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AN OVERVIEW OF LOCATION SEMANTICS TECHNOLOGIES AND APPLICATIONS

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A localization system is a coordinate system for describing the world, organizing the world, and controlling the world. Without a coordinate system, we cannot specify the world in mathematical forms; we cannot regulate processes that may involve spatial collisions; we cannot even automate a robot for physical actions. This paper provides an overview of indoor localization technologies, popular models for extracting semantics from location data, approaches for associating semantic information and location data, and applications that may be enabled with location semantics. To make the presentation easy to understand, we will use a museum scenario to explain pros and cons of different technologies and models. More specifically, we will first explore users' needs in a museum scenario. Based on these needs, we will then discuss advantages and disadvantages of using different localization technologies to meet these needs. From these discussions, we can highlight gaps between real application requirements and existing technologies, and point out promising localization research directions. Similarly, we will also discuss context information required by different applications and explore models and ontologies for connecting users, objects, and environment factors with semantics. By identifying gaps between various models and real application requirements, we can draw a roadmap for future location semantics research.

Keywords: Location semantics; indoor localization; user model.

1. Introduction

Information exists in the world with many different forms. Because of human's perceptual limitations, there is no way for a person to perceive and process a large

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amount of information in short time. To reduce people's information overload, Information Retrieval (IR) is a must for obtaining information resources relevant to an information need from a collection of information resources. Because human, objects, and information co-exist in a physical space, time and location data provides us an efficient and reliable way to index information and retrieve information. This idea results in the location-dependent information access paradigm, known as location-based services (LBS). With LBS, applications persistently keep track of users' or objects' location in an unobtrusive manner and proactively offer the user useful information and services. To make the LBS based information delivery useful, the system must clearly know the real-time position of users and other objects, the semantics associated with the current position (e.g. no cellphone rings during a presentation in a meeting room), and the preferences associated with the current position (e.g. no commercials at work places).

We define location semantics as information that can be associated with a specific location. The information may be a person's identification, a group of people's identifications, or a file id. It may also be a room id or an object id with that location. Additionally, it may be rules for regulating human-human relations, human-object relations, or object-object relations etc. For example, we can associate a painting with a specific position in the museum; we can also register a multimedia file for the painting explanation to the same location. We may also define a rule for playing the multimedia file as "when a visitor is within 3 meters of the painting, play the multimedia file on the visitor's smart phone through ear plug." Similarly, we may define another rule as "when the painting is 5-centimeter away from its original position, activate the alarm near the painting and the alarm in the security room." To support this rule, the system should also define several alarm IDs for that location.

To make our LBS technology discussion more concrete and easy to understand, we will use a museum example throughout this paper. In a museum, users' experiences may be affected by many factors such as exhibition design, time of day, tour duration, room environment, personal habit, exhibiting item history, or social activity within a group etc. After careful examination, we can find that many factors in the above list are directly or indirectly related to time/location data. To improve user experiences in a museum, an acting plan or model has to be created for each served user. Assume that you plan to spend some time in the Fine Arts Museums of San Francisco. Before starting your explorations, you may launch an application on your mobile phone which is provided by the museum and ask for recommendations. The application tells you that the most famous works in this museum are de Young's original collections. However, currently there are too many people standing right in front of them and it is very unlikely for you to enjoy these paintings at a good angle. Therefore the application suggests that you can alternatively check out the section of textile art first, which is also a popular place based on historical visiting data and you seem interested to them as well according to your preference. Moreover, it also shows the path from your current position to the textile art section on your screen. Since the museum is really large, each time a turn is needed, the application will remind you with voice command. And once you reach the section, the application can also talk to you about the history and other information about each collection.

Beyond location data, user's profile, such as artwork preferences, energy level, physical ability, and tour goals also play important roles on providing appropriate service. Semantic information such as point of interest, events, and the relation between different places is also crucial for good LBS services. For example, if a user is using a wheelchair navigating inside the museum, the proposed path for him should not contain stairs or narrow corridors that the wheelchair cannot pass through. In order to provide semantic information to the system, we can build frameworks to systematically collect users' feedback or train complex models with accumulated data. For example, we may use historical data to infer the probability of the place ***B*** visits after the place ***A*** visits. In this way, we can predict the potential museum traffic and therefore systematically avoid collision of big visitor groups.

