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NATURE AND COMPLEXITY ANALYSIS TECHNIQUES OF SURROUNDING SITUATION IN PERVASIVE COMPUTING DEVICES: A REVIEW

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Abstract

Pervasive systems must offer an open, extensible, and evolving portfolio of services which integrate sensor data from a diverse range of sources. The core challenge is to provide appropriate and consistent adaptive behaviors for these services in the face of huge volumes of sensor data exhibiting varying degrees of precision, accuracy and dynamism. Situation identification is an enabling technology that resolves noisy sensor data and abstracts it into higher-level forms that are interesting to applications. This paper provide a comprehensive analysis of the nature and characteristics of situations, discuss the complexities of situation identification, and review the techniques that are most popularly used in modeling and inferring situations from sensor data. We compare and contrast these techniques, and conclude by identifying some of the open research opportunities in the area.

1. Introduction

"The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it," Mark Weiser wrote in his 1991 *Scientific American* article, "The Computer for the 21st Century." To achieve Weiser's vision, the computer needs to move to the background of society's consciousness, extending people's skills to perform complex or difficult tasks without giving additional recognition to a computer's presence." Like a well-balanced hammer disappears in the hand of a builder, the computer needs to act as an extension of human ability. In addition, computers, sensors, and networks need to pervasively (or ubiquitously) surround users, allowing for constant, meaningful interaction. To achieve this vision, technology needs to be utilized in an integrated fashion. However, integrated technology represents more than the sum of its parts.[4]

Pervasive computing systems can be classified in two ways: as an infrastructure or personal system. Infrastructure systems are well suited to create smart environments such as classrooms that automatically record, index, and publish lectures to the web; conference rooms that allow presenters to effortlessly present slide-shows, write on an electronic white board and move between various control points; and homes that suggest the best techniques for warming and cooling, while maintaining optimal energy efficiency. Personal systems are carried and interact with other devices and people on an ad-hoc basis.

There are many applications for pervasive computing technologies, in a wide variety of fields. Infrastructure systems have been developed to monitor the elderly in specially designed residences. Not only does this assist elderly caretakers, but also gives residents more freedom. Wearable computers coupled with a database infrastructure allow warehouse workers to easily inventory incoming and outgoing goods. Portable devices with wireless connectivity can offer location-specific information to tourists and residents, for example, listing all fast-food restaurants within three blocks.

Most challenges of pervasive computing fall into five main classifications: attention, complexity, privacy, security, and extensibility. Other challenges in pervasive computing include the way social interaction is changed because of technology,''' methods for evaluating pervasive computing applications, development cycle issues,' the semantic Rubicon, costs, and hardware and software limitations (such as size and weight, energy use, user interface, and "disappearing software").[3]

In the study of pervasive systems and their components, there are consistent messages from public users concerning privacy and security. The advantage of pervasive computing is that computers are transparently integrated into people's lives, but this benefit raises the fear: what exactly are the computers doing? Research has found that people are generally willing to accept invasive technologies if the benefits are thought to outweigh the risks. It follows, then, that in order for a person to make this judgment, they must first fully understand both benefits and risks. Awareness of benefits and risks is a challenge for developers to show users, especially since pervasive computing is meant to be transparent in its workings.

Development of real-world applications of pervasive computing requires teams with diverse backgrounds in the fields of computer science, computer and electrical engineering, human-computer interaction, and psychology, among others. Before computers will be spread pervasively throughout environments, transparently integrating themselves as an extension of human ability, many of technical, psychological, and ethical challenges remain. However, in applications where user privacy and security are not at high risk, systems are already being implemented.

2. Overview of situation identification in pervasive computing

For clarity we shall define some of the terms that will appear frequently later. Sensor data encompasses raw (or minimally processed) data retrieved from both physical sensors and 'virtual' sensors observing digital information such as user calendars and network traffic.

This data is aggregated to form context – the environment in which the system operates, understood symbolically – which may be further sub-divided into context derived directly from sensors (primary context) and that inferred and/or derived from several data streams (secondary context). An important form of secondary context is activities representing small, higher-level inferences about contextual information, such as the activity of 'chopping' derived by observing motion over time [4]. Finally, a situation is an abstraction of the events occurring in the real world derived from context and hypotheses about how observed context relates to factors of interest to designers and applications. Situations typically fuse several sources of context, as well as domain knowledge, and spatial and temporal models of the expected behavior of the phenomena being observed.

