Sensor-based Behavioral Monitoring for Early Detection of Cognitive Decline.

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Abstract

The advancement in medical science has increased life expectancy in developed countries, which results in a rise in the elderly population. Consequently, age related health issues are also increasing and aging societies are continuously searching for new technologies to provide better healthcare services to the elderly population. One of the prominent health issues relates to the elderly population is cognitive impairment. The decline in cognitive health does not only affect day to day matters of the individual, but also creates difficulties for clinicians and caregivers in terms of providing necessary support to individuals suffering from cognitive disorder. Therefore, an early detection of cognitive impairment is very important, so that clinicians, caregivers, and individuals can take necessary measures to support a cognitively impaired person.

In medical literature, the term Mild Cognitive Impairment (MCI) is recognized as a transitional phase between normal aging and dementia. Several studies show that in early stages of the disorder, signs are quite subtle. Hence, it is difficult to capture subtle signs through episodic medical workups. Studies in this domain also conclude that the deteriorated cognitive health significantly affects the ability of an elderly person to correctly perform routine life activities. Therefore, a continuous monitoring of the daily routine of the elderly can be helpful for clinicians to diagnose the early onset of MCI. Thanks to the recent advancement in the pervasive technology, which allows us to develop such systems which can continuously monitor daily routine of the elderly through a smart space.

This thesis focuses on the *detection of fine-grained anomalies* found in the daily behavior of the subject; an elderly person who lives independently in a smart home. We particularly focused on those anomalies which reflect early onset of MCI. In order to model abnormal behavior, we have collaborated with neuro-science experts and clinicians. The medical model provides

natural language descriptions of fine-grained anomalies.

We proposed *FABER*, a novel technique for Fine Grained Abnormal BEhavior Recognition (FABER). FABER is a modular architecture and relies on artificial intelligence techniques for the recognition of abnormal behavior. FABER is developed with the objective to support clinicians for a proper diagnosis of MCI. In FABER, we have exploited a combination of statistical, symbolic, and hybrid techniques to infer fine-grained anomalies. Complex human activities are characterized by wide variability; a person can adopt several different patterns of simple actions to perform an activity. Simple actions are detected by various multi-modal sensors deployed in a smart space. For the sake of privacy, we do not consider audio and visual sensors. The data stream from multimodal sensors contain several activities performed by a smart home resident. FABER recognizes boundaries of activities i.e., the start and end time instants of an activity. We have considered various techniques to recognize boundaries of activities. These techniques include supervised machine learning such as Random Forest and hybrid techniques such as Markov logic network (MLN).

After recognizing activities, the next step is the detection of fine-grained anomalies. We constructed a *knowledge-base* to recognize these fine-grained anomalies. For this purpose, we have represented knowledge using a symbolic technique: *first-order logic*. Knowledge is acquired from various sources: 1) experts provide us knowledge of abnormal behavior and other necessary information required for the detection of fine-grained anomalies such as a medical prescription to detect an anomaly missed medicine; 2) contextual information is acquired from multi-modal sensors which includes spatio-temporal information; 3) recognized activities are obtained from activity recognition module.

In order to infer anomalies, natural language descriptions of fine-grained anomalies are translated into first-order logic *rules*. In an if-then rule, the *antecedent* is based on conditions defined by the clinical model for an anomaly and the *consequent* is a single class of fine-grained anomaly to be recognized. The clinical model also specifies seriousness level of each anomaly such as a critical anomaly or a non-critical anomaly. The critical anomaly alerts clinicians for a serious behavioral modification, whereas the non-critical anomaly indicates routine life errors that may occur due to negligence, hastiness or personal habits.

In general, knowledge representation is a challenging task and depends on several factors. These factors include smart home layout, environmental conditions, personal habits of the subject, and physical health of the subject. In order to formulate rules, a knowledge engineer must understand the hidden relationship between these factors and the relevant anomaly class. Moreover, manually formulated rules are not seamlessly portable to different environments. In order to solve these issues, we have considered a *rule induction* technique, *RIPPER*, which automatically learns rules from a set of features. In this way, we can automatically generate anomaly detection rules for different environments while using same feature set for each environment.

In order to evaluate the proposed framework, we have conducted experiments with two datasets: 1) a smart home lab data set in which actors simulated daily behavior of MCI patients; 2) a real home dataset in which a real patient performed activities. According to the directions of clinicians, we have selected *three activities* for the experimentation which includes *taking medicines* according to a medical prescription, *preparing a meal* during mealtime, and *eating a meal* during mealtime. The system periodically infers fine-grained anomalies, in our case we infer anomalies at the end of each day i.e., by 12:00 a.m. midnight. We have used k-fold cross validation to validate the performance of the system. In each fold, the data acquired for exactly one day serve as test set, whereas data acquired for the rest of days serve as training set.

Dedication

To my parents ...

