better understanding of the ubiquitous visitor's requirements to enable the system to offer the required museum services. For formulating CC and ECR, the corresponding reference structures with varied combinations of context information of museum ubiquitous visitors are designed in advance. However, among the several available combinations, some of the combinations may be considered as invalid which are insignificant from the perspective of museum ubiquitous visitors. The interdependent reference structures of multiple combinations according to the acquired context information of museum ubiquitous visitors are dynamically used to formulate CC and in succession ECR.

## 5. Formation of Composite Context of Museum Ubiquitous Visitors

Composite Contexts (CC) are formulated as varied combinations of context information which gives a comprehensive perception to decide museum services for the ubiquitous visitors. Each combination as CC has its own meaning and provides more realistic information about museum ubiquitous visitors. The three categories of context information are combined in two's, three's, and other higher order combinations to formulate as CC. These different combinations of context information specifically lead to an exhaustive number of CC. On matching with the reference structures of different context information combinations, valid CC are formulated. The matching is obtained by computing cosine similarity of term vectors of different context information combinations [45]. The procedure to formulate CC is given in Algorithm 1.

Consider a case, where eight context parameters are obtained from the three categories of context information. These context parameters can be further extended depending upon specific requirements. For example:

PECI = {Visitor/Device Location, Time Duration of Service Used}; Input: CI Parameters from the three categories of context information; **Output:** Set of formulated *Composite Contexts (CC)*; Acquire CI={PECI, VACI, NCI} using CI-Constructs; /\* Let PECI consists of *i* context information parameters; \*/ /\* Let VACI consists of *j* context information parameters; \*/ /\* Let NCI consists of k context information parameters; \*/ /\* Let n = i+j+k, be total number of context parameters acquired from three categories; \*/ for Available CI do Obtain total *n* number of context parameters; /\* Let  $CC_{val}$  = total number of valid formulated CC \*/;Initialize *CC*<sub>val</sub>=0; for x = 2 to n do Generate *k* combinations of *CI* such that  $k = \frac{n*(n-1)*\cdots*(n-r-1)}{1*2*\cdots*r}$  with r=x; **for** *i* = 1 *to k* **do for** j = i to k **do** if Matched with the reference structures of combinations of context information then  $CC_{val} = CC_{val} + 1;$ Formulate valid  $CC_i = CI(i,j+1) \cup$  $\cdots \cup CI(i,j=k)$  with r combinations of CI; end end end end Obtain set of valid CC; end

Algorithm 1: Formation of Composite Contexts

#### *VACI* = {*Visitor Activity, Educational Qualifications*};

NCI = {Type of Device, Device Battery, Type of Network, Network Capacity};

Using these eight context parameter values two's combinations of context information, for example,  $\binom{8}{2}$ , result into a total of 28 combinations of *CC*. However, according to the reference structures of two's combinations of context information, 12 valid *CC* are obtained. Similarly, three's combinations of eight context parameter values  $\binom{8}{3}$ , result into a total of 56 combinations of *CC*. However, based on the reference structures of three's combinations of context information 24 valid *CC* are obtained. An example reference structure of *CC* from three's combinations of context information is depicted in Figure 1.

Similarly, four's combinations of eight context parameter value  $\binom{8}{4}$ , result into a total of 70





Figure 1. CC from Three's Combination of Context Information



Figure 2. CC from Four's Combination of Context Information

combinations of *CC*. However, based on the reference structures of four's combinations of context information 14 valid *CC* are obtained. An example reference structure of *CC* from four's combinations of context information is depicted in Figure 2. Further, five's combinations and other higher combinations of context information result into a total of 247 *CC*. However, on matching with reference structures of multiple combinations a total of 60 valid *CC* are obtained. These *CC* with varied combinations are further used to formulate *ECR*.

Next, we process *CC* by considering the relevant context information parameters and their percentage accuracy of acquisition. The effect of a lower percentage of inaccurately available context information of museum ubiquitous visitor is compensated by exploiting combinations interdependencies of other accurately available context information. As discussed earlier, since *CC* are formed from varied combinations of context information. Accordingly, based upon the interdependency of context information and its percentage accuracy of acquisition, *CC* is processed as follows.