2.1. Sensors and sensor data

Service provision of a pervasive computing system relies on the perception of an environment, supported by a range of sensors. Sensing technologies have made significant progress on designing sensors with smaller size, lighter weight, lower cost, and longer battery life. Sensors can thus be embedded in an environment and integrated into everyday objects and onto human bodies. Sensors in pervasive computing can capture a broad range of information on the following aspects [2]:

- ❖ Environment: temperature, humidity, barometric pressure, light, and noise level in an ambient environment and usage of electricity, water, and gas;
- ❖ Device: state of devices (such as available or busy), functions of devices (such as printing or photocopying), the size of memory, the resolution of screen, or even embedded operating systems;
- ❖ User: location, schedule, motion data like acceleration of different parts of bodies, and biometrical data like heart rate and blood pressure;
- ❖ Interaction: interacting with real objects through RFID and object motion sensors [5], and interacting with devices through virtual sensors like monitoring frequencies of a user using his keyboard and mouse [6,7].

The diversity of sensors leads to high complexity in interpreting their output, including huge data volumes, different

modalities, inter-dependence, real-time update, and critical ageing. In dealing with the real world, these sensors typically produce imperfect data. Noisy sensor data may result in misunderstanding of a user's or an environmental state, which will lead to incorrect application behavior. These sensors also have their own technical limitations, are prone to breakdown, or may be disconnected from the sensor network or be vulnerable to environmental interference. This leads to the uncertainty issue of sensor data, which can be out of date, incomplete, imprecise, and contradictory with each other [8]. These features of pervasive sensor data complicate the process of making themselves immediately understandable or usable to applications. A pressing challenge is therefore how to use them in recognizing patterns that could give us a better understanding of human interactions with an environment [9]. Different sensors produce different types of sensor data, including binary, continuous numeric, and featured values. The types of data will have an impact on techniques chosen to analyze them. A binary value is the simplest type of sensor data: true (1) or false (0). RFID sensors produce a binary reading: an object with an RFID tag is detected by a reader or not; or a binary-state sensor developed in the University of Amsterdam [10] produces 1 when it is fired. Continuous numeric values are produced by most sensor types, including positioning sensors, accelerometers, and all the ambient sensors.

Featured values are typically produced from relatively more sophisticated sensors such as a camera and an eye movement tracker, whose data needs to be characterized into a set of categorical measurements. For example, motion features can be extracted from video streams recorded in cameras, including quantity of motion and contraction index of the body, velocity, acceleration and fluidity [11]. Eye movements captured in electrooculography signals are characterized into two types of features: saccades that are the simultaneous movement of both eyes in the same direction and fixations that are the static states of the eyes during which gaze is held upon a specific location [12]. Table 1 summarizes the commonly used sensors and their types of sensor data.

2.2.1. Features of situations

A situation is a subjective concept, whose definition depends on sensors in a current system, which decide available contexts used in a specification; on the environment where the system works, which determines the domain knowledge to be applied (e.g., a spatial map); and on the requirement of applications, which determines what states of affairs are interesting.

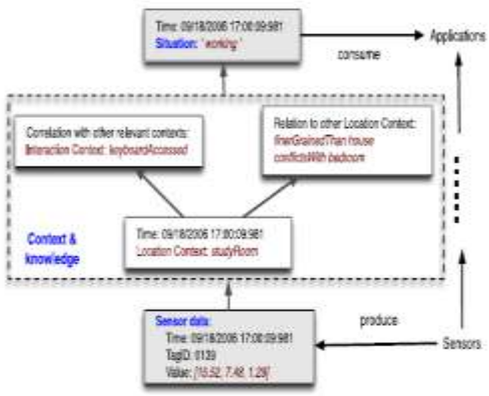

Fig. 1. Information flow in pervasive computing.

The same sensor data can be interpreted to different situations according to the requirements of applications. For example, based on the location data for a number of users, we can define (1) user-centered situations (meeting — the users are gathering in a meeting room), and (2) location-centered situations (occupied — a room is occupied). A situation is a particular state that is abstracted from sensor data and is interesting to applications so that certain actions can be taken when this situation is occurring.