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Author 's Publications

1. Z. H. Janjua, D. Riboni, and C. Bettini, *"Towards automatic induction of abnormal behavioral patterns for recognizing mild cognitive impairment,"* 31st ACM Symposium on Applied Computing (SAC), April 04-08, 2016, Pisa, Italy, 2016

2. D. Riboni, C. Bettini, G. Civitarese, Z. H. Janjua, and R. Helaoui, *"Fine-grained recognition of abnormal behaviors for early detection of mild cognitive impairment,"* 2015 IEEE International Conference on Pervasive Computing and Communications (PerCom), Mar 2015

3. D. Riboni, C. Bettini, G. Civitarese, Z. H. Janjua, and V. Bulgari, ‘*‘From lab to life: Fine-grained behavior monitoring in the elderly's home,"* 2015 IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops), Mar 2015

4. G. Civitarese, Z. H. Janjua, D. Riboni, C. Bettini, *"Demonstration of the FABER System for Fine-grained Recognition of Abnormal Behaviors,"* 2015 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops), Mar 2015

5. D. Riboni, C. Bettini, G. Civitarese, Z. H. Janjua, and R. Helaoui, *"Smartfaber: Recognizing fine-grained abnormal behaviors for early detection of mild cognitive impairment,"* Artificial Intelligence in Medicine, Jan 2016.

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Chapter 1

Introduction

The advancement in medical science and availability of better healthcare services result in a rapid increase in life expectancy in developed countries. According to the United Nations, the percentage of elderly population will rise from 5% in 2013 to 11% in 2050. Several other recent studies also validate this fact; for instance, the proportion of people aged 65 or older is projected to increase by 45% in Europe in the next 20 years [66]. As a consequence, a growing portion of people is at high risk of experiencing non communicable diseases, frailty and social exclusion, and may need long-term care, including nursing at home or frequent hospitalization. Of course, the inability of living independently may not only spoil the quality of life of elderly people and those caring for them, but will also challenge the sustainability of entire health system.

In particular, if we only consider the elderly people suffering from cognitive health issues, then the global demographics show that prevalence of dementia is steadily increasing across the globe. According to an estimate from the World Health Organization, in 2015, around 47.5 million people are suffering from dementia in the world. This figure will rise to an estimated 75.6 million by 2030, and triple by 2050 [1]. These statistics are alarming and alert both the scientific community and aging societies to take appropriate measures to counter negative effects of the disorder on the individual as well as on the society.

Dementia is a slowly growing disorder, which progresses gradually from an asymptomatic phase to a symptomatic phase, and then to its final stage. In literature, the term Mild Cognitive Impairment (MCI) is used to identify a transition phase between normal aging and dementia. According to clinicians and health professionals, it is not trivial to define clear demarcations between the three interleaved phases of the disorder, i.e, normal aging, MCI, and Dementia [62]. However, the research carried out over the past few decades has revealed that the elderly people suffering from MCI exhibit different behaviors than normal elderly persons. Studies show that extensive clinical examinations are required for a proper diagnosis of the stage of the disorder; particularity at its initial stage.

According to Alzheimer's Society, the medical work-ups required for MCI diagnosis may involve several different types of procedures: medical history analysis of the individual; assessment of independent function and daily activities; reports from family members and trusted friends; mental status assessments through various tests such as memory evaluation, planning, judgment, and thinking skills; clinical neurological examination; evaluation of mood; and laboratory tests which include blood tests, brain imaging, and cerebrospinal fluid test. However, normally a clinical examination is initiated when a substantial evidence is found regarding the decline in cognitive health of the subject. Apart from the success rate of these diagnostics, there are certain limitations of these methods and among them the primary one is their episodic nature. The elderly persons have to regularly visit clinics and have to pass through the suggested clinical tests.

In the early stage of the disorder, the subject manifests subtle deficits which may be difficult to capture during episodic clinical examinations [87]. In this situation, clinicians have to trust the subject's or informant's reports regarding functional difficulties faced by the subject in his/her daily routine. However, studies show that clinicians cannot fully ignore the doubt of biased reporting, which could be due to several reasons such as stress, forgetfulness, and lack of reporter's skills in judging behavioral changes of the subject [87]. Thus, for a reliable diagnosis, clinicians are interested to use methods involving continuous and longitudinal monitoring of daily routine of elderly persons, while they live independently in their own homes.

The technological advancement in sensing devices, over the past few years, has realized the concept of smart homes. Smart homes are not only aiming to provide an environment for assisted living [35], but are also enabling longitudinal monitoring of elderly people in an unobtrusive manner [18]. Several studies conclude that decline in cognitive health affects normal daily routine of the elderly [79]. Therefore, a continuous monitoring of the daily behavior may help practitioners for an early detection of the disorder.

1.1 Problem formulation

Consider a typical scenario which explains the importance of using a pervasive system for the early detection of MCI. Suppose an elderly woman, named Anna, lives independently in her home. Anna is suffering from hypertension and few other age related health problems. Therefore, her physician prescribes a few medicines for her and she has to take these medicines regularly during prescribed times. A caregiver visits her regularly and takes care of her routine life essentials such as food items and medicines. With the passage of time, the caregiver has noticed that sometimes Anna exhibits a peculiar behavior and face functional difficulties while performing routine life activities. For example, sometimes she spends unusually long time to prepare a meal, and sometimes she forgets to take her regular medicines. However, the frequency of such peculiar behavioral episodes is quite low. The caregiver decided to contact neuro-physicians to investigate the problem. Neuro-physicians used standard cognitive assessment screening tests [20] to assess her cognitive condition. However, assessment tests do not provide sufficient evidence that Anna is suffering from any type of cognitive impairment. Neuro-physicians then decided to *monitor* her daily behavior, inside her home, while she performs her routine life activities such as maintaining personal hygiene, taking medicine(s) during prescribed times, preparing meals, and eating meals. Neuro-physicians are interested to discern various abnormalities in her routine life, so that they can differentiate between her normal aging problems and signs of cognitive impairments. Neuro-physicians can face the following potential difficulties while monitoring the daily routine of Anna.

