Human-Behaviour Study with Situation Lattices

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Abstract—Most research in the area of smart environments focuses on improving the accuracy with which human activities can be recognised. Relatively little research has been done into how designers can gain insights into the behaviours their systems are observing, and feed these insights back into improving systems design. We describe a mathematical structure, the situation lattice, and show how it can be used to discover knowledge about activities and the way in which they can be sensed. We show how this knowledge can be used to improve activity recognition, using the example of a real-world smart home data set.

Index Terms—Smart home, Human Behaviour, Knowledge Discovery

I. INTRODUCTION

Studying human behaviours in a smart environment has been a popular research area over years. One of the typical topics in this area is activity recognition; i.e., recognise human activities from raw sensor data. It has been shown that the ability to correctly identify the day-to-day activities of subjects may have significant implications and applications in human-beneficial areas; e.g., healthcare [1].

Raw sensor data collected in a smart environment include environmental information (e.g., temperature or humidity), interaction information between a subject and objects being used or accessed by the subject (e.g., Radio-frequency IDentification, called RFID), and personal information about the subject (e.g., heart rate). The daily activities are pre-defined with developers’ common sense knowledge in a descriptive manner. For example in the PlaceLab data set [2], an activity “using phone” is defined as using a portable phone or the phone on the fax machine in the office; and an activity “grooming” is defined as getting dressed or undressed, or styling hair. Following these definitions, developers (or the third party or the subject) annotate what a subject is doing from recorded video [2] or audio [11], which will serve as the ground truth for the evaluation of an activity recognition technique; e.g., its accuracy or efficiency.

The process of activity recognition is encapsulated in a black box, where sensor data are input and human activities are inferred as output (shown in Figure 1). The main research focuses on how to efficiently and accurately infer activities. Beyond this research, we are also interested in the underlying research questions:

1) What is an activity pattern from the perspective of sensors; that is, what do sensors (or sensor data) contribute to determining this activity? This question will build up experience for other smart home set-ups.

2) Are activities accurately defined? An accurate definition of an activity means that the pattern of this activity can be described in characterised sensor data according to this definition. A daily activity is intrinsically imprecise so it is difficult to be described precisely. In the above example, “grooming” is not accurately defined, since it covers “styling hair”, which is hardly captured by sensors and thus is not related to any distinguishable sensor data. The imprecise definition of an activity could make unidentifiable some more specific activities that should be recognisable (e.g., getting dressed or undressed). It could also undermine the effect of an activity recognition technique since the technique might try to extract characteristics of an activity that are hardly tractable. Developers need an approach to evaluate their description on activities.

3) What activity does a subject usually conduct given particular sensor data (e.g., the subject is detected in the kitchen)? This question is about deriving the usual pattern of a subject’s everyday activities, which will help to spot abnormal behaviours. For example, a subject could be inferred “sleeping” in the kitchen, which violates his activity patterns, so the subject might actually pass out—in an emergent situation.

4) What relationships do exist between different activities; That is, what activities are subsumed by an activity, or what activities the subject cannot conduct simultaneously? This question can improve the accuracy of a recognition process, and can provide guidance on designing activity-aware applications.

This paper will describe a situation lattice that can be used to address the above research questions by making transparent the knowledge in the activity recognition process. The situation lattice has been used in recognising activities in a
smart home environment and the produced evaluation result is promising [3]. This paper will demonstrate the use of the lattice in exploring human activity patterns. The demonstration will use the lattice built on the PlaceLab data set, the public data set that is gathered in the real-world smart home environment [2]. This lattice [3] covers the following sensors: the wireless infrared motion sensors, electrical current, water, and gas flow sensors, switch sensors, RFID, and object motion sensors.

This paper is organised as follows. Section II reviews the literature in the activity recognition area. Section III introduces the basic theoretical concepts in a situation lattice, which are used to extract activity pattern and explore semantics of activities in Section V. Section VI concludes with some future directions.

II. RELATED WORK

Machine learning (or data mining) techniques have been widely used in activity recognition, including decision tree [4], [2], [5], Bayesian inferencing [6], [7], Hidden Markov Models (HMMs) [8], [9], and Conditional Random Fields (CRFs) [10], [11].

