Mobile Sensing to Suggest Customized Tours to Visitors in Museums

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***Abstract*—Recently, the scientific community has shown a remarkable interest in the mobile sensor networks and in the application of this kind of networks to museums. In our work we use mobile sensor networks to improve the tour quality of a visitor of a museum. In particular, we provide an algorithm that recompute dynamically the best tour for a specific visitor on the basis of his physical reactions induced by each artwork. We originally use MDCs to acquire these reactions.**

I. Introduction

Mobile sensor networks have recently received a lot of attention in the scientific community. A mobile sensor network consists of a distributed collection of nodes with perceptive, computational, communicative, and motion capabilities. Due to these capabilities, mobile sensor networks are used in many eterogeneous applications (e.g., [1], [2]).

We focus our attention on the use of mobile sensor networks in museums. The most works proposed in the literature provide visitors with information on artworks [3]. The information is customized for each specific visitor on the basis of his profile. In this paper, we study a different problem: suggesting a path over the museum artworks to each visitor and adjusting it dynamically during his tour. The data we use to determine the path to be suggested are generated by mobile data collectors (MDCs). In our application, a MDC is a set of sensors able to capture the level of interest of a visitor over a specific artwork. This approach to MDCs is original in the literature.

The rest of the paper is organized as follows. Section II consists in a brief survey on mobile data collectors and describes the peculiarities of our original approach. In Section III we initially state the path suggestion problem in a museum, and then we point out the technical details. In Section IV we provide an experimental valuation. Section V discusses related works. Section VI concludes the paper.

II. Approaches for Mobile Data Collectors

There exist few approaches exploiting mobility for data collection in wireless sensor network. They can be classified with respect to the properties of the sink mobility as well as the wireless communication methods for data transfer [4]. The main approachese are: *mobile base station*, *mobile data collector*, and *rendezvous-base solutions*.

In this paper we consider only MDCs. A MDC is a mobile sink that visits sensors. Data are buffered at source sensors until the MDC visits them and downloads the information

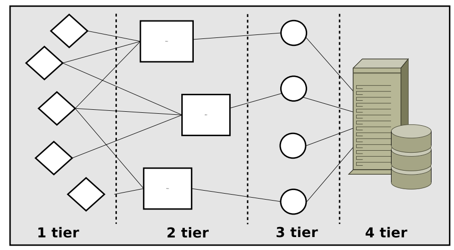

Fig. 1. The four tiers infrastructure proposed.

over a single-hop wireless transmission. It is also possible to further classify the MDC according to the mobility path [5]. There are three different basic mobility paths: *random mobility* (movement pattern of the MDC is not known and MCD moves in a random way) [6]; *predictable mobility* (movement pattern of MDC is known) [7]; *controlled mobility* (movement of MDC is controlled in real time) [8].

We propose an original use of MDCs. As in classical approaches, a MDC is a mobile sink that visits sensors. Differently from classical approaches, a MDC generates data and each specific data depends on the specific visited sensor.

To support our approach, we design a four tiers infrastructure as depicted in Figure 1. In the first tier the sensors are positioned in points of interest for the application. The second tier of the infrastructure is costituted by MDCs. The data generated by the MDCs depend on the specific position of the sensors placed in the first tier. In the third tier there are fixed data collectors that receive data from MDCs. In the last tier there is the server that stores the data collected by the fixed data collectors in a database. The server processes the data and sends back the information to each specific MDC for guiding its movement. As a result, the mobility of a MDC is controlled in real time on the basis of the data that the MDCs have previously generated.

III. The Museum Application

Recently, museums have become part of the "free-time" industry, like theatre and cinema, receiving more and more visitors. Due to this increasing interest in museums, the scientific community has started to consider museum as a scenario in which to apply new technologies. A number of works that used mobile sensor networks to analyse the behavior of the visitors and to provide *ad hoc* information to them. The aim of our work is to suggest to each visitor of the museum the best

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path he can follow according to the preferences he states and the artworks he has already seen. To the best of our knowledge, there is no previous work that accomplishes this task.

In next sections, we specify the properties of sensors in the first three tiers of the infrastructure for our specific case study. We also present the technical details of the application.