- Privacy: Due to privacy reasons, it is difficult that a human can directly observe the daily routine of Anna and gather sufficient clues of her behavioral changes. Even if the subject allows a caregiver or a family member to directly observe her daily routine, still a continuous (24/7) monitoring is not possible due to the observer's inability to be consistently present with the subject while she performs her routine life activities.

- Imprecision: Human based monitoring of the subject involves certain imprecision which can significantly affect the diagnosis. First, since an observer is unable to continuously monitor the subject's routine, the observed behavior is only a snapshot of her daily routine and such snapshots may not provide an adequate evidence to clinicians for a successful diagnosis of MCI. Second, a human observer can influence Anna's natural way of carrying out activities and such an influence may hide the real behavioral changes exhibited by the subject. Third, in order to determine behavioral modifications, clinicians are normally interested to look a history of behavioral changes in the daily routine of the subject, however, it may be difficult for a human observer to maintain a detailed record of long term abnormalities found in her daily routine. Fourth, in some situations, a close observation is required to notice the abnormal behavior, otherwise, a human observer can easily overlook an occurred anomaly. For example, the subject regularly takes a medicine during prescribed time, but one day she has mistakenly replaced the prescribed medicine with a wrong medicine. In this case, the human observer has to closely observe which medicine has been taken by the subject. In conclusion, in early stages of MCI, the subject manifests subtle deficits in routine life activities which are difficult to capture with a high accuracy, by a human observer through the episodic monitoring.

- Cost: A proper monitoring of the subject needs necessary skills in which the observer must possess knowledge about the behavior of an MCI patient. Therefore, it is normally difficult for an ordinary person to capture such symptoms which can indicate an early onset of MCI. The neuro-physicians can invite the subject to a laboratory in which Anna can perform various activities. Another possibility is hiring a skilled caregiver who can observe subject's behavior in her home and then report behavioral changes to neuro-physicians. However, these methods are episodic and also costly because of specific arrangements.

In order to address above mentioned issues, we proposed a pervasive healthcare monitoring system which is described in Chapter 4. Several other research studies have considered sensor based monitoring systems and these methods are reviewed in Chapter 3. However, comparing with the state of the art research happened in this field, we have particularly focused on the following objectives:

- Continuous monitoring of the subject while he/she performs her routine life activities.

- Maintaining a maximum possible privacy of the subject.
- Unobtrusive monitoring, so that the process of monitoring does not interfere subject's daily routine.
- Automatic detection of fine-level abnormalities found in daily behavior of the subject. We are interested to develop a system which can capture subtle changes manifest by the subject while performing activities.

1.2 Contributions

Abnormal behavior recognition through sensor based behavior monitoring is a challenging task. In order to develop such a pervasive system, we have to consider various aspects of the system which include modeling of abnormal behavior, providing a sensing solution, acquiring sensor data from a sensing infrastructure, and processing the acquired data to infer abnormal behavior. Due to the large scope of this project, the overall project is completed by a group of researchers. In fact, this thesis work covers some portions of the overall project which include some primary tasks and some novel contributions. Here it is important to mention that the thesis work has been carried out within SECURE project[1]. SECURE: Intelligent System for Early Diagnosis and Follow-up at Home, a project funded under the Industrial Research and Experimental Development in the strategic sectors of the Lombardy Region and the Ministry of Education, University and Research. The project aims to develop a prototype for monitoring of daily behavior of an elderly person along with his/her physiological parameters to support clinicians for an early detection of cognitive impairment. Contributions of this work in the overall project are summarized as:

1. Sensing infrastructure: Human activities consist of simple actions which can be detected by various multi-modal sensors deployed in a smart environment. Therefore, as an essential step for abnormal behavior recognition, we proposed a sensing solution which can detect simple actions performed by humans during routine life activities. The elderly is supposed to live independently in such a smart environment; where he/she can freely perform his/her routine life activities. In order to

[1] The project details along with the list of industrial partners are available at: `http://secure.ewlab.di.unimi.it/`

maintain maximum privacy of the inhabitant, we have avoided audio or visual sensors. Our proposed sensing solution is based on various off-the-shelf multi-modal sensors which can be easily deployed in a smart space and detect various human gestures and movements executed by the inhabitant.

2. Activity recognition: Human activities are complex and a person can execute an activity in various different ways. The multi-modal sensors deployed in the smart home detects various simple actions performed in different activities. Our proposed method relies on activity recognition for abnormal behavior recognition. In order to recognize activities from multi-modal sensor data, we have exploited various statistical and hybrid techniques. We have performed experiments using various state of the art machine learning techniques such as Support Vector Machine, Random Forest, Bayesian Classifiers, and Multilayer Perceptron.

