A Technological Framework for Personalized Museum Visiting

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Introduction

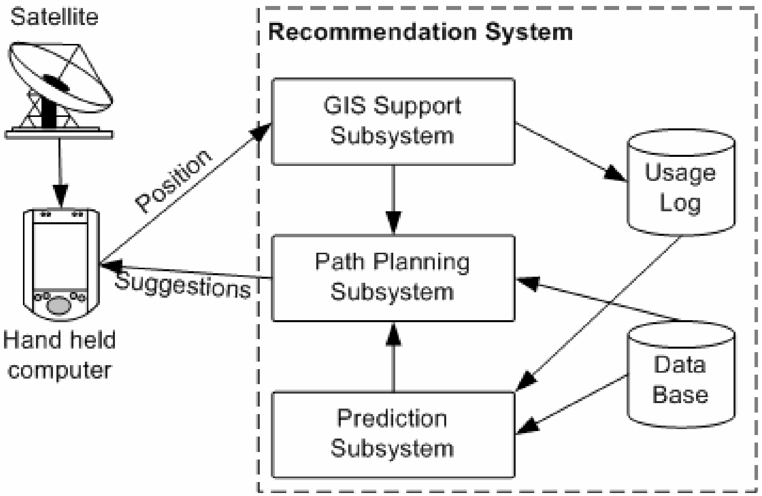
- Visiting museums and archeological sites is usually an amazing experience
  - Sometimes a visitor may get lost in huge exhibitions in which thousands of artifacts are exposed
- Paper or human guides may help to reach interesting items, but the offer cannot be personalized according to the preferences of each user
  - Paper guides are the same for each visitor
  - Human guides usually drive a whole group of tourists

Contribution

- We present a system that assists a user in visiting a museum or an archaeological site, providing useful recommendations, based on an innovative strategy for predicting user behavior
- The strategy we propose
  - makes use of an artificial neural network, for predicting users' behavior, trained on a suitable set of features characterizing the objects of interest
  - takes into account site topological information gathered from a Geographical Information System (GIS)

System Architecture

- GIS Support Subsystem
  - stores in the Usage Log information about users' movements and provides information about objects' location
- Prediction Subsystem
  - predicts the items that a user may be interested to see next
- Path Planning Subsystem
  - proposes a path to the user, based on the data gathered from the other subsystems



GIS Support Subsystem
GPS

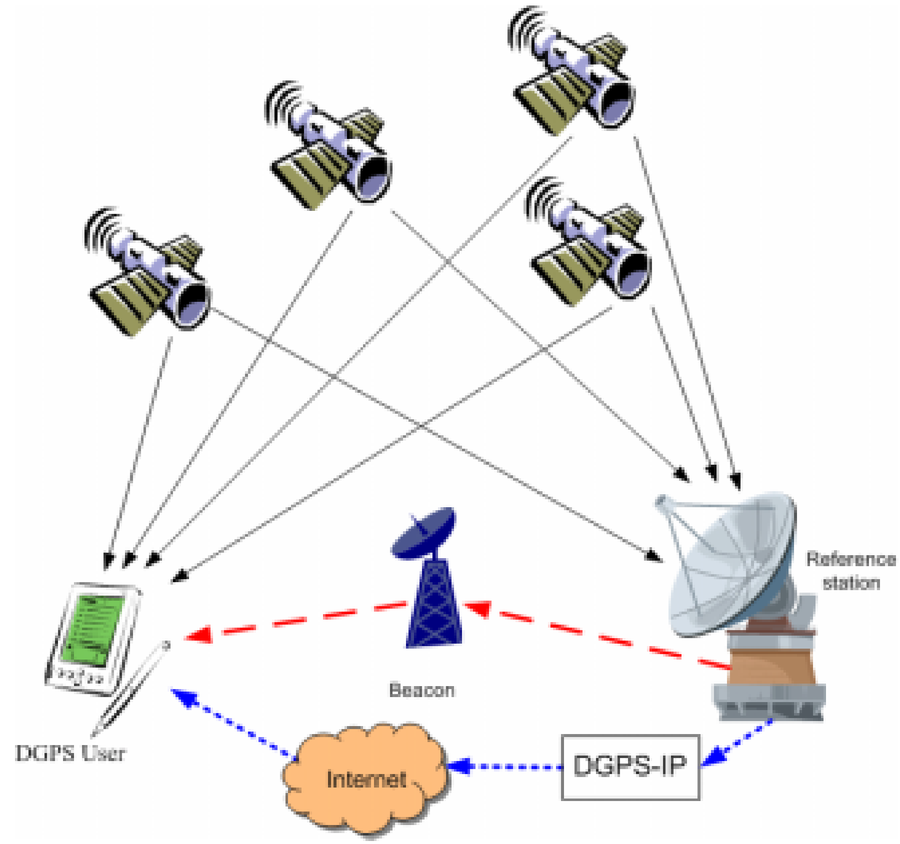
- Standard **GPS** technology is affected by several classes of errors
  - Ephemeris data
    - transmitted location of the satellite
  - Satellite clock
    - transmitted clock
  - Multipath
    - reflected signals entering the receiver antenna
  - Measurement errors in the receiver caused by thermal noise, software accuracy and inter-channel biases

GIS Support Subsystem
From GPS to DGPS

- Errors can be avoided or reduced using the differential correction technique (**DGPS**)
  - A second receiver at a fixed location is used to compute the corrections to the **GPS** measurements
    - Corrections are transmitted through a radio connection (beacon) or an internet connection (DGPS-IP)
  - The accuracy of the measure improves from 15-20 meters up to 2-3 meters.