A. The Museum Problem

In a museum, the sensors we use in the first tier consist of rfids. In particular, the points of interest are artworks and we univocally identify each artwork with an rfid. The MDCs constitute the second tier. Each visitor of the museum is provided with a MDC that measures his physical reactions induced by the view of a specific artwork. In our mind the visitors' physical reactions can be mesured by affective signals, e.g., heartbeat. A MDC, once it has detected the presence of a rfid near it, generates data depending on the rfid itself. More precisely, when a person visiting the museum stays in front of an artwork, his MDC detects the presence of the rfid of the artwork and starts to store affective information on the visitor and associates it to the specific artwork. In the third tier, sensors collect data directly from MDCs and send these data to the fourth tier. When data have been received in the fourth tier, they are stored in the database. The sensors of the third tier are fixed and located in the rooms of the museum. The position of a visitor can be detected by both the sensors of the second (e.g., exploiting the position of the last rfid that causes the last data generation) and third tier (e.g., acquiring the current room in which the visitor is in).

Now we describe the tasks the application have to accomplish to determine the path to be suggested to a visitor. First, when a visitor enters the museum, he has to fill a form with the maximum time he wants to spend in the museum and his preferences about few categories that characterize artworks, e.g., categories could be the artwork typology and the artistic movement to which it belongs. Then the visitor starts the tour of the museum and our software application (described below) cyclically activates. The collection of data, generated by MDCs and received by the fixed sensors in the third tier, can be done according two possible ways. In the first one, each time a MDC generates data, it sends them to the fixed sensor positioned in the room. In the second one, the fixed sensors of the third level collect data from MDCs at regular time intervals. Each time data are collected, the fixed sensor positioned in a room receives the data (temporarily) stored in the MDCs that are in the same room. Without loss of generality, in our work we suppose that the collection is repeated after every artwork the visitor sees, i.e., we use the first of the two proposed alternatives.

Our application consists of the following four steps:

1) Data generated by MDCs (capturing visitors' physical reactions induced by the last artwork they saw) are stored in the database.
2) Among the artworks that the visitor has not seen yet, the server chooses the ones it supposes are the most interesting for the specific visitor. (The criteria used for the artworks selection are specified in Section III-B.)
3) The server decides an ordering for the selected artworks. The aim is to estabilish a customized path in the museum and to propose it to each specific visitor. (The criteria used for the path definition are specified in Section III-B.)
4) The first artworks of the estabilished path are communicated to the visitor.

B. Technical Aspects

In this section we address the problem of computing the most interesting artworks for a specific visitor and the problem of the path definition.

Artworks Selection To understand how artworks are selected, we need to intoduce the concepts of *artwork utility* and *artwork time*. The utility of an artwork is the measure of how this artwork is interesting for a visitor. The time of an artwork is the time a visitor spends to see the artwork. We have two different types of measures, both for artwork utility and artwork time: one is referred to a general visitor, while the other is computed on the basis of the characteristics and preferences of a specific visitor. General artworks utility and general artworks time are stored in the database.

The function that computes a specific artwork utility is the sum of two components: the first one is dependent on the preferences that the visitor expresses in the initial form, while the second one depends on the artworks already seen by a specific visitor, i.e., it depends on the data collected about the specific visitor's physical reactions. Defining the best formulation of this function is an hard task since we need to guarantee a tradeoff between these two components. The specific artworks utility are normalized on the basis of the maximum specific artwork utility value, i.e., we set the utility of the artwork with the maximum specific artwork utility value equal to 100 and we compute in a proportional way the other specific artworks utilties.

A specific artwork time is computed on the basis of the normalized specific artwork utility. We considered different intervals of artwork utility values and, depending on the interval to which the specific artwork utility belongs, we estabilish the specific artwork time.

Once we have calculated the specific artwork utility and the specific artwork time for all the artworks that the visitor has not seen yet, we extract the set of artworks that maximize the utility for the specific visitor. We call this set O_{max}. The set of selected artworks is subject to a time constraint: the sum of the specific artwork time of the selected artworks must be not greater than the remaining visit time. The remaining visit time (RVT) is $\min\{MT - ET, CT\}$, where MT is the maximum time for the tour specified by the visitor, ET is the time that the visitor has already spent in the museum, and CT is the left time before the museum closing.

