Use Cases for Abnormal Behaviour Detection in Smart Homes

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Abstract. While people have many ideas about how a smart home should react to particular behaviours from their inhabitant, there seems to have been relatively little attempt to organise this systematically. In this paper, we attempt to rectify this in consideration of context awareness and novelty detection for a smart home that monitors its inhabitant for illness and unexpected behaviour. We do this through the concept of the Use Case, which is used in software engineering to specify the behaviour of a system. We describe a set of scenarios and the possible outputs that the smart home could give and introduce the SHMUC Repository of Smart Home Use Cases. Based on this, we can consider how probabilistic and logic-based reasoning systems would produce different capabilities.

Keywords: Abnormal behaviour detection, context awareness, use case, smart home.

1 Introduction

During the last twenty years, the ‘smart’ in ‘smart home’ has become more important [1, 2], with a focus on behaviour recognition and subsequent abnormal behaviour detection. There have been many proposed frameworks and algorithms for behaviour recognition [3], but little discussion of what precisely a smart home that monitors behaviour should do. Here we focus on smart homes for elderly care monitoring, discuss Use Cases that describe a situation, and then propose suitable outputs from the smart home.

Software Engineers specify systems by employing Use Cases to define their features in normal language without any preconception of how the system is implemented. Use Cases specify the participants in the task (the ‘actors’), their (single) goal, preconditions, triggers and postconditions. We believe that applying this methodology to smart homes may help to identify what precisely we desire from a smart home. Informal enough to be understood by naive users and formal enough to be used as system specifications by developers, they are popular with standards bodies and developer communities such as W3C and the OMG consortium [4].

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Independent sets of Use Cases have been used not only in computer science, but also in business to describe business cases to compare and evaluate heterogeneous approaches [5, 6].

Our Use Cases identify abnormal behaviours, and present the reasoning behind the smart home's choice of reaction. They have been selected to identify some of the context awareness and behaviour recognition needed by an intelligent smart home. We have identified some Use Cases and suggest that many in the smart home research community could identify others. We aim to stimulate discussion of the desired behaviours of a monitoring smart home. In this paper, it is impossible to present all the Use Cases we have developed; instead we refer the reader to the online, editable repository at `http://muse.massey.ac.nz/shmuc`, a canonical resource that other researchers can draw upon, add to, and modify.

Use Cases can assist smart home researchers to make principled choices between methodologies such as logic-based algorithms [7–9], and probabilistic machine learning algorithms [7, 10], and to benchmark different implementations: an informed evaluation can be made quickly and easily by testing implementations on the Use Cases.

The Use Cases discussed here focus on detecting abnormal behaviour by the inhabitant. The smart home monitors, identifies behaviours, and isolates those that are unusual. We use the classification of abnormal behaviour presented in [11, 12]: (1) statistical abnormality, (2) violation of socially-accepted standards, (3) based on theory of personal development, (4) subjective abnormality, and (5) biological injury. A behaviour's novelty often derives from its context: using the heater is unusual if the temperature is warm, sleeping is unusual behaviour in the kitchen, etc. Therefore, context awareness is important in the detection of abnormal behaviour, as in much smart home research [13].

2 The Use Cases

In our Use Cases, daughter Debbie has a mother Mary who lives alone, but has dementia. Debbie has decided to set up a smart home system to look after her mother so that she can continue in full-time work. This smart home system aims to detect any unusual actions by Mary and send appropriate alerts to Debbie and Carita, a carer who will check up on Mary if required. Fig. 1 show a taxonomy of six classes of smart home Use Case that we have identified to help Debbie to care for her mother by passively observing Mary and detecting abnormal and potentially dangerous behaviour without 'crying wolf' (i.e., producing false positives) too often. We consider only a small number of possible outputs by the system: (1) do nothing and wait for further data, (2) raise an alarm to alert Mary (3) record a message for Debbie to view later, and (4) send an urgent alert to Carita. For space reasons, we include one example only of each of four of the Use Cases in the repository at `http://muse.massey.ac.nz/shmuc`