Based upon the reference structures of context information combinations of museum ubiquitous visitors (available in advanced from the past observations) conditional probabilities of  $p(CC_j|CI_i)$  between  $CC_j$  and  $CI_i$  are calculated. This gives the probabilities of the accuracy of all  $CC_j$  formation obtained from the various dependent combinations of accurately available context information of the museum ubiquitous visitors. As a result, a set of conditional probabilities (CP) of accuracy for each  $CC_j$  formation is obtained as given by Equation 5. Each conditional probability  $p(CC_j|CI_i)$  represents the probability of the accuracy of  $CC_j$  formation corresponding to the percentage accuracy of acquisition of  $CI_i$ .

$$CP(CC_i) = \{p(CC_i | CI_i)\}$$
(5)

$$|i = a, d, ..., p|CI_a, CI_d, ..., CI_p \rightarrow CC_j$$

where, i represent the context information parameters of museum ubiquitous visitors involved in the formation of  $CC_{j}$ .

Next, we evaluate the accuracy of  $CC_j$  formation, which represents the probability of  $CC_j$  formation depending on the individual conditional probabilities of the accuracy  $p(CC_j|CI_i)$  as determined by Equation 6.

$$CC_{j} = \frac{1}{k} * \sum_{i=1}^{k} p(CC_{j}|CI_{i})$$
where,  $p(CC_{j}|CI_{i}) \in CP(CC_{j})$ 
(6)

The conditional probabilities and consequently the accuracy of  $CC_j$  formation will be high with more number of accurately available interdependent context information, that is the size of *i*, which represents the optimal number of context information parameters. The effect of some of the inaccurately available context information of the museum ubiquitous visitors is proportionally mitigated by the other accurately available combinations. The limitation is, this will be true as long as number of interdependent inaccurately available context information of the museum ubiquitous visitors will be less than the accurately available context information.

## 6. Formation of Essential Context-derived Reasons of Museum Ubiquitous Visitors

*Essential Context-derived Reasons (ECR)* are deduced over varied combinations of *CC*. Each deduced *ECR* provides much more vivid and significant information and enables the system to realize the museum ubiquitous visitor's requirements with different aspects. More specifically, the two's combinations, three's combinations, and other higher combinations of *CC* are used to formulate *ECR*. These exhaustively formulated *ECR* provides a different perspective for the system to become fully aware of the required services. *ECR*, therefore, act as underpinning and add more intelligence to the system to decide required exhibit information museum services for the ubiquitous visitors. The procedure to formulate *ECR* is given in Algorithm 2.





Algorithm 2: Formation of *Essential Context-derived Reasons* 

As mentioned in Section 5, suppose at some instance the system formulates 60 valid *CC*. The two's combinations of these 60 *CC* result into  $\binom{60}{2}$ , a total of 1770 *ECR*. On matching with the reference structures of two's combinations, 18 valid *ECR* are obtained. The matching is obtained by computing cosine similarity of term vectors of different combinations of *CC* [45]. An example reference structure of *ECR* from two's combinations of *CC* is shown in Figure 3.

Similarly, three's combinations of 60 *CC* result into 34220 *ECR*. However, on matching with the reference structures of three's combinations, 16 valid *ECR* are obtained. An example reference structure of *ECR* from three's combinations of *CC* is as shown in Figure 4. Further, from four's combinations and other higher order combinations of *CC* a total of 40 valid *ECR* are obtained. *ECR* provides an accurate understanding that a particular museum service is required and further used to provide the required services to the museum ubiquitous visitors.

Further, the accuracy of formation of *ECR* depends on the interdependent combinations reference structures of *CC* and *ECR*. Based upon the reference structures of the combinations of *CC* (available in advanced) the conditional probabilities of accuracies  $p(ECR_k|CC_j)$ between  $ECR_k$  and  $CC_j$  is evaluated. This gives the accuracies of all  $ECR_k$  formation obtained from the several dependent combinations of  $CC_j$ . As a result, a set of conditional probabilities  $CP(ECR_k)$  of accuracies





Figure 4. ECR from Three's Combination of Context Information

for each  $ECR_k$  formation is obtained as given in Equation 7. Each of these conditional probabilities  $p(ECR_j|CC_i)$  represents the accuracy of  $ECR_k$  formation corresponding to the accuracy of  $CC_i$  formation.