3. Fine-grained anomaly recognition: It is the main objective of this research work and also the major novel contribution in the research domain. Fine-grained anomalies are fine-level details of the abnormal behavior found in the daily routine of an elderly person suspected of having MCI. Our proposed model relies on medical models which have been developed over the past several years and indicate fine-level details of abnormal behavior found in activities performed by an MCI patient. Besides thoroughly studying the medical literature, we have also collaborated with neuro-science experts and clinicians to understand the abnormal behavior exhibited by an MCI patient. Neuro-science experts and clinicians provide us natural language details of fine-grained anomalies. In order to recognize fine-grained anomalies, we have translated the natural language descriptions of fine-grained anomalies into rules. Rules are manually formulated by considering background knowledge, contextual information acquired from smart home, and activities performed by an elderly person in a smart home. The fine-grained anomaly recognition method is discussed in detail in Chapter 7

4. Automated fine-grained anomaly recognition: It is another novel contribution in the domain. Knowledge representation is a complex and challenging task. As mentioned earlier, anomaly recognition rules are manually formulated by considering various factors. The manual formulation of anomaly recognition rules is an arduous and time expensive

experience. Moreover, manually formulated rules are not seamlessly portable to different environments. It means an analyst has to develop separate rules-sets for different smart homes or different residents. It is because, while formulating rules, an analyst has to carefully consider various factors that are involved in the process of anomaly recognition. These factors include smart home layout, environmental conditions, clinical model of abnormal behavior, personal habits of a smart home inhabitant, and physical health of the smart home resident. In order to simplify the task, we proposed a semi-automated approach in which a rule induction algorithm automatically learns rules from a set of features. An analyst (formally a knowledge engineer) extracts these features by considering various factors involved in the process of anomaly recognition. In this way, we can automatically generate multiple rule-sets for different cases, while using a generic feature set. The rule induction based method provides us a portable, flexible, and time inexpensive way to generate anomaly recognition rules. The approach is discussed in detail in Chapter 6.

Chapter 2

Modeling Abnormal Behavior

In the Introduction, we have explained the importance of the early detection of MCI and also highlighted difficulties faced by clinicians in the early diagnosis of the disorder. In this chapter, we will try to understand the medical conditions of the disorder and its symptoms in more depth. We will focus on the clinical definition of the disorder and also explain effects of the disorder on the routine life of an elderly person. Afterwards, we will discuss about abnormal behavior exhibited by a cognitively impaired elderly person and also introduce the concept of fine-grained anomalies, which is the core research topic of this thesis. We will also present the clinical model which defines abnormal behavior; our proposed method for fine-grained anomaly recognition relies on this clinical model.

2.1 Mild Cognitive Impairment (MCI)

In medical literature, the term MCI is used to define the medical condition interceding between normal aging and very early stage of dementia. Thus MCI is a prodromal stage of dementia, in which the decline in cognitive abilities is very subtle in the beginning of the disorder. However, MCI is recognized as a pathological condition and its manifestations varies from normal aging. Numerous epidemiological studies show that progression of the disorder is usually slow towards dementia (final stage) and it can take several years when symptoms of the disorder are much evident. Due to slow progression and slight cognitive changes, it is difficult to diagnose the disorder at early stages. However, clinical studies reveal that a continuous monitoring enables clinicians to understand behavioral modifications exhibited by an elderly over a course of time. Unusual changes observed in the behavior of an elderly person can be good indicators to judge the degradation in cognitive abilities in the person. In fact, the aim of this research is to precisely detect these unusual changes and behavioral modifications which can help clinicians to diagnose early onset of MCI.

The clinical diagnosis of MCI at an early stage is not a trivial task and involves various types of screening tests developed for the staging of dementia. Typically, these screening tests have two fundamental objectives: the first is to inspect memory impairment, and the second is to assess an impairment in executive function. Several specialized screening tests, such as MiniMental State Examination (MMSE) [31], have been developed over the past few decades which are mainly based on questions asked to an elderly person suspected with MCI. Questionnaires evaluate different human skills and contain questions from various areas such as memory, orientation, planning and judgment, and problem solving. Similarly, some screening tools also consider information provided by an informant about the subject's cognitive health. Informant's reports normally cover aspects which relates to general living of the subject; such information may be based on the subject's level of activeness in routine life, hobbies, socialization, and personal care. Screening tools normally generate results in the form of numerical scores which are calculated from the answers given by the subject or may also consider the feedback from an informant or a caregiver. For example, Cognitive Dementia Rating (CDR) is a questionnaire-based dementia staging tool in which numeric score reflects the severity of the disorder; scores 0, 0.5, 1, 2, and 3 reflect the cognitive health status as non-impaired, very mildly impaired, mildly impaired, moderately impaired, and severely impaired, respectively. However, due to different clinical cases and stages of dementia, the nature of screening tests varies. Clinical surveys show that today the most debatable issue in this domain is the suitability of a screening tool for a particular case and stage of dementia. Moreover, since MCI is a medical condition in which the symptoms are not much evident, therefore, it is possible that screening tools cannot correctly identify this stage of dementia. Considering this fact, some clinical methods rely on monitoring the behavior of the subject. For this purpose, the subject's behavior is either monitored by clinicians in clinical setups or it may be reported by an informant who observe the subject's behavior in his/her home. Nevertheless, the clinical monitoring of the subject is obtrusive and episodic like questionnaire-based screening tools.