2.1 Abnormality in Duration

SHMUC Use Case A1. *An over-long shower*

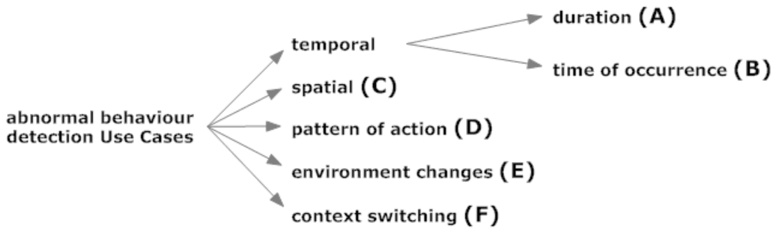


Fig. 1. Classification of the subsets of Use Cases presented in this paper

Goal: To detect an unusually extended activity.
Initial state: Mary was at home alone.
Description: Mary woke up at 0800. She began her morning shower at 0810, as usual, but at 0840 the motion sensor in the bathroom still indicated movement, and the shower tap was still on, so her shower had lasted for 30 minutes.
Norm: Mary normally showers for 10 to 20 minutes.
Outcome: An alert message was sent to Debbie, who called Carita. Carita discovered Mary confused and cold in the shower, having forgotten what she was doing.
System design implications: An excessively long activity may put the smart home inhabitant at risk. This poses the following questions: When does a shower become longer than usual? 1 minute over the average? 5? 10? Or is the amount of overrun relative (1%? 5%? 10%)? Perhaps a more sophisticated statistic is appropriate (>1 standard deviation from the mean).

Note that Use Cases are an informal documentation tool; their structure can best be described as semi-standardised. The structure above is consistent with the spirit of Use Case design, but adapted to suit the particular requirements of Smart Homes. The most notable innovation is the inclusion of a section labelled Norm which presents the 'normal' behaviour that should occur in this case.

There are two other Use Cases in this category, **SHMUC Use Case A2:** A justifiably short shower, and **SHMUC Use Case A3:** A Long Nap. These cases are not presented here in full. A2 demonstrates that some abnormal behaviours must be detected before they are complete if a suitable response is to occur. A3 examines a behaviour where abnormal duration is more difficult to categorise, and demonstrates the high degree of world knowledge that a Smart Home may need if its responses are to be appropriate.

An activity's start time is meaningful: an inappropriate activity start time could imply illness or even dementia, but a forgetful person may only need a reminder to function normally.

2.2 Anomaly in Time of Occurrence

An activity's start time is meaningful: an inappropriate activity start time could imply illness or even dementia, but a forgetful person may only need a reminder to function normally. Use Cases in SHMUC category B concern anomalies in time of occurrence. As with category A, we present one Use Case as an example, and a very brief summary of the others contained in the repository.

SHMUC Use Case B1. *Variation in shower start time*

Goal: To recognise acceptable variation in the start time of an activity.
Initial state: Mary is home alone.
Description: One cold winter morning, Mary awoke at 0800. She decided to wait until 0830 before taking her shower. The system noticed that Mary did not take a shower from 0800 to 0820 as had previously occurred, and generated a reminder for Mary and a warning message for her daughter, Debbie. Mary ignored the reminder, and waited until 0830 as she had intended. After work, Debbie checked the system and recognised that the system had made an incorrect inference that had occurred because it had not observed this activity in the winter. Debbie then provided feedback to the system to update this activity start time.
Norm: Mary's shower starts in the time-range 0800 - 0820.
Outcome: Mary's shower time was accepted at 0830.
System design implications: In general, it is probably safe to assume that activity start times more than 1 standard deviation from the mean are interesting but not inherently problematic behaviours. Therefore it is acceptable to request external (human) input regarding the classification of the behaviour, and it may not be necessary for the Smart Home to rely on pre-loaded world knowledge.

There are currently two other Uses Cases in category B: **SHMUC Use Case B2:** Taking Medicine After Midnight, and **SHMUC Use Case B3:** Late for Church. B2 deals with explicitly scheduled events, and B3 presents a situation in which there is some data that the system cannot possibly know, and which will cause it to reason incorrectly.