We formulate the problem to select a subset of artworks as a linear integer mathematical programming problem. We solve this problem by using AMPL [9] and CPLEX [10]. The linear integer mathematical programming problem is (we call SAU_o and SAT_o the specific artwork utility and the specific artwork time of artwork o, respectively):

$$\max \sum_{o \in O} SAU_o \cdot x_o \tag{1}$$

$$RVT \geq \sum_{o \in O} SAT_o \cdot x_o \tag{2}$$

Equation (1) is the objective function of the problem, it maximizes the utility of the selected artworks for a specific visitor; constraint (2) imposes a upper bound limit (RVT) over the sum of the SAT of the selected artworks. The variables of the problem are $x_o, \forall o \in O$ (O is the set of the artworks that the visitor has not seen yet). These are binary variables: x_o is equal to 1 if $o \in O_{max}$, x_o is equal to 0 otherwise.

Path Definition Once the set of artworks O_{max} is computed, we decide the path to be suggested to the visitor by using a greedy heuristic (the exact algorithm cannot be used for real time applications).

We assign a weight to each couple of rooms whose artwork are in O_{max}. This weight depends on three parameters: the phisical distance between the rooms, the difference between the themes of the artworks exhibited in the two rooms, and whether or not the visitor has already seen an artwork in the second room. In particular, the themes difference is evaluated by experts on art. In case the visitor has already seen an artwork in the second room of the considered couple, we sum a penalty to the weight. We adopt this strategy to avoid paths that continuously suggest to the visitors to go in the same rooms multiple times.

The greedy heuristic starts considering the current position of the visitor and then chooses, as next artwork to add to the path, the artwork with the maximun value of $W_o \cdot SAU_o$. W_o is the weight of the couple of rooms in which the first one is the room of the last artwork added to the path and the second one is the room of the artwork o. This artwork selection is repeated among the artworks in O_{max} (without the artworks already chosen) until the sum of SAT of the chosen artworks is at least equal to a fixed minimum time. Now we motivate the need for a fixed minimum time. Computing the whole path is not the best approach to the problem: since we want to compute the best path for a special visitor after each artwork he has seen, computing the whole path requires an unnecessary use of resources, i.e. time and computational capabilities of the server. Our idea is to determine only the artworks at the begining of the best path, in particular the artworks that guarantee a partial path of time length equal to a fixed minimum time. This approach allows one to avoid problems due to computational delay or due to brief interruption of the application execution on server side.

We recall that in the paper we present the application for the case in which the MDCs communicate the generated data immediately after the visitor has seen an artwork. Now consider the other possible way proposed in the previous section (the fixed sensors of the third tier collect data from MDCs at constant time intervals). We can adapt the proposed greedy heuristic simply by setting the minimum time used to define the length of the partial path to compute, equals to the time of the constant time interval (plus an amount of time to avoid the problems discussed above). In Algorithm 1 we propose our greedy heuristic in a schematic way.

Algorithm 1: GreedyTour

for *all* $o \in O_{max}$ **do**
  compute $W_o \cdot SAU_o$
time = 0;
path $\leftarrow$ actual position of the visitor
if *time* $<$ *minimum time* **then**
  $o' = o \in O_{max}$ such that $\max_o\{W_o \cdot SAU_o\}$
  path $\leftarrow o'$
  $O_{max} = O_{max}/o'$
  time = time + $SAT_{o'}$

IV. Experimental Valuations

In our experiments we simulate a museum with 69 rooms and 600 artworks. The function we use to determine the specific artwork utility is (we call GAU the general artwork utility):

$$SAU = GAU \cdot (1 + n_e) + GAU \cdot (1 + \prod_{i \in C} \Gamma_i)$$

The first component of the function is: $GAU_o \cdot (1 + n_e)$. In the initial form, the visitor can express $n = 4$ different preferences, one for each category that characterizes the artworks. We calculate the number of specific visitor preferences that match with the characteristics of the considered artwork, we call n_e this number. The second component of the function is $GAU \cdot (1 + \prod_{i \in C} \Gamma_i)$. C is the set of categories, that characterizes an artwork. Γ_i is defined as follows: $\Gamma_i = \frac{\sum_{j \in S} \gamma_j}{\sum_{h \in N} \gamma_h}$. γ_x is the level of liking for the artwork x registered by MDC, and the set S and the set N are the sets of artworks that the visitor has already seen and that have the same value of category i of the considered artwork, and the set of all artworks that the visitor has already seen, respectively.

