Location-based Context-Aware System

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Abstract

Context is a service-oriented abstract model of situations which enables software agents can provide best services to users. Therefore, the spectrum of contexts is very wide, from location contexts to group mood contexts. Location-based context awareness is the ability to infer semantic meanings from location and orientation data from sensors. Higher level contexts are derived from location-based contexts; therefore, location-based contexts are very important in ubiquitous systems. We propose a four-layered location-based context aware system assuming centralized location tracking sensor networks. Based on location and orientation data from sensors, qualitative model is constructed using two qualitative operators. And then, ubiquitous relation model is built based on the qualitative model to specify the relation between objects. Finally, the semantic model is inferred from the relation model using semantic knowledge base. The proposed system is supposed to be used in in-door ubiquitous home and is successfully simulated to generate semantic contexts.

Key words: Context Awareness, Location-based Context Awareness

1. Introduction

Location is a crucial component of contexts in ubiquitous environment [2]. With the advent of diverse location sensors, location-aware computing may become a part of everyday life in near futures. Location-based context awareness is the ability to infer semantic meanings from location and orientation data from sensors. From temporal sequence of location data, it is possible to derive semantic relationship between mobile objects.

We propose a location-based context awareness framework to infer semantic context information from location-based sensors. Location-based sensors are supposed to provide locations and orientations of moving objects. And, a world modeler based on object models and geometric equation has been used to represent location-based context awareness.

We propose a four-layered location-based context aware system assuming centralized location tracking sensor networks. Based on location and orientation data from sensors, qualitative model is constructed using two qualitative operators. And then, ubiquitous relation model is built based on the qualitative model to specify the relation between objects. Finally, the semantic model is inferred from the relation model using semantic knowledge base. The proposed system is supposed to be used in in-door ubiquitous home and is successfully simulated to generate semantic contexts.

A sequence of location and orientation sensor data is assumed to be given from sensors. Based on these data, temporal and spatial abstraction is processed at discrete layers. At the qualitative layer, changes in qualitative spatial relations are detected. Whenever there is a change in qualitative spatial relation, spatial relations between the objects are derived which specify the starting and ending time of the spatial relations.

At qualitative layer, qualitative changes are detected in real time and recorder. Qualitative relations are associated with starting and ending time. Qualitative relations are recorded and processed by relation and semantic layers. Therefore, relation and semantic layers generate abstractions what a user did. This information is supposed to be used by learning modules to infer user behavior patterns.

This paper describes a layered approach to infer context information from location-based sensors. Qualitative layer is introduced to identify qualitative change between a moving object and static objects. Relation layer is used to represent temporal relation between objects based on approaching and departing orientations. At the semantic layer, functional behavior and knowledge of each object has been used to infer semantic relation between users and objects in ubiquitous systems.

2. Related Works

Modeling location is fundamental to location awareness in ubiquitous computing environments. Many challenges remain unsolved in location-based context problems [3].

Harter et al. proposes to use a quadtree for indexing structure, generated by breaking down the plane containing the spaces into sub-quadrants, where each quadrant cell is represented by a node in a tree [1]. And, they use the containment indexing algorithm to express the spatial containment relation between objects.

However, we propose a layered architecture to identify spatial relations between objects. Our approach employs diverse abstraction methods to derive semantic spatial relations between objects from temporal location and orientation data from sensors.

3. Location-based Context Awareness

We propose a layered architecture to derive location-based contexts from sensor data. Sensors are assumed to provide location and orientation data of mobile and static objects in ubiquitous environment. In addition, these data are tagged with temporal information.

Our model consists of qualitative layer, relation layer, and semantic layer. Each layer abstracts information from the lower layer. Qualitative layer is designed to abstract location and orientation data from any senor inputs. Recently, diverse location sensors such as UWB, ZigBee, and RF are suggested to be used in ubiquitous systems. And, all of them generate sensor data with location and orientation data. Our approach is designed to work with any location-based sensors. Relation layer is on top of qualitative layer to generate relations between objects without considering functions of objects. Location-based context aware systems need to identify relations between objects to learn deeper semantic relations. Relations mean proximity relations between objects, such as on, left-sided, and rear-sides. At relation layer, each object is processed without considering functions of objects in the system and abstracts. At semantic layer, an inference engine is used to infer semantic relations between moving objects and static objects. A knowledge base has been built to encode semantic relations between objects based on functions of objects in the system.

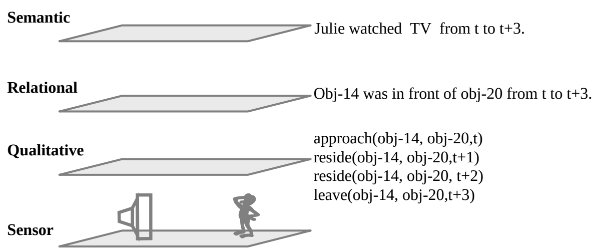

Fig. 1 An Overview of Location-based Context Awareness

Figure 1 describes layers used in this approach. As shown in the figure, qualitative layer is based on sensor inputs and generates qualitative change between a moving object and static objects. Relation layer is used to infer spatial relations between objects in temporal dimensions. And, the semantic layer has been used to infer users' behavior based on functional model of each objects in the system.