$$CP(ECR_k) = \{p(ECR_k | CC_i)\}$$
(7)

$$\{j = m, p, ..., x | CC_m, CC_p, ..., CC_x \rightarrow ECR_k\}$$

where, j represent different CC involved in the formulation of  $ECR_k$  of the museum ubiquitous visitors;

Next, we evaluate the accuracy of  $ECR_k$  formation, which represents the probability of  $ECR_k$  formation depending on the individual conditional probabilities of  $p(ECR_k|CC_i)$  formation as determined by Equation 8.

$$ECR_k = \frac{1}{n} * \sum_{j=1}^n p(ECR_k | CC_j)$$
(8)

where,  $p(ECR_k | CC_j) \in CP(ECR_k)$ 

With more number of accurately available interdependent  $CC_j$ , i.e., the size of j,  $ECR_k$  significantly affects the value of ECR of the museum ubiquitous visitors. Here, j represents the optimal number of accurately available interdependent  $CC_j$  to formulate  $ECR_k$ . However, the limitation is, this will be true as long as the number of accurately available context information of the museum ubiquitous visitors and  $ECR_k$  obtained from their multiple combinations are in the majority.



Based on the accuracy of  $ECR_k$ , the accuracy of ECR formation is evaluated as given by Equation 9.

$$ECR = \frac{1}{r} \sum_{k=1}^{r} ECR_k \tag{9}$$

where, r is total number of formulated  $ECR_k$  of the museum ubiquitous visitors;

### 7. Case Study

This section discusses two cases to exemplify the proposed scheme. As shown in Figure 5, the museum environment comprises of a wide variety of exhibits, an exhibit information server, multiple WiFi and cellular network units, and a museum network to provide the required exhibit information museum services to the ubiquitous visitors.



Figure 5. The Layout of Museum Environment

The museum environment is also enriched with an embedded sensing and computing infrastructure to acquire context information of the ubiquitous visitors. We consider the following two cases: (i) Providing exhibit information to the museum ubiquitous visitors, and (ii) Providing next exhibits location to the museum ubiquitous visitors. At each instance, according to context information of the museum ubiquitous visitors, *ECR* is formulated and the required exhibit information museum services are pro-actively triggered for the visitors.

# 7.1. Case 1: Providing Exhibit Information to the Museum Ubiquitous Visitors

Consider the case when a professional ubiquitous visitor is standing at Swami Vivekananda exhibit, spending more time, has a smartphone with high battery power, high WiFi network bandwidth, and looking for exhibit information. The formulated *ECR* of the museum ubiquitous visitor is mapped to the specific museum service i.e., Swami Vivekananda exhibit information at an advanced level of details for a smartphone device, according to which the required exhibit information available at  $URL_{e_i}$ :  $SVinfo_l 3@pet.iisc.ac.in$  is provided to the professional ubiquitous visitor as shown in Figure 6.

Swami Vivekananda (12 January 1863 to 4 July 1902) was born in Calcutta, India. He was a Hindu Monk and chief disciple of Indian mystic Ramkrishna. He founded Ramkrishna Mission. His initial beliefs were shaped by the Brahmo followers who believed in the deprecation of idolatry and in a formless God. He was a fervid reader of several subjects including subjects of art and literature, social science, history, religion, and philosophy. Swami Vivekananda attended parliament of world religion at art Institute of Chicago in 1893 and gave speech representing India and Hinduism. He extensively traveled India (1888-1893), United Kingdom and United States and has given lectures on Hindu Veda, Upanishads and Purana. Swami Vivekananda had published many books like Karmayoga, Rajayoga, Vedanta philosophy to name few. Swami Vivekananda Rock Memorial is one of the popular tourist place in Kanyakumari, India.

**Figure 6.** *Swami Vivekananda* Exhibit Information for a Professional Ubiquitous Visitor

# 7.2. Case 2: Providing Next Exhibit Locations to the Ubiquitous Visitors

Consider the case when a school kid standing at scientific exhibit had spent sufficient time, has a smartphone with high battery power, high WiFi network bandwidth, interested in moon exhibits, and is looking at other exhibits with the constraint of limited available time. The formulated *ECR* of the museum ubiquitous visitor is mapped to the specific museum service i.e., location of next exhibit information at a basic levels of details for a smartphone device, according to which the location of moon exhibits information {E10, E11} available at  $URL_{e_i}$ : *Moonpath\_l1@pet.iisc.ac.in* is provided to the school kid ubiquitous visitor as shown in Figure 7.