What distinguishes situations from activity, and situation recognition from activity recognition, is the inclusion in situations of rich temporal and other structural aspects, including time-of-day — a situation may only happen at a particular time of the day; duration—it may only last a certain length of time; frequency—it may only happen a certain times per week, and sequence — different situations may occur in a certain sequence. A situation can be a simple, abstract state of a certain entity (e.g., a room is occupied), or a human action taking place in an environment (e.g., working or cooking). A situation can also be composed of or abstracted from other finer-grained situations; for example, a 'seminar' situation includes the finer situations like 'presentation', 'questioning', and 'group discussion'.

Rich relationships exist between situations, including: Generalization A situation can be regarded as more general than another situation, if the occurrence of the latter implies that of the former; for example, a 'watching TV' situation is considered more specific than an 'entertainment' situation, because the conditions inherent in the former situation subsume or imply the conditions in the latter situation [15].

Composition A situation can be decomposed into a set of smaller situations, which is a typical composition relation between situations. For example, a 'cooking' situation is composed of a 'using stove' situation and a 'retrieving ingredients' situation. McCowan et al. propose a two-layered framework of situations: a group situation (e.g., 'discussion' or 'presentation') is defined as a composition of situations of individual users (e.g., 'writing' or 'speaking') [16]. Dependence A situation depends on another situation if the occurrence of the former situation is determined by the occurrence of the latter situation. Dependence can be long- or short-range, as proposed by [17]. Sometimes long-range dependence can be more useful in inferring high-level situations. For example, a situation 'going to work' may be better in inferring a situation 'going home from work' than other short-range dependent situations. Contradiction Two situations can be regarded as mutually exclusive from each other if they cannot co-occur at the same time in the same place on the same subject; for example, a user cannot be in a cooking situation and a sleeping situation at the same time.

Temporal Sequence A situation may occur before, or after another situation, or interleave with another situation; for example, 'taking pill' should be performed after 'having dinner' [18].

3. Research topics on situation identification

In pervasive computing, the principal research topics on situation identification involve the following issues:

- Representation how to define logic primitives that are used to construct a situation's logical specification.
- Specification how to form a situation's logical specification, which can be acquired by experts or learned from training data;
- Reasoning how to infer situations from a large amount of imperfect sensor data; how to reason on situations' relationships; and how to maintain the consistency and integrity of knowledge on situations.

Unlike the well-known situations used in the Natural Language Processing domain, situations in pervasive computing are highly related to sensor data, domain knowledge on environments and individual users, and applications. As discussed in the above sections, sensor data occur in large volumes, in different modalities, and are highly inter-dependent, dynamic and uncertain. Situations are in a rich structural and temporal relationship, and they evolve in diffuse boundaries. In addition, the complexity in domain knowledge and applications makes studying situations a very challenging task. In representation, logical primitives should be rich enough to capture features in complicated sensor data (e.g., acceleration data), domain knowledge (e.g., a spatial map or social network), and different relationships between situations. Also a pervasive computing system is assumed to be highly dynamic in the sense that it might introduce new sensors that yield new types of context, so the logical primitives should be flexibly extensive; that is, new primitives will not cause modifications or produce ambiguous meanings on existing ones [19]. In specification, it is difficult for experts to locate relevant contexts to a situation, decide their different contribution weights (i.e., to what degree the contexts contribute to identifying a situation), and quantify their uncertainty measurements (i.e., to what degree the input sensor data validate the contexts). In reasoning, one of the main processes is called situation identification — deriving a situation by interpreting or fusing several pieces of context in some way. The performance of reasoning is usually undermined by the complexity of the underlying sensor data.

The diversity of applications complicates these issues even more. One of the main requirements of a pervasive computing system is to deliver correct services to the correct users at the correct places at the correct time in a correct way. It is assumed that a system should host a large number of applications that can be finely tuned for different situations. This requires a situation model to support evolution of situations' specifications and to be able to maintain consistency between original and evolving specifications. These applications can also have different degrees of significance to the system, user, or environment. Some applications can only be triggered if a situation is critical and the confidence of identifying this situation is high; for example in a smart home environment, an application could be to make the emergency call when the house is in a fire or electrical accident or the occupant suffers a heart attack. This type of application will be triggered if these hazardous situations are inferred, even if inferred with a lower confidence relative to other situations. The situation model must not only be able to handle uncertainty, but also be informative about inference results; that is, what situations are most likely to happen while what situations are possible or impossible to happen [20]. This section has introduced the basic elements of information flow in pervasive computing: sensors, contexts, situations, and applications. It has described the research on situation identification and the impact of the characteristics of sensors and applications on this research. In the following, we will provide an overview of the existing techniques that have been popularly applied in the research on situation identification.