Bao et al [4], [5] use decision trees to learn user body motions (such as bicycling, shaking hands, or typing) from the raw sensor data provided by accelerometers on the human body. Van Kasteren et al [7] carry out activity recognition using a Bayesian framework. They use a static Bayesian model to learn the relationship between different sensor data and human activities, and also use a dynamic Bayesian network to model the temporal aspects of activities. Bui et al [6] use a multi-layer Bayesian dynamic structure, called an Abstract HMM, to track an object and predict its future trajectory in a wide-area environment. This structure is used to explicitly encode the complex and scalable spatial layout; i.e., the hierarchy of connected spatial locations. Trained with coordinate-based location data, it can predict the evolution of the object’s trajectory at different levels of detail.

Modayil et al [12] use interleaved HMMs to recognise multi-tasked activities where a person switches frequently between steps of different activities such as making a stir-fry, making a jello, and drinking a glass of water. The interleaved HMM records the last object observed from wrist-worn RFID sensors for each activity as a hidden state.

Liao et al [10] employ CRFs to construct models of high-level activities such as work, leisure, and visit. They use a person’s GPS data to learn his activities over a few weeks, and then determine the relationship between the activities and places that are important to this person.

All these works make effort on improving the accuracy of inferring human activities from a number of advanced sensors (mostly on-body motion sensors). However, the knowledge discovered in these techniques is barely usable other than inferring activities. For example, decision tree is assumed to be able to represent the knowledge into rules, but the rules are sometimes not understandable since they could be contaminated by much noise in the sensor data. Our earlier work has used the C4.5 decision tree in Weka software [13] to learn human activities from raw sensor data [3]. The derived rules do not follow the human natural understanding of the activities. The reason is that decision tree learns the knowledge simply based on the characteristics of data while no domain knowledge is involved. When the data are imperfect, then the knowledge would be inaccurate.

In contrast, the situation lattice will allow developers to represent their domain knowledge; that is, the knowledge about sensors and environments. Incorporating this knowledge in a training process, the lattice can learn more knowledge about sensor data and human activities. Since the newly discovered knowledge is constrained by domain knowledge, it will make more sense and be useful in studying human behaviour patterns.

III. INTRODUCTION TO SITUATION LATTICES

This section will briefly introduce the basic concepts in a situation lattice, which provides the foundation for the following sections. A more detailed theoretical description can be found in our earlier work [14], [3].

A. Theoretical Model of Situation Lattices

A situation lattice is built on the basic concepts of lattice theory. It is used to study the relationship between sensor data, and relationships between activities and different types of sensor data. Within a situation lattice, sensor data are abstracted in characteristic functions, called context predicates in our work. The lattice consists of a set of nodes, each of which represents a logical description of context predicates, which takes context predicates as input and applies the logical conjunction on them. Each node is associated with a set of activities, which implies that when the logical description on this node is satisfied by the current sensor data, a user is possibly conducting any of the activities in this set.

All nodes are organised with a specialisation relationship. A node $n_i$ is considered more specific than another node $n_j$, labelled as $n_i \sqsubseteq n_j$, if and only if the logical description on $n_i$ entails that on $n_j$. The specialisation relationship implies that a node will be activated if and only if all its more general nodes are activated.

Context predicates can have rich relationships, including different levels of abstraction level, conflicting, and overlapping [15]. A situation lattice supports representing these relationships and uses them to explore semantic relationships between human activities.

Given two context predicates $p_i$ and $p_j$ and their corresponding nodes $n_i$ and $n_j$ such that $n_i.l = p_i$ and $n_j.l = p_j$, where $n_i.l$ represents a logical description on a node $n_i$,

- If $p_i$ is finer grained than $p_j$, then $n_i \sqsubseteq n_j$. The different levels of granularity is defined as: a context predicate $p_i$ is finer grained than another predicate $p_j$, if any sensor data that satisfies the former context predicate also satisfies the latter one. For example in Figure 2 (a), the context predicate inLivingRoom is finer grained than the predicate inHouse, since the living room is contained in the house.
Fig. 2. Semantic relationships between context predicates

- If $p_i$ conflicts with $p_j$, then $n_i \cap n_j = n_\bot$, where $\cap$ is the meet operator and the bottom node $n_\bot$ is the unique node whose logical description is the logical contradiction FALSE [3]. The conflicting is defined as: two context predicates are conflicting if any sensor data that satisfies one of them cannot satisfy the other. For example in Figure 2 (b), the context predicate inLivingRoom is conflicting with the predicate inBedRoom, since they are spatially disjoint.

- If $p_i$ is overlapping with $p_j$, then $n_i \cap n_j = n_k$, where $n_k$ is the overlapped predicate. The overlapping is defined as: two context predicates are overlapping if they can be satisfied at the same time by certain sensor data, but there exists sensor data that satisfies one of them but not the other. For example in Figure 2 (c), the context predicate inLivingRoom overlaps with another predicate inDiningRoom, since they share a common location – the foyer. If two context predicates are overlapping, the more specific node under their corresponding nodes is the node with their overlapped logical description; e.g., inFoyer.