### 8. Simulation Results

In this section, we present the simulation of the proposed scheme. In the simulation, we show how the number of context information parameters and the



Related Exhibits	Location of Next Exhibits to be Visited
E10:Scientific Exhibit	URL:Moonpath_l1@pet.iisc.ac.in
E11:Moon Exhibit	URL:E <sub>12</sub> -path.pet.iisc.ac.in

Figure 7. Locations of Next Exhibits to be Visited by School Kid Ubiquitous Visitors

percentage accuracy during the acquisition will affect the accuracy of ECR formation. For the simulation, we consider the eight context information parameters of the museum ubiquitous visitors. At some instance, these parameters may have any one the possible values as shown in Table 1. The simulation is executed over 200 experiments using Python scripts. Each experiment consists of one of the possible values of context parameters and with the accuracy of acquisition of 30%, 70%, and 90%, respectively. The simulation is executed to check how the proposed approach function correctly in the presence of low, moderate and higher accuracy of context information acquisition.

Table 1. Context Information Parameters with Possible Values



Figure 8. CC and ECR Formation Time for Museum Ubiquitous Visitors



Figure 9. Accuracy of CC Corresponding to the number of **Reference Structures of Context Information Combinations** 

acquisition of the museum ubiquitous visitors. Accuracy of CC formation is evaluated as the ratio of deviation of formulated CC from the true value of CC to the true value of CC as given by Equation 10, where the true value of *CC* is determined corresponding to the

	$\pm$ ne true value of UU is determined corresponding to the
Visitor/Device Location= {at exhibit, near exhibit, away from	n available reference structures of CC formation
exhibit};	available reference structures of ee formation.
<i>Time Duration of Service Used= {less time, longer time};</i>	
Visitor Educational Qualifications= {professional, college student	t, Accuracy of CC Formation = $\frac{Deviation of formulated CC from the True Value}{CC}$
school kid};	True Value of CC (10)
<i>Visitor Activity= {standing, sitting};</i>	(10)
Type of Devices = {Laptop, SmartPhone, Tablet};	The variation in the accuracy of CC formation
Device Battery = {Low, High};	with 200/ 700/ and 000/ accuracy of CC formation
Type of Networks = {WiFi, Cellular};	with 50%, 70%, and 90% accurately available context
Networks Canacity - {Low RW High RW}	information of the museum ubiquitous visitors is as

The simulation results are discussed as follows. We measure CC and ECR formation time based upon the number of context information parameters of the museum ubiquitous visitors, with their multiple combinations. The increase in the number of context parameters increases multiple combinations which accordingly increases CC and ECR formation time. As shown in Figure 8, eight context information parameters of the museum ubiquitous visitors with varied combinations takes approximately 80 ms to formulate CC and 24 ms to formulate ECR.

Further, we evaluate the accuracy of CC formation based upon the accuracy of the context information

shown in Figure 9. The accuracy of CC formation increases with the increase in the number of reference structures of accurately available context information combinations. The higher accuracy of CC is observed, as the proposed approach exploits the combinations interdependencies, which proportionally mitigates the effect of a lower percentage of inaccurately available context information of the museum ubiquitous visitors with the other accurately available context information with their multiple combinations. The accuracy of CC is higher as long as the number of reference structures of multiple combinations of accurately available context information will be higher in comparison to others.

Similarly, the variation in the accuracy of ECR formation from 30%, 70%, and 90% accurately



available *CC* is as shown in Figure 10. Accuracy of *ECR* formation is evaluated as the ratio of deviation of deduced *ECR* from the true value of *ECR* to the true value of *ECR* as given by the following Equation 11, where the true value of *ECR* is determined corresponding to the available reference structures of *ECR* formation.

Accuracy of ECP Formation -	Deviation of Deduced ECR from the True Value
Acturacy of LCRT or mation =	True Value of ECR
	(11)

Further, we evaluate the accuracy of *CC* and *ECR* over 200 experiments. During the experiments, we found that for 90% accurately available context information of the museum ubiquitous visitors, with their multiple combinations, the accuracy of CC varies from 0.69 to 0.89, whereas the accuracy of ECR varies from 0.77 to 0.95 as shown in Figure 11. The higher accuracy of ECR is observed, as the proposed approach exploits the combinations interdependencies, which proportionally mitigates the effect of a lower percentage of the inaccurately available CC of the museum ubiquitous visitors with the other accurately available CC with their multiple combinations. The accuracy of ECR formation is higher as long as the number of reference structures of multiple combinations of accurately available CC will be higher in comparison to others.