As with the abnormal duration, the abnormal start times presented in the three Use Cases in Category B seem easy to detect. However, context and other issues may be important:

i) Some people have quite variable schedules. And even the most regular people, move behaviours from their normal times in response to unexpected events such as an upset stomach. It may be that behaviours will need to be categorised into regular and irregular ones.

ii) Identifying contextual factors may help to increase the detection accuracy. For example, after Debbie's feedback, the start time of Mary's shower would be from 0800 to 0830. However, the system would be more useful if it used the seasonal context to estimate start times: 0800 to 0820 in summer, 0830 to 0850 in winter, updatable as more situations were observed.

iii) As with duration, there are questions about how long the system should wait before issuing an alert and what constitutes a suitable alert. For example, if the system could interact with Mary rather than just raising an alarm, then it could ask her if she had forgotten to go to church, or issue other reminders.

2.3 Performing Activities in the Wrong Places

Performing an action in the wrong place (e.g., jumping on the bed or lying on the kitchen floor) may be dangerous or signify that something has gone wrong. Use Case category C concerns the relationship between an activity's location and abnormal behaviour.

SHMUC Use Case C1. *Lying down in the kitchen*

Goal: To react to some abnormal behaviours immediately, as they are potentially very significant.
Initial state: Mary was at home alone.
Description: At 0815, Mary went to the kitchen to prepare her breakfast. She got some bread and put it in the toaster. She walked around the kitchen while she was waiting, and then suddenly lay down on the floor. The behaviour was recognised, and then the spatial properties of the activity checked. As this behaviour should not be seen in the kitchen, an alert was created, and marked urgent as the behaviour was potentially serious.
Norm: Inhabitants do not lie down in the kitchen.
Outcome: An alert message was sent to both Debbie and Carita.
System design implications: There is a class of activities that fall outside the bounds of normal behaviour and can be prima facie assumed to be both interesting and problematic. This should reduce the computational effort involved in deciding how to react to an observed activity. However, complementing that is the difficulty of foreseeing all possible inappropriate behaviours. It's difficult enough to build a world model that allows for normal behaviours, but the size of the problem is potentially much larger if the system has to detect all possible dangerous abnormal behaviours.

Detecting abnormality of activity spatial property requires the spatial data to be stored by the system and attached to behaviour. In comparison to the previous Use Cases, this is more static; the information does not change frequently.

2.4 Abnormality in a Behaviour Pattern

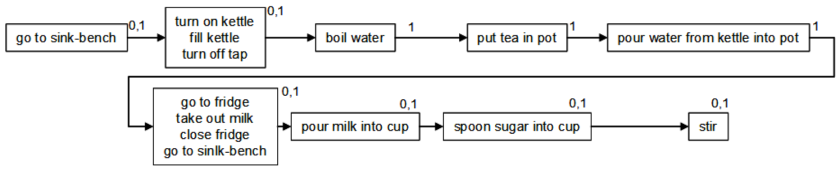
The sensor patterns generated by 'standard' behaviours are variable. Evidence from various smart home datasets suggest that cooking dinner involves between 4 and 58 actions (e.g. MIT Activity Recognition Data, MavLab Sensor Data [14]), and other behaviours exhibit similar variation. In such situations it is difficult to decide what a smart home should be able to detect, and how to avoid false positives. We use tea-making to illustrate the complexity of identifying errors even in simple task.

SHMUC Use Case D1. *Making tea with sugar*

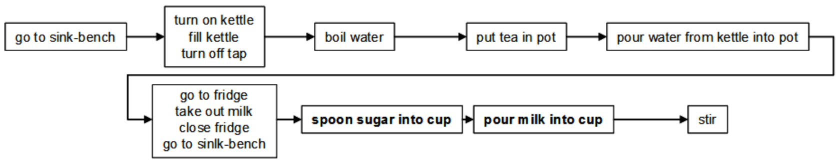
Goal: Mary wishes to make a cup of tea.

Initial state: Mary was at home alone.