With these predicates and their semantics, a situation lattice can be completed [3]. A built situation lattice organises the context predicates and their combinations in an ordered hierarchy. Each of them is labelled with activities and their occurrence ratio: when a combination of context predicate is satisfied by the current sensor data, then any associated activity can be occurring with a certain likelihood. For example, a set of activities \{“watching TV” 0.8, “reading” 0.7\} could be associated on the node inLivingRoom $\land$ elecCurrentInLivingRoomOn, which means that when these predicates are satisfied, then the subject is watching TV with the possibility 0.8 and is reading with the possibility 0.7. Figure 3 represents part of a situation lattice built on the PlaceLab data set.

In the lattice, the basic semantics between context predicates are automatically preserved on nodes that contain them. Given two predicates at different levels of granularity: e.g., their preliminary nodes $n_i \subseteq n_j$, when combined with another node $n_k$ whose predicate has no relationship with these two, then their compound nodes $n_i \otimes n_k$ and $n_j \otimes n_k$ preserve different levels of granularity: $n_i \otimes n_k \subseteq n_j \otimes n_k$. If two predicates conflict, then any two compound nodes that contains each of them will conflict with each other.

IV. QUERYING ACROSS MULTIPLE LEVELS OF ABSTRACTION

A situation lattice can be used to observe human activities from the perspective of sensors, which can help developers to understand activity patterns of the user and thus spot abnormal activity (e.g., “passing out”). To achieve this, the lattice supports a broad range of queries that involve characteristic sensor data in single or different types and across different levels of abstraction, such as \textit{“what does the subject usually do in the living room?”}, \textit{“what does he do at 21:00 in the living room with its light on and its current flow off?”}, and even \textit{“what does he do in the foyer (part of the living room)?”}.

Situation lattices facilitate answering these queries. The process is similar to the activity recognition process in the lattice [3]. In a query, characteristic sensor data are mapped to a preliminary node, and a compound node whose logical description matches all the sensor data will be located. Developers can check the activities that are associated on the node. For example in the PlaceLab data set, the query \textit{“what does the subject usually do in the living room?”} can be simply answered by checking the preliminary node whose context predicate is inLivingRoom. The result will contain activities and their occurrence likelihood; that is, \{“watching TV” 0.5, “eating” 0.46, “using phone” 0.23, “using computer” 0.08, “reading” 0.08, “grooming” 0.14 \}. This result provides the insight about the subject’s activity pattern: when he is in the living room, he is more likely to watch TV, eat, or use phone, but he does not sleep or prepare a meal there.

Take another example of a query \textit{“what does he do at 21:00 in the living room with its light on and its current flow off?”}. This query consists of four parts: a time predicate – 21–22, a location predicate – inLivingRoom, and two current predicates – lightInLivingRoomOn and elecCurrentInLivingRoomOff. A compound node will be located, which represents the conjunction of these four predicates. Its activities are \{“using phone” 0.03, “using computer” 0.002, “reading” 0.007, “eating” 0.005\}. Combined with the result on the former query, this result uncovers that the subject is impossible to watch TV when the electrical current in the living room is off.

The situation lattice is an effective tool to observe human activity pattern from the view of sensors by supporting these rich queries. A query with a single type of sensor data or multiples types of sensor data will be easily executed on the lattice. It does not need to re-train the structure or execute any other complicated process, while most machine-learning techniques and rule-based system will do.

V. DERIVING SPECIFICATIONS AND RELATIONSHIPS BETWEEN ACTIVITIES

Section IV studies the typical activity recognition process by observing activities from sensor data: what activity does a user usually conduct given the sensor data? This section will

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1 Given two nodes $n_i$ and $n_j$, their compound nodes is labelled as $n_i \otimes n_j$ such that $(n_i \otimes n_j)_k = n_i \otimes n_j$. 

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explore activity patterns by observing sensor data from particular situations: how sensor behaves when a user is conducting this activity? A more specific question could be “what time does a user usually prepare a meal?”. The activity pattern will be helpful in accumulating experiences on choosing sensors to build a smart home environment, providing feedback on defining activities, and studying semantics between activities.

A. Specification of Activities

A situation lattice supports deriving a specification for an activity. An activity’s specification is a logical description that takes context predicates as input and applies logical operators (disjunction, conjunction, and negation) on them. An activity is considered being conducted if its specification is satisfied by current sensor data.