4. Situation identification techniques

Situation identification techniques have been studied extensively in pervasive computing, and here we highlight those techniques we consider to show the most promise. Fig. 2 shows the development of the situation identification techniques and their correlation to the increasing complexity of problem descriptions.

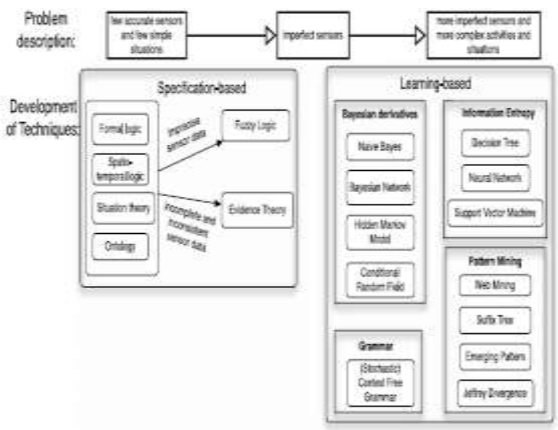

Fig. 2. Development of the main situation identification techniques corresponding to the increasing complexity of problem descriptions.

4.1. Specification-based approaches

In the early stages, situation identification research starts when there are a few sensors whose data are easy to interpret and the relationships between sensor data and situations are easy to establish. The research consists mainly of specification based approaches that represent expert knowledge in logic rules and apply reasoning engines to infer proper situations from current sensor input. These approaches have developed from earlier attempts in first-order logic [21,22] towards a more formal logic model [20] that aims to support efficient reasoning while keeping expressive power, to support formal analysis, and to maintain the soundness and completeness of a logical system. With their powerful representation and reasoning capabilities, ontologies have been widely applied [23–25,19]. Ontologies can provide a standard vocabulary of concepts to represent domain knowledge, specifications and semantic relationships of situations defined in formal logic approaches. They can also provide fully fledged reasoning engines to reason on them following axioms and constraints specified in formal logic approaches.

As more and more sensors are deployed in real-world environments for a long term experiment, the uncertainty of sensor data starts gaining attention. To deal with the uncertainty, traditional logic-based techniques need to be incorporated with other probabilistic techniques [26]:

$$certainty = \sum_{i=1}^{n} w_i \mu(x_i) \qquad \textbf{(1)}$$

where certainty is the certainty associated with an inferred situation, n is the number of conditions that contribute to identification of this situation, wi is the weight on a certain condition, and μ(xi) is the degree that the condition is satisfied by the current sensor data. The above general formula uncovers two issues in situation identification. First, the satisfaction of a condition is not crisply either true or false, which should take into account the imprecision of sensor data. Fuzzy logic, with its strength in dealing with imprecision, has been applied to solving this issue [27]. Second, not every condition contributes to identifying a situation to the same degree, so the problem becomes how to identify the significance of each evidence, how to resolve conflicting evidence, and how to aggregate evidence. Evidence theories like Dempster–Shafer theory have been used to solve this problem [28,29].

4.2. Learning-based approaches

Moving towards the right hand side of Fig. 2, advances in sensor technologies boost the deployment of a broad range of sensors, which however undermine the performance of specification-based approaches. It is less feasible to only use expert knowledge to define proper specifications of situations from a large number of noisy sensor data. To address this problem, techniques in machine learning and data mining are borrowed to explore association relations between sensor data and situations. A large amount of the research has been conducted in the area of activity recognition in smart environments recently.