Monitoring in short intervals at clinics may not be useful to detect behavioral modifications. Similarly, we cannot ignore the doubt of biased reporting in home-based monitoring of the subject. In short, both questionnaire-based screening tests and human-based monitoring methods have their own limitations which can influence the process of MCI diagnosis. Here comes pervasive systems which can overcome limitations found in clinical methods and can also support clinicians to collect better clues required for a proper diagnosis of the disorder.

2.2 Human activities

Human daily routine is based on several activities: ranging from very basic activities to complex activities. In the literature, the term *Activities of Daily Living (ADLs)* is used for routine life self-caring basic tasks such as eating, dressing, bathing, and personal hygiene [73]. According to health professionals, the ability to independently perform these ADLs determines the person's health conditions: both physical and cognitive health. However, in some cases, ADLs do not provide enough evidence in the decline of a person's health. It is particularly true for elderly people suffering from MCI as cognitive health deteriorates slowly over time. In order to fill this gap, *Instrumental Activities of Daily Living (IADLs)* have been introduced. IADLs include complex routine life tasks such as preparing meal, shopping, traveling, and financial management [51]. An elderly person may depend on other humans to successfully complete IADLs.

Human activities are complex and often composed of a pattern of various basic actions performed by a person. In particular, we considered *Instrumental activities of daily living (IADLs)* to model the independent lifestyle of an elderly person. An activity consists of a temporal sequence of *simple actions* performed by a person during an activity. We assume that a simple action is an *atomic step* which is a manipulative gesture or a body movement involving an object (for example, "open refrigerator", "sit on a chair in kitchen"). We also assume that each *atomic step* can be detected by a sensor deployed in the environment. A person can perform an activity with varying sequences of atomic steps. For example, Figure 2.1 shows three different sequences which can be followed while performing an IADL "taking a medicine". In the first sequence (Figure 2.1(a)), the person opens the medicine repository, retrieves the medicine, returns it after *five* minutes, and then close the repository. In the second sequence (Figure 2.1(b)) the person repeats the same task, however, this time he/she retrieves the medicine and then close the repository. After thirty minutes he/she accesses the repository again and then returns the medicine. The third sequence (Figure 2.1(c)) is same as (a), but here the person forgets to close the repository at the end of the IADL. Depending on the person's lifestyle and habits, he/she can adopt various ways for executing the same IADL.

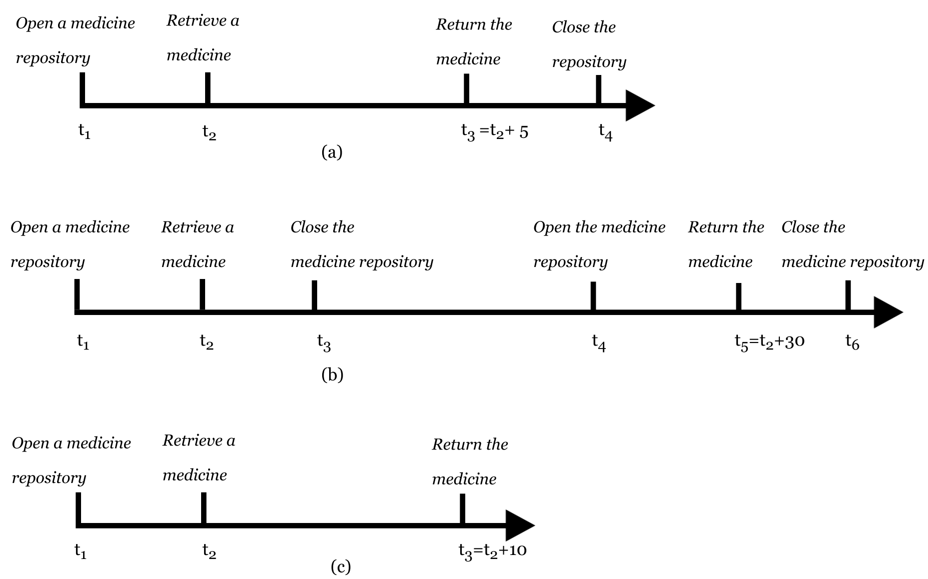

Figure 2.1: Example of an IADL: "taking a medicine"

2.3 Fine-grained anomalies

The objective of this research is to detect the fine-grained anomalies found in the daily routine of a smart home resident. We use the term *fine-grained anomalies* to define fine-level details of abnormalities observed during the execution of quantifiable activities. An activity is characterized as abnormal if it is executed in a way that diverges from the expected one. We consider the detection of fine-grained anomalies in the activities which are observed within a relatively short period: ranging from a few seconds to a whole day.

In general, an activity is characterized anomalous if it exhibits the following characteristics:

- The person tries to perform an activity, however, fails to complete it.
- The activity is performed at an unusual or inappropriate time.
- A non-existence of an expected activity.
- The activity is completed, but performed in an improper way.