Even though localization technology has been studied for decades, it still has problems for helping users in the above simple scenario. For example, WiFi-based infrastructure-free localization systems are the most popular systems. Although reasonable accuracy (e.g., 3 ~ 4 meter) can be achieved, there always exist large errors (e.g., 6 ~8 meter) [1, 2] unacceptable for many scenarios. That accuracy is not enough for identifying which showroom a visitor is in or which collection a visitor is interacting with. With that accuracy, we obviously cannot rely on the system to tell us which artwork a visitor is looking at or guide the wheelchair for a disabled visitor. [3] found that high accuracy for WiFi localization (e.g., sub-meter median and 2m maximum) can be possible but hundreds of Access Point (AP) are needed, which is infeasible in practice. Meanwhile, infrastructure-free inertial positioning systems suffer from the inherent noise and accumulated error of sensors, and mitigating such errors and other environmental factors is a challenge [4]. Besides, a starting point is always required for inertial sensor based localization systems. Since both accuracy and precision are still big problems for most localization systems, there are few inference systems that explore location semantics in fine granularity.

Furthermore, few systems have exploited spatial relations among human and objects in the environment in reasoning about contextual information. Most systems implemented context as programming language objects (e.g., Java class objects) or informally described in documentation. Since these representations often require application-specific knowledge at too low a level of abstraction, they cannot facilitate knowledge sharing in an open and dynamic environment and cannot decouple application composition from context acquisition and representation. In order to build interactive systems that are able to operate at higher levels of abstraction, we believe that ontologies of context related information should be designed to provide universal models and mechanisms with shared semantics. Such a design can be shared across multiple applications and only low-level application-specific logic has to be implemented for future applications.

To the best of our knowledge, there are no indoor localization systems or technologies that can automatically locate people, devices, and other tangibles in a fast and highly accurate way and provide generic user models to describe user characteristic from the perspective of both localization and navigation. The Cyberguide system present in [5] is one of the first indoor guiding systems to guide users through indoor environments. The system not only displays an arrow on a room map based on the user's current position, but presents the information of interesting sights within the building, or pathways that users can access and visit. The authors also tried to improve this system by collecting real contextual information. For facilitating the calculation of evacuation routes in indoor environment, [6] presents one of the early 3D indoor navigation applications and a semantic model of interior space. But the system only computes the shortest path from one place to another or the exit areas without considering the real contextual situation or user preference. iNav [7] is another navigation framework aiming to provide real time routing and guidance in indoor environments. It provides the user with both his location information and details of events occurring around him. It also exploits the COMPASS [8] middleware in order to achieve localization and service discovery, so the location and event information can be regularly updated by service providers, which makes the system more contextually aware. iNav targets typical users. It restricts users to update the base information based on their own needs and does not provide advanced user interaction features.

Other indoor localization and user modeling efforts try to address the problem of automatic location-sensing and provide adaptive services. Each of these approaches solves a slightly different problem with its own configuration, such as infrastructure versus portable equipment, power requirement, and resolution and accuracy in time and space. The systems presented in [9, 10] provide routes to their users regardless of user's need and preference. The techniques shown in [11, 12, 13] focus only on navigation for general purposes. MINSKLI [14] does take into account uses' special needs and preferences by eliminating inaccessible hallways from the potential hallway network. But it fails to inspect the connectivity of the resulting network, which may not contain any valid path for users. Besides, the simplest path algorithm in MINSKLI can only apply to connected two-dimensional graphs [15], which means the system can only find valid routes if user's origin and destination are located on the same floor.

As we strongly believe that the key for building user-centered systems is to design the systems on the basis of the user needs, we provide several typical scenarios of how semantics-enhanced indoor localization systems can be used in a way to provide seamless services in the next section. From these scenarios, we should be able to obtain what kinds of location semantics are most useful in indoor environment beyond spatial coordinates, and how they can be obtained from users' location data. In section 3, related indoor positioning methods are surveyed, from which we can see why they are not sufficient for providing more personalized services. Following that, section 4 then focuses specifically on user modeling with location semantics. We provide a detailed description of the key challenges of semantics-enhanced indoor localization as well as other open issues in section 5. We conclude with future issues and research direction in section 6.