3.1 Qualitative Layer

Qualitative model inputs a sequence of temporal location and orientation data from sensors. Each object in ubiquitous environment is modeled geometrically. And, the contact area of each object is also modeled to infer dynamic relations between objects. Qualitative model derive qualitative spatial relations between objects using the sequence of temporal location and orientation data. Qualitative operators such as *overlap* and *containment* are used to describe relations between objects. For instance, overlap(+, $object_i$, $object_j$, $time_k$) means that $object_i$ approaches $object_j$ at $time_k$.

The following is a pseudo code for generating qualitative model.

PROCEDURE
Generate_Qualitative_Model(WorldModel, H)
  let t = current time
  WM is the set of geometry model of each object in world model
  H is the location and orientation of agent

  let loc_{agent} = location and orientation of human agent

  for each object O in WM
    evaluate scope(loc_{agent}, object O);
  let UM = {object O | scope(loc_{agent}, object O) is within threshold}

  for each object O in UM
    evaluate overlap(loc_{agent}, object O, t);
    evaluate containment(loc_{agent}, object O, t);
  for each object O in UM

    generate qualitative overlap from
      overlap(loc_{agent}, object O, t) and overlap(loc_{agent}, object O, t-1);
    generate qualitative overlap from
      overlap(loc_{agent}, object O, t) and containment (loc_{agent}, object O, t-1)

Qualitative model is important in our system because it describes basic relations between moving object and static objects. We describe relations between moving object and other static objects in temporal dimension. Since sensor provides location and orientation information of objects continuously, qualitative relation can be obtained in temporal ways. Based on this information, we can derive temporal relation between objects at the next layer.

At the qualitative layer, each operator is generated in real time to describe users' dynamic behavior. Whenever a qualitative change begins, relation and semantic layer infer users' behavior. Qualitative model plays a main role in generating spatial and temporal behavior of users in ubiquitous systems. All the remaining modules are based on results of the qualitative layer.

3.2 World Model

In order to derive qualitative relations between moving and static objects, a world model has been created. Each object in ubiquitous systems has been modeled based on geometric equations. We assume sensors provide information about static objects in the system. Actually, a world model needs detailed data about shapes on objects. However, our system is designed to be used in ubiquitous systems based on location-based sensors. Therefore, we assume our system has geometric models on static objects to be used in ubiquitous systems. Our system is supposed to be used in digital home or office. And numbers of objects used in such ubiquitous environments are countable. Each object is modeled based on geometric equations. Square, rectangular, and circular models are used to describe objects in the system. Of course, more detailed equation may be necessary to describe complex objects.

Beside geometric models on static objects, boundary models play important role in the world model. In order to represent relations between moving objects and static objects, boundary information of static objects has been described by geometric equations. Different boundary is described in different equation of each object. In order to represent qualitative relation between moving and static objects, boundary information of static objects are described by square and semi-circular geometric equations.

And, moving objects are described by location and orientation information. A view of each moving object is modeled based on location and orientation of each object. Orientation is modeled based on temporal location information of each moving object.

3.3 Relation Layer

From a qualitative model, relation model can infer temporally abstract information by analyzing a sequence of qualitative operators. We use this model to represent qualitative model in more abstract ways. From a sequence of qualitative operators, overlap(+, object$_i$, object$_j$, time$_k$), containment(+, object$_i$, object$_j$, time$_l$), overlap(-, object$_i$, object$_j$, time$_m$), relation model abstracts them into stay(object$_i$, object$_j$, time$_{k,}$ time$_m$). At the relation layer, each qualitative change is detected and when there is a change, relation model is generated. When a moving object approach a static object and leaves the object later, a relation is generated to represent the moving object was in the boundary of the static object. This information is useful for representing when a moving object stayed around static objects.

At relation layer, temporal and spatial relations are derived based on changes of qualitative operators. Each qualitative operator becomes associated with the starting time and ending time. When a qualitative event occurs with starting and ending times, a temporal relation is derived. This means that a user was doing an action during the period.

In order to generate information to service agents related to location-based services, semantic model infers what a user is going to do. In order to produce such inferences, relation model generates whenever a positive qualitative operator is detected. For instance, when a person approaches to a monitor, relation and semantic model infer the user is going to use the monitor and service agents can perform proactive actions based on the user's preferences. Hence, the relation and semantic modules are responsible for infer users' behavior in real time.