A series of Bayesian derivative models are popularly applied, including naïve Bayes [30,31] and Bayesian networks [32,22] with the strength in encoding causal (dependence) relationships, and Dynamic Bayesian Networks [33], Hidden Markov Models [34,35] and Conditional Random Fields [36,10] with the strength in encoding temporal relationships. Inspired from the language modelling, grammar-based approaches like (stochastic) context free grammars are applied in representing the complex structural semantics of processes in hierarchical situations [37–39]. Decision trees [40,5], Neural Networks [41], and Support Vector Machines [42,43] as another branch in machine learning techniques, which are built on information entropy, have also been used to classify sensor data into situations based on features extracted from sensor data.

Even though the above learning techniques have achieved good results in situation identification, they need a large amount of training data to set up a model and estimate their model parameters [44]. When training data is precious, researchers are motivated to apply web mining techniques to uncover the common-sense knowledge between situations and objects by mining the online documents; that is, what objects are used in a certain human activity and how significant the object is in identifying this activity [45–47]. Some unsupervised data mining techniques have been applied as well, including suffix-tree [48,49] and Jeffrey divergence [50,51].

5. Open research questions

In studying situations, researchers are more and more interested in recognizing interleaved situations where more than one user are involved or more finer-grained temporally overlapping situations are involved. Because of the rich structure, hierarchical HMMs are the most popular technique that is used in identifying such complex situations [9]. However, the complexity of computation also increases greatly with the complexity of the structure. Currently, an underlying assumption of situation identification is that situations are pre-defined in specification based approaches or pre-labelled in supervised learning-based approaches. When it comes to short, non-repetitive, and unpredictable situations while significant to applications (like a heart attack), it would be difficult to spot them [154]. For continuous situations, it is still challenging in mining implicit and noncontiguous temporal sequences between them and detecting boundaries where situations change.

As a bridge that links sensor data to applications, a situation model should not only be able to predict situations, but also to provide insights on how a system infers situations, and on how sensors perform, which is called intelligibility in [155,88]. By analysing formed logical specifications of situations, developers can learn which sensors are better in recognizing a certain situation, how users behave or interact with sensors. The ability of users to understand system decision making in order to develop a mental model of the system is critical to its acceptance. Therefore, a challenge is to ensure that situation models are sufficiently informative and transparent to enable intelligibility. Current research has largely focused on data sets collected in research labs or by environments occupied by researchers. When real-world environments are used, more complexities appear, such as situation interruption, multi-tasking, multiple users, and unexpected user behaviour, as described by Logan et al., where they look at activity monitoring in a smart home. As part of this problem, the research community will need to examine new measures for evaluating which reasoning techniques should be used. At present, the focus is on classification accuracies using traditional machine learning measures; that is obtaining the 'right' answer for as many instances, akin to classifying static knowledge such as documents. But in pervasive environments, situations are dynamic, of varied duration, sequential, interleaved; and application behaviours and transitions need to be smoothed and controlled. For example, rather than checking the proportion of a situation correctly recognised, it may be more useful to check whether an activity was detected at all over a period of time; e.g. in a monitored smart home, did the user prepare breakfast today at all? Boundaries between situations may be important for health applications [5]; for example, whether a person's heart rate has moved from normal to high within a certain period of time. For the next phase of research, researchers should examine what real-world complexities need to be addressed, and what new measures should be considered for evaluation in the future.

One of the challenges in pervasive computing is the requirement to re-create a model of each new environment in which an application will reside. An activity monitoring application, for example, may need to cater for different sensors, different user behaviours and so forth when applied across different homes. With machine learning approaches, training data must be collected for any change in environment. This issue of 'transfer learning' [156] addresses the problem of how to use annotated training data from one environment to label training data from another environment. This is an important issue for machine-learning techniques in order to avoid the costly collection and annotation of data sets for each application environment.

6. Conclusion

In this paper we have described the state-of-the-art research in situation identification in pervasive computing. This research is challenged by the complexity of pervasive computing in terms of highly sensorised environments and contextual applications customized to a variety of factors. We have discussed different aspects of situation research: representation, specification, and reasoning, and have elicited the requirements and challenges in each aspect. Wehave introduced the existing techniques in recognizing situations, and compared them against the qualitative metrics. Based on the analysis, we suggest a hybrid approach of specification- and learning-based techniques, where a specification based technique is responsible for knowledge representation and sharing while a learning-based technique is responsible for deriving new knowledge and dealing with uncertainty in sensor data. In the end we also discuss some open research opportunities in the area of situation identification.

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