2. Usage Scenarios of Location Data

Different indoor localization technologies have been proposed today that can locate users at different levels, such as room level, sub-room level, and even to their exact point, depending on the underlying technology. Departing from their generic list of applications of user localization technologies, we consider a typical museum tour scenario, where users can interact with each artifact in it. We consider museums are a suitable context for exploring the use of location semantics. For example, location semantics may be used to guide users and improve their experience while interacting with the environment. Indeed, the settings of museum generally imply a number of visitors at the same time and many objects (artwork in this setting) in the environment with which users can interact. This provides a great context for exploring how location semantics can facilitate the interaction among human, objects and the environment both at an individual level and a

Fig. 1. Visitors in the Fine Arts Museums of San Francisco

cooperative level.

Traditionally, a museum visit is limited to audio guides and interactive kiosks. While in fact, a museum experience can be social, cultural, and historical and visitors might have abundant information to deal with when they visit a museum. User's experience in a museum could be influenced by visitor's previous knowledge, the presence of the artifacts and collections, as well as the dynamics in the environment around them including friends, family, and strangers. Other factors such as the time of the day, room temperature, and duration of visit may all have an impact how visitors enjoy their visit.

In response to these issues, location semantics, by taking into account user's location, visit history, user's preference, as well as environmental dynamics, intends to predict user's behavior and make recommendation to them. In the setting of a museum, visitors will spend less time finding out which collections are desirable, thereby being able to go directly to the place of certain items they are looking for. Additionally, determining what information a visitor is trying to pull from an exhibit can be modeled by determining relationships between artifacts. If visitors examine multiple items in a certain period of time, we can use the information overlap to determine what information the visitors are trying to pull from the exhibit. This overlap can then be used to find collections with similar content and those collections will be recommended to visitors.

In this section, we create a number of use cases on how people interact with the context and other people, from which we intend to find the nature of context information and determine the design requirements for our context model and user model.

Number of people: Consider the following scenario. Visitors usually need some time to enjoy a painting, but the space around a specific item is limited and the time for visitors should be limited especially if the museum is crowed. If too many people are standing in front of a particular painting, other people might be blocked. This situation poses a challenge to a localization system, which needs to detect both the number of people in such areas and how much time they have stayed individually. And this information can be used to trigger a notification to visitors who have stayed too long to make room for other visitors.

Moving speed: Consider a scenario where an evacuation from a museum is needed and all the people in the building need to leave in a limited time. In order to be safe, all the people have to move at a minimum speed so that they can leave the building in time. And the localization should monitor people's movement and if it finds some abnormal situation, say one person is moving really slow, then it should notify security that there might be some emergency with this specific person.

Staying duration: People may spend different amounts of time at specific locations depending on what they would do there. This timing information can also be used for detecting abnormal behaviors in some scenarios, such as visitors who spend too much time in the restroom may have an emergency situation and need help.

Acceleration: Indoor localization with high refresh rate can be used to detect user's acceleration. A good application would be fall detection for people that need special care like the elderly or places where many people may stay together in a limited space, such as a museum. With high refresh rate, the system can analyze people's location data in real time and further classify events such as falls or other normal and abnormal events.

Usage time of a place: From the number of people staying at a particular place and how long the duration of stay is, the system can further reason how popular a place is. In the case of a museum, certain items usually attract a lot of people. And they tend to spend much time around these artifacts. It would not be a good idea to put two popular painting next to each other, or put a popular item in a tight space.

Group of people: In a typical party scenario, there are usually many people talking and laughing and the place can be very crowded. It would not be a trivial task to find a particular person even though he/she can be just nearby. A possible way to address this challenge is to estimate the relative positions of surrounding people and classify the crowd based on their group activity, such as "5 persons walking from the middle to the corner" and "3 persons talking at the corner". The underlying scheme is that in such situations, people tend to move together with others and form different groups. They might be grouped by friends, families and colleagues, or just strangers who are moving towards the same direction. This requires the localization system to detect the location of all the people in real time and analyze the similarity of their movement.

In spite of all the use cases we discuss above, we envision a system that could provide real-time location information for both human and objects in the environment, and it can provide customized navigation path for users by adapting its behavior to changes of user's location. Take the museum scenario as an example, the system is expected to create different tours based on visitor's interests, his current location, schedule, physical capabilities and environmental dynamics. Moreover, the system should also update the recommended tours as these conditions change.

3. Current Indoor Localization System Review

The state-of-the-art indoor localization is quite sophisticated. A variety of methods has been investigated to estimate indoor location of human and objects and they can be grouped into four different techniques: (1) dead-reckoning, (2) proximity sensing, (3) triangulation, and (4) scene analysis, which will be discussed next separately.