At relation layer, we use boundary information of static objects to represent relation between moving object and static objects. For instance, when a moving object approaches a static object from the front side, we need to represent the approaching directions. This approaching direction is very important in location-based context awareness. When a person approaches to monitor from the front side, we can infer that the person is going to use the monitor. However, when the person approaches the monitor from the behind, s/he is not going to use the monitor at this moment and willing to do other actions. And, when a person approaches TV monitor from the front side, s/he may want to turn on the TV or change the channel.

The relation model represents when a moving object stayed around a static object. In addition, it represents which side of static object the moving object stayed. This information can be used by semantic layer model to infer users' behavior. For instance, when a person stayed in front of a monitor, s/he may have used the monitor. But, when the person approached the rear side of the monitor, s/he did not use the monitor for browsing. In order to represent such behavior, the qualitative layer produces users' approaching ways based on world model and the relation layer utilizes the information to represent users' behavior accordingly.

At the relation layer, temporal relation information between objects is described. And, the relation information includes approaching direction information as well. Relation model uses clustering algorithm to identify a set of associated qualitative operators and then applies diverse methods to infer relations between ubiquitous mobile objects.

3.3 Semantic layer

Semantic model infers semantic meanings of derived relations using domain specific knowledge. We use a knowledge based approach to model semantic relations between objects. If object$_i$ is John and object$_j$ is a monitor, we can infer that John was watching the monitor between time$_k$ and time$_{m.}$ In order to derive semantic meaning from movements, we use heuristics to encode relations between objects in ubiquitous environments.

At the semantic layer, we use a knowledge base and inference engine to infer semantic relations between users and objects. Since each object has its own function, the system can infer why a person approaches the object. For instance, when a person approaches a bed in the evening, we can infer that s/he is going to go to bed based on rules. Inference engine is used to infer semantic relations based on the outputs of relation layer. Since each object has its own functions and this function is related to time, each rule in the semantic layer is associated with time and function of each object.

We introduce functional model of each static objects at the semantic layer. For instance, when a person is in front of TV monitor, s/he is watching TV. But, when a person is in front of audio, s/he is listening rather than watching. And, it is possible to model current states of each device and model semantic relations based on current states of each objects. For instance, when a person is in front of TV monitor, a current state of TV channel may be identified by functional model of TV monitor. Based on this information, we can infer what the person is watching and what the favorite of the person is.

Semantic model uses inference engine to derive semantic spatial meanings from relations. Domain specific semantic relation rules are used in the system to derive semantic meanings. Our learning model learns user preferences in location-based contexts by applying learning methods over the set of temporal spatial semantic relations.

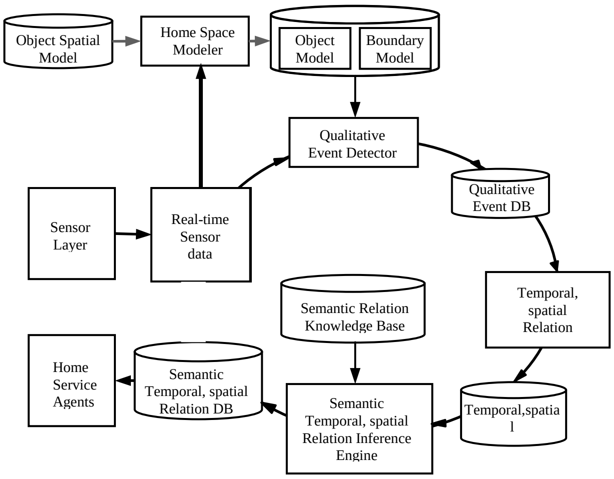

Fig. 2. Control Flow of Location-based Context Awareness

Figure 2 describes control flow of location-based context awareness proposed in this paper. At each layer, temporal sensor data is abstracted with respect to qualitative and spatial relations. And, at relation and semantic layers, an inference engine has been used to infer relations and semantic meanings of humans' behavior. Whenever a qualitative change is detected by qualitative module, appropriate relation and semantic module infers what a user is going to based on functional model of static objects and user preferences of the user.

In addition to providing real time services, records of semantic behavior can be used by learning module to infer user behavior. Current system is using clustering and classification approaches to infer user behavior. COBWEB and C5.0 are used to generate user preferences.

4. Conclusion

Location-based context awareness becomes an essential feature in in-door ubiquitous applications. Sensors can provide location and orientation of objects in ubiquitous environments. It is important to derive semantic spatial relations between objects and to learn user preferences in location-based behaviors. We propose a four-layered location-based context aware system assuming centralized location tracking sensor networks. Based on location and orientation data from sensors, qualitative model is constructed using two qualitative operators. And then, ubiquitous relation model is built based on the qualitative model to specify the relation between objects. Finally, the semantic model is inferred from the relation model using semantic knowledge base. The proposed system is supposed to be used in in-door ubiquitous home and is successfully simulated to generate semantic contexts.

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