Given a built situation lattice with $N$ nodes, there exists a set of the most specific nodes (except the bottom node) $N_s \subseteq N$ whose activity set contains a certain activity $s$. The specification of this activity $s$ is generated by applying the logical operator OR on the logical description of these nodes $N_s$. That is, a specification of $s$ is $\bigvee_{i=1}^{m} n_i.l$, where $\{n_1, n_2, \ldots, n_m\} = N_s$. Algorithm 1 describes the procedure of locating the most specific nodes related to a situation. To check whether a node is the most specific node, we simply check that no other node except the bottom node is more specific than this node. Algorithm 2 applies the OR operator on all the logical descriptions from the most specific node set.

Algorithm 2 works when the size of a situation lattice is small. When the size is relatively large, a specification of an activity can be tedious. For example, the situation lattice built on PlaceLab data set consists of 27647 nodes, among which 3423 are the most specific nodes. Thus, an activity’s specification might contain a disjunction of conjunct context predicates from hundreds of the most specific nodes. Among these nodes, it is possible that a subset of them are all the immediately more specific nodes from a more general node. The specification can be simplified by replacing these subset of nodes with the more general node. For example in Figure 4 (a), for an activity, a subset of its most specific nodes $n_1, n_2, \ldots, n_i$ are all the children nodes under the same more general node $n_j$, then in this activity’s specification $l$, the subset of nodes can be replaced with $n_j$; while in (b), they cannot since the subset nodes do not cover all the children nodes of $n_j$. Algorithm 3 describes the process of refining an activity’s specification from its most specific node set.

Algorithm 3 simplifies the expression of a situation’s specification greatly with increased complexity $O(n^3)$, where $n$ is the size of $N_s$. We use these algorithms on the situation lattice of the PlaceLab data set, and derive specifications of activities.

Fig. 3. Part of a situation lattice built on the PlaceLab data set

![Diagram of a situation lattice](image)

**Algorithm 1**: Locating all the most specific nodes for a situation

<p>| input: a situation $s$ and a trained lattice $(N, \sqsubseteq)$ |</p>
<table>
<thead>
<tr>
<th>output: a set $N_s$ of the most specific nodes that contributes to identify $s$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_s = \emptyset$</td>
</tr>
<tr>
<td>foreach Node $n \in N$ do</td>
</tr>
<tr>
<td>if $s \in n. S$ then</td>
</tr>
<tr>
<td>$IsMostSpecific = \text{TRUE}$</td>
</tr>
<tr>
<td>foreach Node $n' \in N$ do</td>
</tr>
<tr>
<td>if $n' \neq n \land n' \neq n \land n' \sqsubseteq n$ then</td>
</tr>
<tr>
<td>$IsMostSpecific = \text{FALSE}$</td>
</tr>
<tr>
<td>if $IsMostSpecific$ then</td>
</tr>
<tr>
<td>$N_s. add(n)$</td>
</tr>
<tr>
<td>return $N_s$</td>
</tr>
</tbody>
</table>

**Algorithm 2**: Defining a specification for a situation

<p>| input: a set $N_s$ of the most specific nodes that contributes in identifying $s$ |</p>
<table>
<thead>
<tr>
<th>output: a specification of $s$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$specification = \text{FALSE}$</td>
</tr>
<tr>
<td>foreach Node $n \in N_s$ do</td>
</tr>
<tr>
<td>$specification = specification \lor n.l$</td>
</tr>
<tr>
<td>return $specification$</td>
</tr>
</tbody>
</table>

2In this algorithm, $n! \sqsubseteq n_p$ means that $n$ is the immediately child node under $n_p$. 

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Some of the activities have a relatively small number of nodes in that they have a tractable activity pattern. For example, the activity “hygiene”, its specification is listed as follows:\(^3\):

```
hygiene = (inPowderRoom ∧ 18-19
 ∧ waterInPowderRoomOff
 ∧ lightInPowderRoomOff
 ∧ nothingInPowderRoomAccessed)
∨ (inBedroom ∧ 23-24
 waterInBathroomOff ∧
 lightInBathroomOn)
```

Some of the activities are associated with a large number of the most specific nodes. For example, “using phone” has 245 most specific nodes, since the subject could use phone anywhere at any time. Part of its specification is listed as follows:

```
using phone = inLivingRoom ∧
((elecCurrentInLivingRoomOff ∧
 nothingInLivingRoomAccessed ∧
 16-18) ∨ (lightInLivingRoomOn ∧
 (((18-19 ∨ 20-21) ∧
   remoteControlAccessed) ∨
   nothingInLivingRoomAccessed ∧
   18-20)))
```