3.1. *Dead-reckoning*

These systems estimate a user's location by keeping track of travel distance and direction of turns based on a previously estimated or known position. While a user is moving, the system obtains his current velocity from sensors on his body, and uses this information in conjunction with the amount of time that has elapsed since last update to derive user's current position. These sensors could be accelerometers [16, 17, 18], magnetometers [19], gyroscopes [20], or a combination of some of those sensors [21, 22]. Other sensors, such as EMG [23], pressure sensors [24], Ultrasonic [25], have also been explored.

The major drawback of this approach is that the position estimation errors quickly accrue over time if external references are not available, since the estimation process is recursive. RFID tags [26], ultrasound beacons [27], and map-matching [28] are often used to correct this accumulated errors. Because of its cumulative error propagation and the need to combine it with other localization techniques for eliminating errors, this method might also introduce other drawbacks. If the system uses RFID for error correction, the system would have most of the disadvantages of the RFID localization such as change in the infrastructure and the need for users to carry a RFID reader. If map matching or landmarks are used for error correction, some previous knowledge of the environment is required. Also a starting point is also required, typically determined by the external references.

3.2. *Proximity sensing*

Proximity refers to a class of methods which determine the presence of human subjects or objects in the vicinity of sensors, which alone has limited sensing range and analysis capabilities. Common architecture of proximity sensing system is having a fixed number of sensing stations installed in the environment and determining the location of the user through receiving signals from identifiers or tags carried by users. It can also be the other way around with users carrying receivers or tag readers in their mobile devices [29], shoes and canes [30] and many transmitters or tags being installed at fixed locations in the environment. If a user can be contacted by a station, then the user is coarsely located to the station position. Since these tags or readers can provide a unique identification for each person or object, localization errors will be limited and location data can be either retrieved from the tag itself, which requires the data stored beforehand, or retrieved from a database using the tag's unique identification. Additionally, the user's orientation can be determined from relative changes in location from continuing readings of tags. Six different technologies to implement this kind of systems have been proposed:

Radio Frequency Identifier Description (RFID) tags are used extensively in many indoor localization systems, where one or more reading devices can wirelessly obtain the ID of RFID tags present in the environment. The reader transmits a RF signal and the tags present in the environment reflect the signal, modulating it by adding a unique identification code. The tags can be active, powered by battery, or passive drawing energy from the incoming radio signal. Active tags usually have a larger range, which could reduce the number of tags that need to be installed in the environment. But the batteries they use would need replacement after 3~5 years. While passive tags are much less expensive, they have much shorter range. Therefore, more tags would be needed to cover a certain amount of area.

The main drawback of this method is that even though RFID tags are relatively inexpensive, deploying enough of them to cover a large area can be costly. An alternative way is to embed them in the carpet [31], which might reduce the cost.

Infrared (IR) has been used in various ways for detection or tracking of objects or persons. One of its advantages is that its wavelengths are longer than that of visible light, but shorter than that of terahertz radiation. Therefore it is invisible to the human eye under most conditions, making it less intrusive compared to indoor positioning based on visible light. There are three general methods of exploiting infrared signals for localization:

1) Active beacons approach, which is based on IR transmitters that are installed in known positions where each transmitter broadcasts a unique ID in a cone shaped region. The user carries an IR receiver that picks up data from IR transmitters in range. The system may include only one transmitter in each room for room-level localization [32, 33] or several transmitters deployed in every room to disambiguate sectors of a room.

2) Infrared imaging approach, where sensors operate in the long wavelength infrared spectrum, known as the thermography region, to obtain a passive image of the environment from natural thermal emissions. The advantage of this approach is that there is no need to deploy active infrared illuminators or any other dedicated thermal source, and the infrared radiation can be used to determine the temperature of human body or other objects without wearing any tags or emitters [34, 35]. As its main drawback, passive infrared approaches are comprised by strong radiation from the sun.

3) Artificial infrared light approach can be a common alternative to indoor localization systems using visible light. It might be based on active IR light sources [36] or retro reflective targets [37, 38]. Microsoft Kinect [39] used for video game console Xbox uses continuously projected infrared structured light to capture 3D scene information with an infrared camera. The 3D structure will be computed from the distortion of a pseudo random pattern of structure IR light dots. And people can be tracked simultaneously up to a distance of 3.5 m at a frame rate of 30 Hz. An accuracy of 1cm at 2m distance has been reported.