GIS Support Subsystem
Current implementation

- Outdoor positioning has been implemented using **DGPS**
- Mobile devices are equipped with IEEE 802.11b wireless Ethernet to allow internet connection



GIS Support Subsystem
Outdoor and indoor positioning

- Outdoor positioning
  - GPS has been successfully adopted in a lot of applications
- Indoor positioning
  - GPS receivers are blind into indoor spaces
  - Different kinds of positioning systems should be used
    - Infrared or ultrasound sensors
    - Radio Frequency sensors
    - WLAN-based positioning

GIS Support Subsystem
Distance between objects

- Let us consider a network in which the nodes represent objects and the arcs represent paths between pairs of objects
- The spatial distance between two objects o_i and o_j can be defined as

$$dist_s(o_i, o_j) = \min_h \{\omega_h(o_i, o_j)\}$$

  - ω_h is the length of the *h*-th path between o_i and o_j
- The distance between two objects is the length of the shortest path between them

Prediction Subsystem
Timestamped Usage Paths

- Prediction is realized through an Artificial Neural Network trained on the behavior of past users
- Behavior is represented through the usage paths of the users
- A Timestamped Usage Path (TUP) *p* of length *k* is defined as

$$p = ((o_{i_1}, t_{i_1}), \ldots, (o_{i_k}, t_{i_k}))$$

  - o_{ik} is the *k*-th object visited by the user and t_{ik} is the time that she ha spent in front of o_{ik}
- Let *P* denote the set of all the timestamped usage paths of past users and *O* the set of all the objects

Prediction Subsystem
Artificial Neural Network

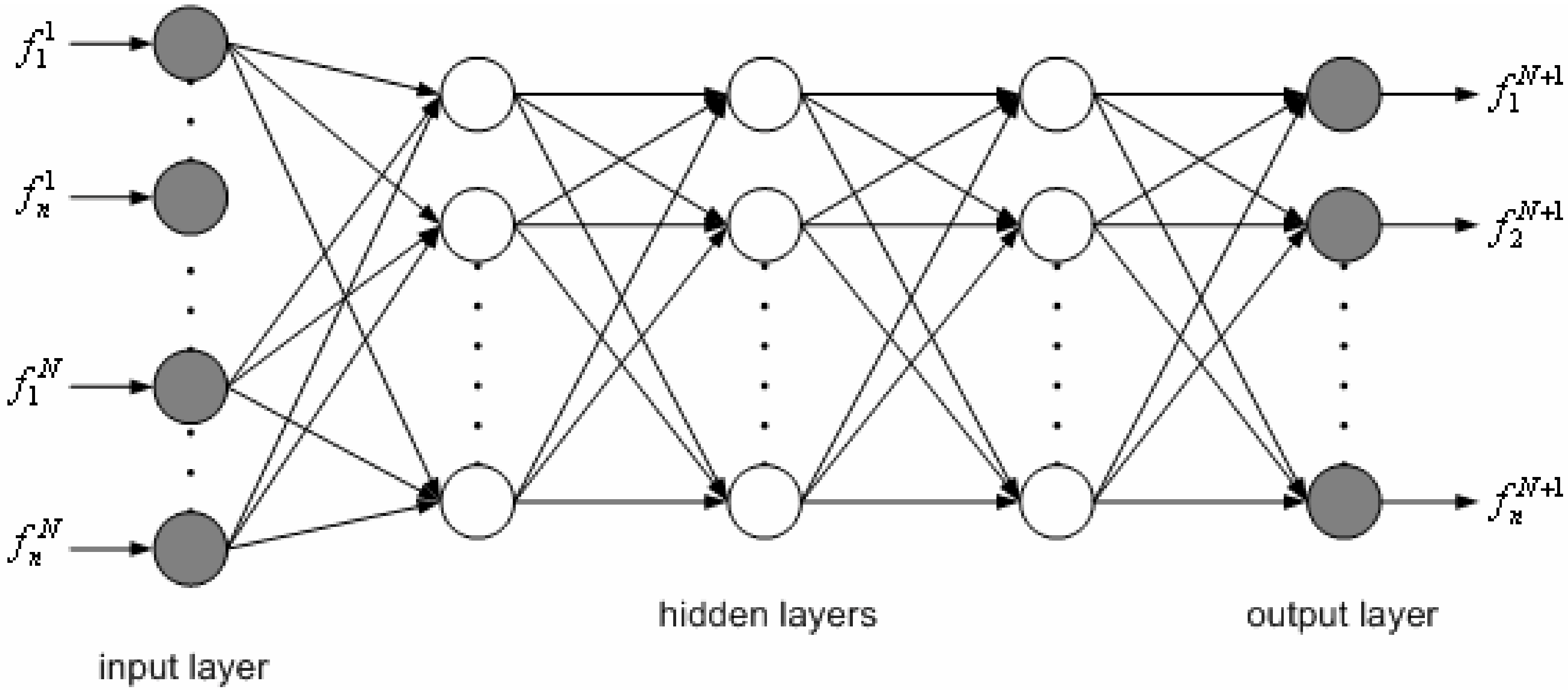
- We have designed a 4-layer feed-forward network
  - The inputs to the network are the feature vectors of the last N objects visited by the current users and their respective visit times