The intervals of specific artwork utility and the function to compute the specific artwork time follow (we call GAT the general artwork time):

- $[0, 20]$: $SAT \simeq 0$
- $(20, 40]$: $SAT = GAT - \frac{GAT}{2}$
- $(40, 60]$: $SAT = GAT$
- $(60, 80]$: $SAT = GAT + \frac{GAT}{2}$
- $(80, 100]$: $SAT = GAT + GAT$

Our experimental evaluation aims to analyze the ability of the algorithm to dynamically adjust the proposed path on the basis of the data collected by a MDC during the tour of the museum. The experiments consist in the comparison of two paths: *(i)* a path dynamically proposed to a visitor that explicitly states his preferences and *(ii)* a path dynamically proposed to a visitor with the same preferences but not explicitly stated or partilly stated. In order to evaluate the two paths we first establish a visitor profile (setting few preferences in the initial form). Then we consider the profile to compute the SAUs at the beginning of the tour for all the artworks in the museum. We use the SAUs as the artworks liking level for any visitor with that specific profile. The liking level obtained evaluating the path *(i)* is the upper bound of the utility reachable by a visitor with that specific profile. We estimate the quality of the algorithm by comparing the liking level obtained by path *(ii)* and this upper bound value.

In Table I we show the results of our experimental evaluations. We performed experiments for tours of one and two hours, and tours in which the visitor specifies no preference (the column "0 categories" in Table I) or the preference for two categories (the column "2 categories" in Table I).

	0 categories	2 categories
1 hour	75,70%	95,42%
2 hours	77,74%	95,89%

TABLE I
RESULTS OF THE EXPERIMENTAL EVALUATIONS.

Comparing the results of the "0 categories" case with the results of the "2 categories" case we can see the effect of the first part of the SAU function:the more the visitor expresses his preferences, the more the proposed path is close to the path that gives the upper bound value. Comparing the results of the 1 hour case with the results of the 2 hours case we can see the effect of the second part of the SAU function:the more the visitor stays in the museum, the more the proposed path is close to the path that gives the upper bound value.

V. RELATED WORKS

A. Mobile Sensor Network Existing Applications

Due to the heterogeneous capabilities of mobile sensor network's nodes, in the recent years many applications that use this kind of networks have been developed. We survey a few of these applications emphasizing their peculiarities.

- Mobile sensors on vehicles (e.g. Octotelematics [11], CarTel [1]): they can be used for traffic monitoring, environmental monitoring, civil infrastructure monitoring, automotive diagnosis, geo-imaging, and data muling.
- BikeNet [2]: BikeNet is a mobile sensing system for mapping the cyclist experience; it uses a number of sensors embedded into a cyclist's bicycle to gather data about the cyclist's rides. These data can reveal important factors such as exposure to air and noise pollution, and danger due to car density, or they can be used for health studies and to obtain fitness metrics.
- Inspection of natural gas pipelines [12] (in PicoSmart project [13]): in this project mobile sensor networks are used for industrial inspection tasks that are too expensive or impossible with traditional industrial sensing technologies.

B. Museum in the Mobile Sensor Network

In the litterature there exist some works, using mobile sensor networks, that try to analyse the behavior of the museum's visitors, to provide them with *ad-hoc* information depending on the visitor's specific characteristics. For example, in [14] a wearable computer which orchestrates an audiovisual narration as a function of the visitor's interests gathered from his physical path in the museum and length to stop is described. Another work focused on narrative space is presented in [3].

VI. CONCLUSION AND FUTURE WORKS

Recently, the scientific community has shown a remarkable interest in mobile sensor networks and in their application to museums. Some approaches focused on the behavioural analysis of the visitors with the aim to provide them with customized information about the artworks. Differently, in our work we use mobile sensor networks to improve the tour quality of each specific visitor. In particular, we capture the physical reactions induced by each artwork on each visitor exploiting MDCs in an original way. A MDC is a mobile sink constituted by a set of sensors provided to each visitor at the beginning of the tour. In our work, unlike classical approaches, instead of collecting data, a MDC generetes them. Data generated by a specific MDC are used to dynamically compute the best customized path for the corresponding specific visitor.

In future works, we would like to refine the functions used to compute the specific artwork utility and the specific artwork time. We would like to consider not only the data of a single visitor of the museum during the computation of his path, but also data of other visitors: since in museums there are a lot of visitors, it could be a good idea to define a path also considering the positions of other visitors. The idea is that having an uniform distribution of people in the museum rooms could lead to improve the quality of each specific visitor's tour.

Moreover, as future work, we would like to use the idea here proposed for other application, e.g., to develop an electronic shopping assistant for shopping centers.

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