Ultrasound identification (USID) determines a user's position based on distance between ultrasound emitters carried by human users and static receivers installed in the environment [40]. Other systems may have the user carry the receivers and emitters are mounted at the ceilings or walls [41]. The relative distance between an emitter and a receiver can be estimated from Time of Arrival measurements or Time Difference of Arrival of ultrasound pulse. A disadvantage of ultrasound is that walls may reflect or block ultrasound signals, which result in less accurate localization. The other drawback of using ultrasound for localization is required line of sight between the receivers and emitters.

Bluetooth beacons have been designed as a short-range communication system with range of comparable size to a room [42], making proximity-based location simple to implement and relatively reliable. Basically, a group of fixed beacons continually issue inquiry packets on each possible channel, and mobile devices need to be set "discoverable" to respond to these packets, identifying themselves. Since the location of these fixed beacons is known in the system, users or their mobile devices can be located although users will have to walk slower than with other techniques because of the device delay. One of the advantages of this design is that no custom code need to be deployed on the user's side, but is often considered as a privacy issue since anyone in the environment can track the devices by creating their own stations. Thus, more recent researches have concentrated on the user's side scanning for the fixed beacons. Although it is more secure since Bluetooth technology does not require scan packets to identify their source address, it does require custom application code on user's mobile device.

Some of the Bluetooth beacon-based indoor tracking systems also attempt to use RSS measurement [43], techniques first developed for WiFi location system either based on radio propagation models or "fingerprinting" (matching current radio conditions to a previously-measured radio map). However, the deployment cost and environment changes may become big barriers for accurate localization using this technology.

Though most systems use only one type of technique for the identifiers, there exists positioning systems [44] that uses a combination of identifiers, e.g., active and passive RFID tags, or infrared beacons. While using multiple localization techniques might improve the accuracy, the main drawback is the additional equipment that the user has to carry.

3.3. *Triangulation*

Different from most proximity sensing techniques which locate the user by sensing one unique identifier, a number of systems use the location of at least three known points and locate the user by triangulating the tags installed in known positions. These systems might use technologies of WLAN/WIFI [45, 46, 62, 63, 64, 65, 66, 67], RF [47], ZigBee [48], Cellular Network [49], FM Radio [50], Digital Television [51], Bluetooth [52] and visible light [53, 54]. Depending on the type of radio signal measurements, triangulation can be divided into angulation and multi-lateration method. In angulation systems, specific antenna designs or hardware equipment are needed and angle of arrival (AOA) measurements [55] are used for inferring the receiver's location from the angular measurements of at least three known points. In multi-lateration systems, time of arrival (TOA), time difference of arrival (TDOA), or received signal strength (RSS) measurements from multiple reference points (RP) are used to estimate the receiver's location with the help of a radio propagation model. However, indoor environment can be harsh and characteristics of the wireless signal channel in such environments might be changeable and unpredictable, which makes multipath and non-line of propagation conditions common. Therefore, these systems cannot guarantee an adequate performance. A few hybrid systems have been developed as well, in order to compensate for the shortcomings of a single technology [17, 18, 56, 57] and did show some progress on localization accuracy, coverage, or robustness. But as [74] has presented, fusing several technologies requires reliable measurements and complex fusion techniques. It also increases the overall system complexity.

3.4. *Scene Analysis*

Scene analysis based localization is a pattern recognition method which extracts features from data collected by one or more sensors carried or worn by users or installed in the environment and compares these features with a set of prior collected sensor data that has been coupled with a specific environment. The scene can be visual images, acoustic sound, and radio frequency waves. The advantage of using this method is that accurate physical quantities, such as distance, are not required for calculating a user's location. However, the observed features are usually specific and unique, and are subject to re-evaluation if the environment is changed.

Computer vision based localization techniques, which cover a wide field of applications at all levels of accuracy, provide a number of advantages. While users navigate in an environment, a camera captures images of the environment, and then by matching the images against a database of images with known location, users' position and orientation can be determined [40, 58]. Recently a number of researchers have also contributed to vision-based localization using smartphone cameras [59, 60]. The main advantage of this method is that both the camera and computation power are inbuilt. This simplifies the process of deploying and using such a system. Besides, most of the state-of-the-art phones already have a variety of inertial sensors, such as accelerometer and gyroscope. Hybrid systems of camera and inertial sensors for localization have also been getting more popular.