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 nothingInLivingRoomAccessed ∧
 16-18) ∨ (lightInLivingRoomOn ∧
 (((18-19 ∨ 20-21) ∧
   remoteControlAccessed) ∨
   nothingInLivingRoomAccessed ∧
   18-20)))
```

By examining the specifications of the activities, developers can have an intuition on what sensors are useful in recognising an activity. For the activity “hygiene”, the most effective sensor is probably a positioning sensor that could detect the subject in the powder room or the bath room. Also the number of most specific nodes on each activity can reflect the accuracy of its descriptive definition; that is, a large number of nodes suggests that either this activity occurs frequently (e.g., the activity “using a computer” has 395 most specific nodes, and it occurs in 20.14 hours, 42.9% of the time through the data set) or this activity is less tractable. Under the latter circumstance, developers might need to refine its descriptive definitions by removing trivial activities (e.g., styling hair) or split the activity into sub activities.

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\(^3\) As stated in [3], the PlaceLab involves a couple of subjects and non-person-specific sensors, which introduces extra noise in the data set. Also only the activities on the male subject have been annotated. To compromise the noise, a most specific node is chosen for an activity only if the activity ratio on this node is beyond a certain threshold. Therefore, some nodes could be removed from the specification due to the low occurrence ratio of the activity on them.
B. Semantics of Activities

Based on specifications of activities, we can explore semantic relationships between activities: type-of and conflicting. These two relationships can be inferred from the specifications of activities based on their corresponding most specific node sets. One activity \( s_i \) is a type of another activity \( s_j \), if when a subject is conducting \( s_i \) he is also considered conducting \( s_j \). It requires that for any of the most specific nodes on \( s_i \), there exists at least one most specific node on \( s_j \) such that the node on \( s_i \) is more specific than the node on \( s_j \) (as presented in Definition 1). Thus if a specification of \( s_i \) is satisfied, then the specification of \( s_j \) will be satisfied as well.

Definition 1: \( s_i \) is a type of \( s_j \), iff \( \forall n_k \in N_{s_i}, \exists n'_k \in N_{s_j}, n_k \subseteq n'_k \).

One activity \( s_i \) conflicts with another activity \( s_j \), if it is impossible for a subject to conduct both activities at the same time. It requires that any of the most specific nodes associated with \( s_i \) conflicts with any of the most specific nodes associated with \( s_j \) (as presented in Definition 2).

Definition 2: \( s_i \) conflicts with \( s_j \), if \( \forall n_k \in N_{s_i}, n_l \in N_{s_j}, n_k \cap n_l = n_\bot \).

If two situations share some of the same most specific nodes, then they are likely to occur at the same time when any of these nodes are activated. However, this leads to another question: if one of these nodes are activated, it is possible that both the situations occur, or one of them is occurring while the other is not. For example in the PlaceLab data set, “watching TV” and “eating” can share the same most specific node, whose context predicates are 19–20 \( \wedge \) inLivingRoom. When this node is activated, the subject can be “watching TV” and “eating” simultaneously, or he can be either “watching TV” or “eating”. This issue is related to the discernability of sensors in precisely identifying situations, which has been covered in more details in [3].

We apply the above two definitions on the lattice of the PlaceLab data set. There are no specialisation relationships between the activities. Since the location predicates on each individual rooms conflict with each other, the activities that occur in different rooms should conflict, such as “dishwashing” and “hygiene”. Due to the imprecision of the positioning sensors, the activities that should be conflicting are not inferred as conflicting, such as “watching TV” (in the living room) and “meal preparation” (in the kitchen).

VI. CONCLUSIONS

This paper has demonstrated how the situation lattice is used to study human behaviour patterns. The lattice supports a range of rich queries, which is useful in observing typical activities of a subject such as to spot abnormal activities. The specifications of activities derived from the lattice help to uncover the activity pattern of the subject and indicate the sensors (or sensor data) that contribute to identifying an activity. Based on the specification and semantics of predicates, developers can also extract semantic relationships (i.e., type-of and conflicting) between different activities. The discovered knowledge will provide guidance for other developers on choosing sensors and defining activities in building a smart home environment.

At the current research stage, the situation lattice only supports the conjunction of context predicates, which limits its ability in representing expressive logical descriptions. In the future, we will look into how to make a lattice scale with the other two logical operators: disjunction and negation. Following this, the technique in deriving specifications and semantics of activities will be updated to support more efficient and complicated reasoning.

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