**Figure 10.** Accuracy of *ECR* Corresponding to the number of Reference Structures of *CC* Combinations



**Figure 11.** Accuracy of *CC* and *ECR* Formation over the Number of Experiments

#### 9. Conclusion and Future Work

The formation of Essential Context-derived Reasons from context information of museum ubiquitous visitors is presented to provide the required exhibit information museum services to the ubiquitous visitors. The context information of the museum ubiquitous visitors is acquired and processed with multiple combinations to formulate CC which further leads to ECR. ECR provides an accurate understanding of museum ubiquitous visitor's requirements and further used to provide exhibit information museum services to the visitors. We conducted simulation with relevant context information parameters and their percentage accuracy of acquisition and evaluates the accuracy of ECR. Over 200 experiments, we found that for 90% context information available with high accuracy, the accuracy of CC ranges from 0.69 to 0.89, and the accuracy of ECR ranges from 0.77 to 0.95. The simulation results show that the accuracy of ECR increases with the increase in reference structures of multiple combinations of the accurately available context information of the museum ubiquitous visitors, which further enables to provide required exhibit information museum services to the visitors. In the future, we consider the Interests of the museum ubiquitous visitors to provide personalized services to enhance the individual service experience.

#### References

- Pallapa Venkataram and M. Bharath. Context based service discovery for ubiquitous applications. In *International Conference on Information Networking (ICOIN)*, pages 311–316, Jan 2011.
- [2] Dmitry Korzun, Svetlana Yalovitsyna, and Valentina Volokhova. Smart services as cultural and historical heritage information assistance for museum visitors and personnel. In *Baltic Journal of Modern Computing*, volume 6, pages 418–433, Jan 2018.
- [3] Hamed Vahdat-Nejad, Mohammad Sadeq Navabi, and Hosein Khosravi-Mahmouei. A context-aware museumguide system based on cloud computing. In *International Journal of Cloud Applications and Computing (IJCAC)*, volume 8, pages 1–19, 2018.
- [4] Tsvi Kuflik, Alan J. Wecker, Joel Lanir, and Oliviero Stock. An integrative framework for extending the boundaries of the museum visit experience: linking the pre, during and post visit phases. In *Information Technology and Tourism*, volume 15, pages 17–47, 2015.
- [5] P. Osche, S. Castagnos, A. Napoli, and Y. Naudet. Walk the line: Toward an efficient user model for recommendations in museums. In 11th International Workshop on Semantic and Social Media Adaptation and Personalization (SMAP), pages 83–88, Oct 2016.
- [6] Lorenzo Monti, Giovanni Delnevo, Silvia Mirri, Paola Salomoni, and Franco Callegati. Digital invasions within cultural heritage: Social media and crowdsourcing. In Smart Objects and Technologies for Social Good. EAI Third



International Conference, GOODTECHS 2017, March 2018.