Since the system only relies on a camera and sufficient processing power and there has been great success in actuator miniaturization (e.g. lasers) and particularly advancement in the technology of detectors (e.g. CCD sensors), low-cost positioning solutions are in view and have the potential to serve the mass market. The main challenge of vision-based technique is that it requires reference images, which need to be gathered first and assigned to each location. High storage capacity is required for storing these images.

Fingerprinting localization techniques fingerprint the unique signal measurement or its distribution over time from one or multiple sources at every location in the area of interests to build a map of prerecorded data. When the user is navigating, his location is estimated by mapping the currently received signal measurement against the map to find the closet match. Common metrics for fingerprinting include AOA, RSS, or time of flight (TOF) of the incoming radio signal [61]. Due to its increasing prevalence in indoor environments and the existing infrastructures, WLAN/WIFI [62, 63, 64, 65, 66, 67] has been exploited extensively with fingerprinting schemes. Other technologies, such as Ultra wideband (UWB) [61], GSM [72] and PowerLine [73], have been studied as well.

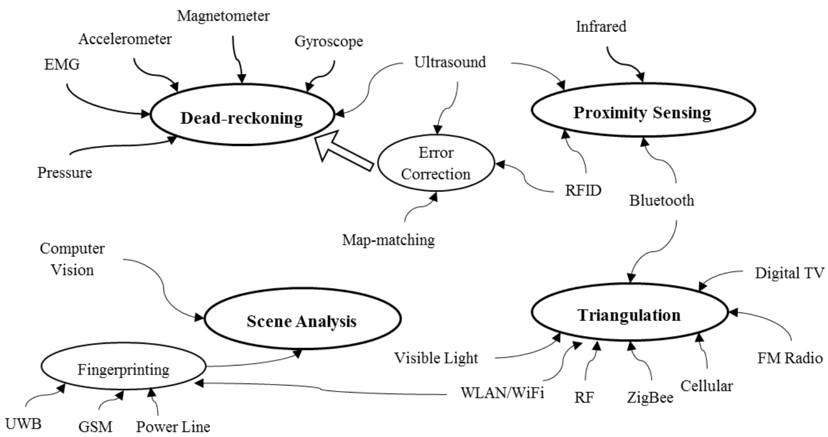

Fig. 2. Indoor localization technologies

3.5. *Fundamental Limitation of Positioning Using Wireless Network*

Due to the availability and low cost, indoor localization systems based on WIFI, ZigBee, Bluetooth, and other radio frequency signals have dominated these days. In this section, we aim to present the underlying mathematical methods of all these systems. Suppose that one of the receivers in these kinds of systems receives a set of signals arriving from n base stations placed at known location $x_i, i = 1, \ldots, n$, which is common setting in wireless indoor localization systems. From these stations, the receiver obtains a set of measurement $r = \{r_i\}, i = 1, \dots, n$, in order to compute its current location x. The relationship between the measurable variables and the unknown position may be written as [68]:

$$r = h(x) + e$$

where h is a function which implicitly contains the positions of the base stations, x_i, and e is the error affecting the measurement, with a probability density function $p_e(e)$. The functional dependencies $h(x)$ and $p_e(e)$ completely characterize the measurement process [69]. The maximum likelihood (ML) estimation of the position is the one which maximizes the conditional probability:

$$\hat{x} = \arg\max\{p(r|x)\}$$

Theoretical bounds can be established for the ultimately attainable precision of any estimation method by using the Fisher information matrix and the Cramer-Rao Lower Bound (CRLB). This bound has been analyzed thoroughly in the literature, primarily for AOA, TOA, and TDOA, but also for RSS and with specific attention to the impact from non-line-of-sight.

The Fisher Information Matrix $J(p)$ is defined as

$$J(p) = E\left(\frac{dlogp_E\big(y - h(p)\big)}{dp}\right)^T \frac{dlogp_E\big(y - h(p)\big)}{dp}$$

In case of Gaussian measurement errors $e \sim N(0, R(p))$, $J(p)$ can be further simplified

$$J(p) = H^T(p)R(p)^{-1}H(p)$$

$$H(p) = \frac{dh(p)}{dp} = (\frac{dh(X,Y)}{dX}, \frac{dh(X,Y)}{dY})$$

The Cramer-Rao Lower Bound is given by

$$Cov(\hat{p}) = E(p^o - \hat{p})(p^o - \hat{p})^T \geq J^{-1}(p^o)$$

where p^o denotes the true position. The general Cramer-Rao theory states that computing the right hand side of the above equation gives a good idea of how suitable a given sensor configuration is for positioning. And the larger gradient $H(p^o)$, the more information is provided from the measurement, and the smaller potential estimation error. Since the luminous intensity distribution of LED is very local, which can give us a much larger $dh(p)/dp$ than it is for temperature, magnetic field, RFID, and other sensors [70], it may meet the requirements for higher positioning resolution.