Type of anomaly	Description	Example
Substitution	A different object than appropriate is used or a different component action than expected is performed	Using spoon to spread butter
Replacement	The subject replaces a correct action with a wrong one	Putting the butter inside a non-refrigerated cabinet
Improper activity	The subject performs an activity that is not consistent with the model	Taking a medicine that was not prescribed
Repetition	The subject repeats the same action or activity more times than expected	Consuming the morning breakfast twice in a day
Improper order	The subject performs actions in different order than appropriate	Putting pasta before boiling water
Quality	The activity is performed to minimize its complexity	Preparing meal by only pre-heating the same food every day

Table 2.1: Different types of commission anomalies

We are interested in anomalies which indicate an early onset of MCI or reflect cognitive decline in elderly persons. There are several clinical models which describe indications of abnormal behaviors for the early onset of

MCI [33, 81]. Considering these models, we collaborated with local clinicians and neuro-science experts to understand the nature of the abnormal behavior exhibited by a person having tendency of MCI. We have developed the clinical model after having comprehensive discussions and meetings with experts from the Institute Fatebenefratelli[1], Lombardy —a leading center in the field of mental health research on neurodegenerative disorders —within the SECURE[2] research project funded by Lombardy region and MIUR Italian ministry. Based on medical practices and relevant literature [13], a list of fine-grained anomalies has been identified during different project meetings among technical and medical partners of the project. Note that, these meeting were conducted in the local language (Italian) without affecting the modeling process. Anomalies are defined in natural language by clinicians; e.g., an anomaly occurs when a person with MCI prepares a meal but forgets to consume it. In general, these indications can be categorized as:

- Omissions: occurs when the subject forgets to attempt a step or a sequence of steps which are essentially required to complete an activity. For example, the subject is on a prescription and he/she has to take a medicine during the prescribed time. An omission occurs if the subject forgets to take a prescribed medicine during the prescribed time.
- Commissions: occurs when the subject attempts a step or a sequence of steps in an inaccurate manner. Commissions include a variety of anomalies which are shown in Table 2.1.
- Additions: occurs when the subject attempts a step or a sequence of steps which are irrelevant to an activity. For example, the subject is cleaning his/her house and retrieves a cooking pot from the cooking pot cabinet which is not required for this particular activity.

For a proper diagnosis of MCI, clinicians also demanded an orthogonal classification of fine-grained anomalies i.e., critical and non-critical anomalies. Critical anomalies are considered stronger indicators of possible MCI onset. Further explanation of the orthogonal division of anomalies is given as:

[1]IRCCS (Research and Care Institute) St. John of God Clinical Research Center, Brescia, Italy – http://www.irccs-fatebenefratelli.it

[2]SECURE: Intelligent System for Early Diagnosis and Follow-up at Home, http://secure.ewlab.di.unimi.it/

- Non-critical anomaly: an anomaly is considered non-critical when the subject skips a relevant action while performing an activity or spends too much time to perform the activity, but still he/she is able to correctly complete the activity. For instance, we consider a non-critical anomaly occurs when the subject forgets to close a repository after taking something from it (a non-critical omission).

- Critical anomaly: a critical anomaly occurs when the subject: 1) skips one or more necessary actions while performing an activity; 2) forgets to perform an expected activity; 3) unnecessarily repeats an activity, for example, forgets to turn off a stove after cooking pasta is a critical omission.

2.4 Anomalies and human behaviors

There are several factors which influence the execution of an activity in the daily routine of a person. A few of these factors are: contextual conditions, individual habits, and personality traits. Consequently, an activity may be executed with some anomalies which are not necessarily due to the decline in cognitive abilities. It is particularly true for non-critical anomalies, such as leaving a repository door open, which may occur in activities performed by cognitively intact persons due to negligence and hastiness. Similarly, some anomalies may occur due to a temporary change in the routine of a person. For example, the person may suffer from a mild seasonal illness like cough or cold. He/she can take an over-the-counter medicine for the cure of this disorder. Although this behavior diverges from his/her routine life, it is certainly not an anomaly and a clinician can ask the person the reason of such an action.

Due to such ambiguous situations, we consider anomalies as indicators of abnormal behavior which could support clinicians in diagnosing cognitive disorder. The proposed automated system periodically (e.g., end of a day) infers anomalies from the daily routine of the subject. Recognized anomalies are then reported to clinicians. The frequency of anomalies and their temporal trends are used to trigger alarms for clinicians or caregivers for further inspecting the history of abnormal behavior and corresponding fine-grained descriptions.

Chapter 3

Related Work

In this chapter, we will review state of the art research[1] carried out in behaviorial monitoring and abnormal behavior recognition. Activity recognition systems proved to be effective for supporting the diagnosis and improving healthy ageing [47, 61]. In the literature, various strategies have been proposed to devise effective and unobtrusive activity monitoring systems by exploiting pervasive computing technologies [89]. A popular research direction for activity recognition consists in exploiting audio-visual information recorded by cameras and microphones with the help of sound, image and scene recognition software. Audio data can be used to assess mood and other emotional conditions [84]. Speech and voice recordings have been used for diagnosis of early-stage dementia [78]. However, those methods are considered too invasive in a home environment; due to privacy issues they determine. Hence, in the following we restrict our attention to non-invasive sensor-based techniques.