$$v_f^i = (f_1^i, .., f_n^i)$$

  - The output is a vector containing the desired features of the objects that the user is likely to visit next

$$v_f^{N+1} = (f_1^{N+1}, .., f_n^{N+1})$$

Prediction Subsystem
Artificial Neural Network



Features extraction

- We assume that each object in the collection has a digital representation
  - A digital representation is usually a picture of the object itself
- We then consider color and texture features evaluated after applying Wavelet Transform to the original pictures
- Wavelet Transform
  - reduces the amount of data to be analyzed
  - provides a suitable color and texture representation

Features extraction
Color

- Color features
  - Color histograms

$$h(I) = \{h_b^I\}, \quad b \in [1, B]$$

- Color Distance
  - comparison of color histograms
    - computed on the low-pass components (a smoothed copy of the original picture)

$$dist_c(I_1, I_2) = 1 - \sum_{b=1}^{B} \min\left(h_b^{I_1}, h_b^{I_2}\right) / \sum_{b=1}^{B} h_b^{I_1}$$

Features extraction
Texture

- Texture features

$$\Sigma_C^2 = \{\sigma_{X,Y}^2\} \qquad \sigma_{X,Y}^2 = \sum_{x,y} \left\{ \frac{1}{|D_p|/4} \sum_{k=1}^{3} X_k(x,y) Y_k(x,y) \right\}$$

- Texture Distance

$$dist_t(I_1, I_2) = \frac{1}{R} \sum_{i=1}^{|\Sigma^2|} \frac{\left|\Sigma_{C_1}^2[i] - \Sigma_{C_2}^2[i]\right|}{\min\left(\left|\Sigma_{C_1}^2[i]\right|, \left|\Sigma_{C_2}^2[i]\right|\right)}$$

  - R is a normalization factor
  - $|\Sigma^2|$ is the number of features

Feature Distance

- We have used a feature vector that contains both color and texture features
  - color and texture features have proved to be powerful descriptors for pictorial images
- The Features Distance between two images I_1 and I_2 is defined as

$$dist_f(I_1, I_2) = \alpha_c \cdot dist_c(I_1, I_2) + \alpha_t \cdot dist_t(I_1, I_2)$$

- α_c and α_t are two weighting factors
  - chosen by maximizing the correlation w.r.t. human judgments

Path Planning Subsystem

- Considerations
  - When visiting a museum or an archaeological site a user
    - would like to see interesting artifacts
    - doesn’t want to go up and down through the site to accomplish her cultural needs
- Solution
  - Proposing a path to the user based both on visual content of objects in the museum and their spatial location

Path Planning Subsystem

- Given the last *N* objects visited by the current user, let us consider the desired feature vector returned by the neural network and an hypothetic object o_d characterized by this feature vector
- We define a distance that combines feature and spatial distances as follows

$$d(o_j) = \alpha \cdot dist_f(o_d, o_j) + \beta \cdot dist_s(o_{i_N}, o_j),\ o_j \in \mathcal{O}$$

- In conclusion, the path proposed to the user is a list of the top-k artifacts $\{o_j\}$ ranked by ascending values of $d(o_j)$

Experiments
Qualitative evaluation

- Step 1
  - We set up an exhibition in the campus of the Faculty of Engineering - University of Napoli and asked a group of about 60 people to use the system for some days, in order to collect a significant amount of usage paths for training the neural network
- Step 2
  - We asked a different group of 20 people to visit the exhibition
    - without the support of the recommendation system
    - with the assistance of the recommendation system
  - 81% of the people found the system helpful, while the remaining 19% did not appreciate significant differences

Conclusions

- We have shown that the proposed system provides the following interesting insights:
  - the recommendation system does not use any preliminary knowledge about the users' behavior
  - the paths through the museum are proposed based both on visual descriptors of the objects and on their location within the museum
  - the impact on the users at this early stage of the experimentations is promising
- Open issues
  - Extending analysis and experiments to more general scenarios
  - Integrating outdoor and indoor positioning

Acknowledgements

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