3.6. *Identifying navigation route*

In order to provide practical services in real scenarios, indoor localization systems should also be able to provide directions to users between any two points in the environment and update the routes dynamically based on users' real-time location.

A common approach to calculate potential routes is to use a shortest path algorithm, where turning points and path in the building are considered as points and edges respectively, and the possible routes are represented as graphs approximating the floor plans. However, the shortest paths may not be the best option for different individuals in reality, such as users with disabilities [40, 71]. Therefore, the identification of the possible routes needs to exploit context information and take into consideration a user's location, his/her preferences and physical or cognitive capacities, and match the characteristics of the environment with their infirmities to produce appropriate paths.

4. Location Semantics Modeling

Building context-aware applications to provide adaptive services is complicated. This situation can be remedied by creating a suitable user model which captures features such as user interests, user location, and other context information. Since we cannot find established models specifically defined for a museum scenario, we provide our own opinions based on state-of-the-art technologies. This section presents an object-based user model in which context information is structured around a set of entities, including human, object, and relations among them. These entities provide a formal basis for representing and reasoning about some of the properties of context information we discussed in section 2.

An entity cannot behave alone. In our museum scenario, a visitor cannot stand still without interacting with artifacts or other visitors. An entity should be linked to other entities by directional relationships noted as interaction. Each interaction should have two or more participants. Therefore, an interaction model will also be proposed to characterize the complex relationships among these entities

4.1. *User model*

The core of a location semantics system is a user model that is dynamically updated as the user moves in the museum by considering user's current location and events occurring during user's visit. It is driven by the directional location tracking of users, their relative positions, as well as their interactions with the environment.

The user model also performs the functionality of a recommendation system. In our museum scenario we will use the knowledge-based modeling techniques to recommend visiting routes and artwork collections to visitors. Knowledge-based recommendation systems usually require three types of knowledge: knowledge about the objects to be recommended, user knowledge, and functional knowledge of the mapping between user needs and object. In our case of adaptive services in a museum, the functional knowledge could include the knowledge of the environment, such as room temperature, time of the day, or number of visitors in the same exhibit.

Based on the above, the user model could be designed to contain two parts: one that tracks the user's location and maintains context data; the other one that infers user's preference, his relationship with all the objects in the environment and other users and that provides personalized information.

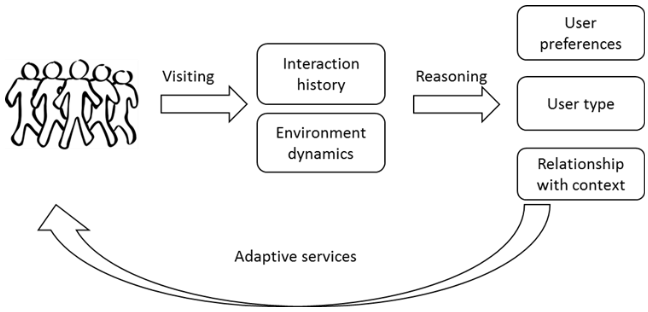

Fig. 3. User modeling in the museum scenario

The detailed structure is given as follows:

(1) Data component, including information about users and environment
  (a) Interaction history, which contains how the user interacts with the environment. Two types of data could be stored in the interaction history.
    - User location, which can be used to form the user's path through the museum.
    - Usage data, such as how long the user has stayed in front of a specific painting, and how much time the user has listened to the description of certain artworks, by which user's favorite types of artifacts and preferences can be assessed.
  (b) Environment Dynamics
    - Physical factors, such as room temperature, time of the day, and the number of people within an area.
    - Knowledge about all artworks, such as their location at the museum, author, chronology, material, and artwork category (e.g., sculpture, painting, and photo/picture).

(2) Inference component, which will analyze stored data to infer
  (a) User preferences, which is dynamic, evolving with user's interaction with the artifacts and environment. User model should be able to monitor user's behavior and make predictions about the user based on their interaction with various items in the environment.
  (b) User type, which is related to user preference and knowledge. In the case of a museum, one may want to know and see as much as possible, and review almost every artifact on his path, and another user may be more selective and prefer to explore artifacts that have only certain concepts. Some visitors do not want to

spend much time on a single artifact preferring to go through the museum in order to get a general idea of the exhibition.