3.1 Applications of activity recognition to MCI diagnosis

Over the past few decades, several clinical studies have been conducted to delineate various stages of cognitive impairments. For example, Reisberg and et al. [67] described various stages of cognitive impairment, ranging from asymptomatic to symptomatic phases, along with the symptoms of

[1]The material in this chapter is from our publication [69]

each stage. Studies in the neuro-psychology research field also show that it is possible to distinguish between cognitively healthy adults and cognitively impaired individuals based on subtle differences in their behavioral patterns [88, 83]. For instance, in [76], subjects were asked to execute a set of predefined activities in an observation room of a clinical center, while two cameras recorded their activities. Researchers annotated the dataset manually based on the observation of video recordings, giving partial scores to the performed activities considering different factors, including activity duration, omitted steps, and number of repeated steps. Partial scores were then aggregated to obtain a comprehensive score, which proved to be effective in distinguishing MCI subjects from Alzheimer's patients, and cognitively healthy seniors from MCI subjects. There is a growing interest in exploiting pervasive computing technologies to automatically capture and measure those differences [61].

Machine learning methods applied to accelerometer data and video recordings were used in [19] to distinguish between cognitively healthy seniors and Alzheimer's patients based on activity execution and gait events. Similarly, sensors and video recordings were used in [46] to distinguish between MCI and Alzheimer's patients. Those methods were applied in controlled environments, while we aim at monitoring the elderly's activities and detect exhibited abnormal behavior at a fine-grained level at home.

Several European projects have considered ICT technologies for enhancing active and healthy aging [74, 54, 30] and for supporting people with dementia at home [26]. Based on this line of research, different methods have been proposed which apply machine learning techniques on data acquired in sensor-rich environments, for assessing the cognitive health status of an individual performing a set of activities. For instance, motion sensors and contact sensors have been used in [34] to measure low-level activity patterns such as walking speed and activity level in a home. Results have shown that the coefficient of variation in the median walking speed is a statistically significant measure to distinguish MCI subjects from healthy seniors. A sensor-based infrastructure has been used in [80] to unobtrusively monitor the execution of activities by older adults in a smart-home. Results have shown a significant correlation between the cognitive health status of the subject and the level of assistance that he/she needs to complete activities. Another research approach relies on tracking activities through prolonged monitoring and then measuring intra-individual changes. As an example, the Oregon Centre for Aging and Technology at the Oregon Health and Science University has developed various smart sensing platforms, which enable continuous and unobtrusive monitoring of various human activities for the detection of early symptoms of cognitive impairment in elderly persons [53]. Their studies considered a range of routine life activities that may reflect a cognitive deterioration. These activities include sleeping, computer use, walking patterns, medication adherence, and social interaction.

In the work of Dawadi et al. [24], patients were invited to execute a list of routine activities (e.g., write a letter, prepare lunch) inside a hospital smart-home. Different kinds of sensors were used to detect movements inside the home and to track the use of furniture and appliances. Based on the data coming from sensors, supervised machine learning methods were used to assign a score to each performed activity. The score measures the ability of the subject to perform an activity correctly. Achieved scores were used to predict the cognitive status of the patient (cognitive health or dementia). Supervised learning approach has been applied in other works, including [22, 23, 17], using several other learning methods. However, while a significant correlation exists between inferred activity scores and the cognitive health status of the individual, these methods do not provide a description of observed behavioral anomalies. On the contrary, the medical assessment would benefit from detailed knowledge of the abnormal behavior of the patient. For this reason, in our approach we do not rely on statistical deviations from the "normal" behavior; instead, we aim at recognizing fine-grained anomalies, modeled according to neuro-science experts as possible indicators of MCI, using a hybrid statistical and knowledge-based approach.

Besides the recognition of abnormal behavior, it is also important to report necessary details of the recognized abnormal behavior to concerned persons: clinicians and caregivers. For this purpose, we need data visualization tools which enable concerned persons to visualize outcomes of behavioral monitoring such as recognized critical situations. For example, in [43], a spatiotemporal data visualization model has been proposed which visually represents temporal information of activities performed by an elderly person at different locations in a smart home. Considering this requirement, a dashboard has been developed in this research which is a web-based application and displays recognized fine-grained anomalies along with associated activities and time at which anomalies occur.

3.2 Recognition of simple activities

Several techniques have been proposed to recognize *simple* activities, which rely on data acquired from body-worn sensors and on the application of supervised learning methods [6, 45]. Early attempts in this sense are mainly based on the use of data acquired from multiple body-worn accelerometers [8], possibly coupled with bio-metrical sensors and integrated in clothes [60], to recognize locomotion types and simple physical activities. A major limitation of these early systems is that they do not consider contextual information, such as current location, environmental conditions, and surrounding objects, that could be usefully exploited to improve the accuracy of recognition. Hence, other activity recognition approaches take into account the user's context by acquiring environmental data from several sensors [52]. For instance, in [3] authors have proposed the use of machine learning and data acquired from body-worn sensors (an ear microphone, sensor collar integrating electromyogram and microphone, and four upper body accelerometers) to accurately monitor food intake activities (movement, chewing and swallowing). However, being mainly based on body-worn sensors, those methods are not well suited to recognize more complex activities, which are characterized by the interaction of the individual with several objects and furniture.