Description: During the training phase, the system identified a tea making behaviour that consisted of the following actions (where $[\cdot]_{0,1}$ describes an activity that occurs 0 or 1 times):



After training, this system was ready to monitor Mary's activity. One afternoon Mary made a cup of tea, using the following set of actions:



The system treated this sequence as a novelty, as the items in bold are reversed in order with respect to the syntax created during training. However, it did not cause an immediate alarm, as the system identified that the order of two actions, i.e. "get sugar" and "get hot water", does not affect on the final state of the activity. Therefore, the system did not create an alert, but modified its representation of tea-making instead.

Norm: The tea-making sequence conforms to the syntax specified by the Finite State Machine (FMS).

Outcome: The activity pattern was automatically updated, a notification was issued.

System design implications: Activities often comprise a partially ordered sequence, and there is no guarantee that observation of any number of instances will reveal all the orderings. The system should therefore be able to distinguish between abnormal event sequences and previously unseen, but valid event sequences. The system may be unable to infer this without external input from a competent source (which might rule out the inhabitant, if the inhabitant were dementing).

The Use Cases in category D demonstrate massive potential variation in behaviour presentation and the difference between a 'safe' one and one that demonstrates illness can be subtle. They also highlight differences between using logic-based methods and probabilistic-based methods. The valid but unusual order of tea-making activities in the first scenario, is reasonable, but it can be a challenge to recognise it depending on how behaviours are represented. A Markov-based approach may ignore the difference, while an FSM would have to learn this and store the updated syntax. In order for the learning to be as trivial as suggested by the description in the Use Case, some kind of knowledge-based reasoning system would need to identify the importance of order; clearly removing the cup from the cupboard after the water has been poured would not be valid. A hierarchical knowledge base that associated the essential tea-making goals (dissolving tea in hot water) with the actions required to achieve the individual goals might facilitate this. An alternative could be to use partial orders for the patterns.

3 Discussion and Conclusion

We seek to demonstrate that Use Cases can expose behavioural requirements of a smart home, not to document them all within an 8-page format. Our Use Cases address the following questions: (1) what types of abnormal behaviour may occur? (2) how does the system reason about its inhabitant's behaviour? (3) how should it react to abnormal behaviour? (4) what information should be involved in abnormality detection?

Use Cases are implementation-independent, but they can guide implementation choices between, say, probabilistic methods, and techniques based on symbolic logic and reasoning. They have clarified some of the common types of abnormality. Although we have not addressed some types of abnormality included in the psychological definition of novelty that we reported earlier, those related to biological injury are implicit in some of the use cases that we have presented.

The discussion has identified some ways that smart homes can reason about unusual behaviour. Temporal abnormalities can be detected using statistical analysis of prior observation (e.g. a training phase). Contextual data is also important, but it can conjure up the 'curse of dimensionality', as isolating important factors is a very difficult machine learning problem. We suggest that it may be appropriate to combine statistical machine learning methods and logic, e.g., inductive logic programming [15]. From examples, the system could learn some rules with context awareness: 'Mary usually goes out around 1500 to 1530 at the weekend if she is not sick and it is not raining'. Obviously, this would allow learnt rules to be used to detect abnormality more accurately than current approaches based solely on abnormal start time detection. However, problems of performance remain to be solved for this technique, which is still a research focus for us.

There are also many different approaches to detecting abnormality in behaviour patterns such as Markov models (Hara et al. [7]), and temporal logic (Jakkula and Cook [16]). The above scenarios on abnormal presentation of behavioural patterns show that abnormality in patterns depends on many factors other than the order of actions. We have followed the line of NAF ('negation as failure', i.e. unidentifiable patterns are abnormal), with feedback to teach the system about failed cases that are in fact normal. In addition, the wide variety of normal ways to accomplish a 'standard' task such as making a cup of tea makes isolating an abnormal pattern of observations difficult. The NAF approach is limited, as it relies on complete coverage in the training data. A system that can generalise from examples may compensate for limited training sets.

The Use Cases presented here would be improved by the inclusion of non-functional aspects such as scalability and Total Cost of Ownership; the latter would improve system evaluation and comparison. While it might be easier with a logic-based system to address many of the requirements discussed, such a system would require comprehensive and expensive initial setup work. On the other hand, logic-based systems might be easier to maintain as they offer users reflection and introspection facilities such as explanations (such as derivation logs) and configuration options (such as customising thresholds).

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