(c) User's relationship with nearby objects and other people.

4.2. *Interaction model*

Based on all the potential applications we discussed in section 2 for our museum scenario, we recognized several classes of interactions that exhibit different properties in accordance with their persistence and source. In this section, we formalize the analysis in a scheme for categorizing interaction based on the entities involved in the interaction.

4.2.1. *Human to object*

In a traditional museum setting, interaction between human and object, such as a specific painting, could be limited to audio guides and interactive kiosks. However, if both the location of visitors and artifacts are available, many customized services could be enabled:

(1) Multimedia presentation for different artworks could be dynamically generated and delivered to visitors taking into consideration their real-time location.

(2) A visitor's stay duration in front of certain artworks could be used as the indicator of user interest and the physical path covered by the user during his visit can be used to build a user model for delivery of personalized multimedia information to enhance interactivity in the museum.

(3) The system could recommend certain collections to visitors based on their preference which can be manually input beforehand or their previous interaction with the artworks in the museum and show the path to a specific collection.

4.2.2. *Human to human*

Social interaction among visitors is known to enhance the museum visit experience. By combining the location information of multiple users and integrating the communication channel among them, social interaction is possible:

(1) Visitors could attach virtual comments about certain artworks for other visitors who visit these artifacts later

(2) Visitors could share their comments and experiences for certain artworks with their family or group members who are also in the museum at the same time.

(3) Visitors could see the nicknames of visitors who had already visited a specific artwork, so they would share similar interests at the museum or to keep in touch after the visit.

(4) Multiple visitors could be grouped together to play certain games in teams, such as treasure hunting, to learn the knowledge about the artworks based on observation, reflection and action, and improve their learning experience by challenging themselves.

4.2.3. *Object to object*

A major goal of location semantics is to reveal the rich semantic linkage connecting the artifacts with each other. The linkage can be obtained from the experts who have studied these artworks for years or inferred from visitors according to their inaction history. And this linkage can be used to provide adaptive services to the visitors and enhance their museum visit experience.

(1) From historical data, we can easily find which two or more collections visitors tend to interact with in the same visit. This implies that these collections should not be placed far away from each other.
(2) If two collections tend to attract many people, it is not wise to put them side by side, which might cause congestion.

5. Challenges and Future Directions

Indoor localization is becoming increasingly important. Although many positioning devices and services are currently available, some important problems remain unsolved and it is necessary to develop an integrated and seamless positioning platform to provide a uniform solution for different scenarios and applications. Directions for future research in this area can be summarized as follows:

(1) Fusion techniques: Both indoor and outdoor localization have been addressed separately. While for a number of mixed scenarios where both indoor and outdoor locations are needed, the transitions between indoor and outdoor areas need be managed seamlessly and exploited as a whole. Therefore both system integration and data fusion techniques need to developed, but much work remains to be done in this area.
(2) Direct localization: Most indoor localization systems contain two steps for positioning: parameter measurement and position estimation. This method has the disadvantage of making a premature decision on intermediate parameters in their first step. This can be remedied by direct localization employing the principle of least commitment; these algorithms preserve and propagate all intermediate information until the end of the process and make an informed decision as a very last step. Little work has been done on this problem to date.
(3) Unobtrusiveness: many systems require users to carry sensors attached to the body for location tracking and activity monitoring, and unobtrusiveness becomes a major challenge. Certain progress has been made in the integration of sensor devices in fabric, but the design and development of wearable sensors without violating unobtrusiveness is still a significant challenge.
(4) Security and Privacy: The fundamental security requirements of a localization system are privacy, confidentiality, accountability, and access control. Users should have autonomy and control over their data of any type. Researchers have identified many types of privacy leaks, even when the wireless communication channel in the system is encrypted.

6. Conclusion

In this article, we provide a comprehensive overview of state of the art positioning techniques and how the system can be enriched semantically to provide adaptive services in a museum. The key feature of location semantics is the use of user model (1) to define a general and well-defined user/context model and this model should be independent of a particular positioning system, (2) to perform inference and reasoning to provide environment information and adaptive services at a semantic level. This enables the system to provide personalized services continuously and dynamically.

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This section should come before the References. Funding information may also be included here.

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