- [7] Preeti Khanwalkar and Pallapa Venkataram. Organization of museum exhibit information for ubiquitous visitors. In *EAI Endorsed Transactions on Creative Technologies: Online First,* Aug 2020.
- [8] Pallapa Venkataram and M Bharath. A method of context-based services discovery in ubiquitous environment. In *Proceedings of the 2nd International Conference on Context-Aware Systems and Applications (ICCASA)*, November 2013.
- [9] Andreas Zimmermann. Context-awareness in user modelling: Requirements analysis for a case-based reasoning application. In Proceedings of the 5th International Conference on Case-based Reasoning: Research and Development, Springer-Verlag, ICCBR, pages 718–732, June 2003.
- [10] Andreas Zimmermann, Marcus Specht, and Andreas Lorenz. Personalization and context management. In User Modeling and User-Adapted Interaction, volume 15, pages 275–302, Aug 2005.
- [11] Inmaculada Ayala, Mercedes Amor, Mónica Pinto, Lidia Fuentes, and Nadia Gámez. imuseuma: An agent-based context-aware intelligent museum system. In *Sensors*, volume 14, pages 21213–21246, Nov 2014.
- [12] Anind K. Dey. Understanding and using context. In Personal and Ubiquitous Computing, volume 5, pages 4– 7, 2001.
- [13] Preeti Khanwalkar and Pallapa Venkataram. A weight based context analysis system to provide a required ubiquitous multimedia service. In *Proceedings of International Conference on Wireless Networks*, pages 153– 159, July 2011.
- [14] Nigel Linge, David Parsons, Duncan Bates, Robin Holgate, P. Webb, David Hay, and David Pratt Ward. miguide : A wireless context driven information system for museum visitors. 2007.
- [15] Dimitrios Raptis, Nikolaos Tselios, and Nikolaos Avouris. Context-based design of mobile applications for museums: A survey of existing practices. In ACM Proceedings of the 7th International Conference on Mobile HCI, pages 153–160, 2005.
- [16] Ivo Roes, Natalia Stash, Yiwen Wang, and Lora Aroyo. A personalized walk through the museum: The chip interactive tour guide. In CHI, Extended Abstracts on Human Factors in Computing Systems, pages 3317–3322, 2009.
- [17] Pallapa Venkataram and M. Bharath. A method of context-based services discovery in ubiquitous environment. In *Context-Aware Systems and Applications*, Social Informatics and Telecommunications Engineering, Lecture Notes of the Institute for Computer Sciences, Springer International Publishing, Volume 128, pages 260–270. 2014.
- [18] Armelle Prigent and Arnaud Revel. Cite content interaction time and space: a hybrid approach to model man-robot interaction for deployment in museums. In EAI Endorsed Transactions on Creative Technologies, volume 4, Oct 2017.
- [19] M. Knappmeyer, S. L. Kiani, E. S. Reetz, N. Baker, and R. Tonjes. Survey of context provisioning middleware. In *IEEE Communications Surveys Tutorials*, volume 15,

pages 1492-1519, March 2013.

- [20] Andreas Zimmermann. Context Management and Personalization: A Tool Suite for Context and User aware Computing. PhD thesis, 2007.
- [21] Guanling Chen and David Kotz. A survey of contextaware mobile computing research. Technical report, 2000.
- [22] A. Fevgas, P. Tsompanopoulou, and P. Bozanis. imuse mobile tour: A personalized multimedia museum guide opens to groups. In *IEEE Symposium on Computers and Communications (ISCC)*, pages 971–975, June 2011.
- [23] Matthias Baldauf, Schahram Dustdar, and Florian Rosenberg. A survey on context-aware systems. In International Journal of Ad Hoc and Ubiquitous Computing, volume 2, pages 263–277, 2007.
- [24] Sergio Inzunza, Reyes Juárez-Ramírez, and Alan Ramírez-Noriega. User and context information in context-aware recommender systems: A systematic literature review. In New Advances in Information Systems and Technologies, Springer International Publishing, pages 649–658. 2016.
- [25] Iqbal H. Sarker. Understanding the role of data-centric social context in personalized mobile applications. In *EAI Endorsed Transactions on Context-aware Systems and Applications (CASA)*, volume 5, Oct 2018.
- [26] Martinez JF Rubio G Li X, Eckert M. Context aware middleware architectures: Survey and challenges. In *Sensors*, volume 15, pages 20570–20607, Aug 2015.
- [27] Willem Robert van Hage, Natalia Stash, Yiwen Wang, and Lora Aroyo. Finding your way through the rijksmuseum with an adaptive mobile museum guide. In The Semantic Web: Research and Applications: 7th Extended Semantic Web Conference, ESWC, Springer Berlin Heidelberg Proceedings, Part I, pages 46–59. 2010.
- [28] Yiwen Wang, Natalia Stash, Lora Aroyo, Peter Gorgels, Lloyd Rutledge, and Guus Schreiber. Recommendations based on semantically enriched museum collections. In Web Semantics: Science, Services and Agents on the World Wide Web, volume 6, pages 283 – 290, 2008.
- [29] Derrick Ntalasha, Renfa Li, and Yongheng Wang. Internet of thing context awareness model. In *EAI Endorsed Transactions on Context-aware Systems and Applications (CASA)*, volume 3, Feb 2016.
- [30] Marco Berni, Nima Dokoohaki, Elena Fani, Eero Hyvönen, Tomi Kauppinen, Mihhail Matskin, Eetu Mäkelä, and Tuukka Ruotsalo. Smartmuseum: a cultural heritage knowledge exchange platform based on ontology-oriented, context-aware and profiling systems. In *Proceedings of Electronic Imaging and the Visual Arts* (EVA), pages 28–30, April 2009.
- [31] Joel Lanir, Tsvi Kuflik, Alan J. Wecker, Oliviero Stock, and Massimo Zancanaro. Examining proactiveness and choice in a location-aware mobile museum guide. In *Interacting with Computers*, volume 23, pages 513–524, 2011.
- [32] Chris van Aart, Bob Wielinga, and Willem Robert van Hage. Mobile cultural heritage guide: Locationaware semantic search. In *Knowledge Engineering and Management by the Masses: 17th International Conference, EKAW Proceedings, Springer Berlin Heidelberg,* pages 257– 271. 2010.



- [33] Zhiyong Yu, Xingshe Zhou, Zhiwen Yu, Jong Hyuk Park, and Jianhua Ma. imuseum: A scalable contextaware intelligent museum system. In *Computer Communications*, volume 31, pages 4376 – 4382, 2008.
- [34] Jongmyung Choi and Jongbae Moon. Myguide: A mobile context-aware exhibit guide system. In Springer Berlin Heidelberg, Computational Science and Its Applications – ICCSA 2008, pages 348–359, 2008.
- [35] Eleni Christopoulou and John Garofalakis. Contextaware cultural heritage environments. In Handbook of Research on Technologies and Cultural Heritage: Applications and Environments, IGI Global, Jan 2011.
- [36] Weijun Qin, Daqing Zhang, Yuanchun Shi, and Kejun Du. Combining user profiles and situation contexts for spontaneous service provision in smart assistive environments. In Ubiquitous Intelligence and Computing, Lecture Notes in Computer Science, Springer Berlin Heidelberg, volume 5061, pages 187–200. 2008.
- [37] Antonio Krüger, Jörg Baus, Dominik Heckmann, Michael Kruppa, and Rainer Wasinger. Adaptive mobile guides. In *The Adaptive Web: Methods and Strategies of Web Personalization, Springer Berlin Heidelberg*, pages 521– 549. 2007.
- [38] Andry Rakotonirainy and Nicholas Lehman. Augmenting a museum visitor's tour with a context aware framework. In *1st International Workshop on Ubiquitous Computing, INSTICC Press,* pages 104–112, 2004.
- [39] Younghee Noh. A study on next-generation digital library using context-awareness technology. In *Library Hi Tech*, volume 31, pages 236–253, 2013.

- [40] Claudio Bettini, Oliver Brdiczka, Karen Henricksen, Jadwiga Indulska, Daniela Nicklas, Anand Ranganathan, and Daniele Riboni. A survey of context modeling and reasoning techniques. In *Pervasive and Mobile Computing*, volume 6, pages 161 – 180, 2010.
- [41] Cristiana Bolchini, Giorgio Orsi, Elisa Quintarelli, Fabio A. Schreiber, and Letizia Tanca. Context modeling and context awareness: steps forward in the contextaddict project. In *IEEE Data Engineering Bulletin*, volume 34, pages 47–54, 2011.
- [42] Asad Masood Khattak, Noman Akbar, Mohammad Aazam, Taqdir Ali, Adil Mehmood Khan, Seokhee Jeon, Myunggwon Hwang, and Sungyoung Lee. Context representation and fusion: Advancements and opportunities. In Sensors, volume 14, pages 9628–9668, May 2014.
- [43] Paolo Bellavista, Antonio Corradi, Mario Fanelli, and Luca Foschini. A survey of context data distribution for mobile ubiquitous systems. In ACM Computing Surveys (CSUR), volume 44, pages 24:1–24:45, Sep 2012.
- [44] Preeti Khanwalkar and Pallapa Venkataram. Contextbased service identification in the museum environment. In Proceedings of the 4th EAI International Conference on Context-Aware Systems and Applications, ICCASA, Springer International Publishing, pages 151–164, 2015.
- [45] Duen-Ren Liu, Chih-Kun Ke, and Mei-Yu Wu. Contextbased knowledge support for problem-solving by ruleinference and case-based reasoning. In *International Conference on Machine Learning and Cybernetics*, volume 6, pages 3205–3210, 2008.