3.3 Recognition of complex activities

The recognition of complex activities relies on the usage of sensors to detect the user's movements and the interaction with objects and furniture. For instance, in [38], authors have proposed a time series data analysis method to segment sequences of sensor events in order to recognize complex activities. The application of Hidden Markov Models (HMM) inference is proposed in [85] to recognize activities based on features extracted from recent sensor events according to a sliding window.

However, the recognition of complex activities turns out to be challenging by solely using supervised learning methods. Indeed, complex activities are characterized by large inter- and intra-personal variability of execution, and it is very hard to acquire a sufficiently comprehensive training set to include most of the possible ways of executing activities. Hence, different frameworks for knowledge representation and reasoning have been investigated to appropriately model complex human activities by means of ontologies. In particular, description logic [7] is emerged among other symbolic formalism, mostly because they provide complete reasoning supported by optimized automatic tools.

In [57], ontological descriptions of activities are used for the segmentation of sensor data streams acquired in a smart home. In particular, a shrinking time window algorithm is proposed to segment temporal sequences of sensor events, in order to discover sequences of events that match the ontological description of a human activity. Our approach is different: we recognize activity instances by aggregating the individual inferences of a machine learning algorithm, considering semantic conditions that the sensor sequence generated by an activity must satisfy. A Web mining technique to derive semantic dependencies among activities and used objects is proposed in [59]; those dependencies are used for activity segmentation. Our segmentation method considers more complex conditions about the necessary sensor events that must be observed during an activity execution. A further method to segment activities based on their semantic description is proposed in [55]; that method also supports the recognition of overlapped activities.

However, as illustrated in [2], both expressiveness and efficiency issues strongly limit the feasibility of ontological approaches to activity recognition. Moreover, the recognition of some complex activities through ontological reasoning has to start from a set of basic observations (e.g., the user's posture, basic gestures, mode of locomotion); this task requires the use of statistical methods to derive semantic information from raw sensor data (e.g., body-worn accelerometers).

3.4 Recognition of complex activities using hybrid techniques

Considering limitations of both statistical and symbolic approaches, some research groups target to use domain knowledge and contextual information together to recognize complex activities. In [77], a similar context aware complex activity recognition technique is proposed which exploits domain knowledge to identify a situation and then use probabilistic and Markov chain analysis to recognize complex activities. As an extension of these methods, a few hybrid activity recognition systems have been proposed in the literature, which vary on the adopted reasoning techniques and on their interaction mechanisms. An interesting instance of these approaches is Markov Logic Networks (MLN) [72]: weighted formulas of first-order logic. Given a training set, and a set of probabilistic formulas, with MLN it is possible to learn a weight for each grounded formula by iteratively optimizing a pseudo-likelihood measure. These weights represent the confidence value of the formula. Deterministic formulas can be added to probabilistic ones to express deterministic knowledge about the domain of interest. Different reasoning tasks can be executed to infer additional information based on formulas and facts. We have also considered MLN in our work to recognize activities [71]. A similar approach was adopted in [36] to model and recognize activities at different levels of complexity using probabilistic description logic. Hybrid ontological and statistical reasoning is proposed in [25] to continuously assess the fall risk of a senior at home, by integrating data acquired from different fall detection systems and environmental sensors. In this work, we have considered a hybrid method to recognize the start- and end-time of activities based on a combination of supervised learning and knowledge-based conditions to refine the statistical predictions.

3.5 Long-term analysis of activity data

In the aforementioned works, the detection of abnormal behaviors is mostly done on a short-term basis and does not take into account the patient's personal habits. Other works have proposed methods to model the patient's usual behavior from activities performed in the past and use this model to detect anomalies as changes from his/her usual behavior. In [86], a method has been proposed to monitor the circadian (24-hours) variability of the patient's activities using location sensors and statistical calculations were performed regularly on sensors data to recognize possible deviations in the patient's behaviour. In [82] in-home activities and sleep restlessness were captured using different sensors and a simple alert system was implemented to detect changes in the activity patterns and generate health alerts that were sent to clinicians to be rated for their clinical relevance. These ratings were then used as ground truth in developing classifiers to recognize relevant alerts. In [29], authors have proposed a technique to detect recurrent activity patterns, as well as their variations, by mining heterogeneous multivariate time-series from sensor data acquired in a smart home.

Another approach based on temporal data mining is presented in [41].

Frequently-occurring temporal relationships between activities are extracted from the observed history of sensor events and used to model the probability that a particular event should or should not occur on a given day. A technique based on unsupervised learning is proposed in [64] to automatically discover activity patterns and their variations. That technique is coupled with an activity recognition module and with visualization tools to allow practitioners inspecting the trend of activity patterns.

Chapter 4

Proposed Framework for Behavioral Monitoring

In the previous chapter, we have presented the state of the art research in activity and abnormal behavior recognition. In order to overcome limitations of existing techniques, we have proposed *FABER*, a novel technique for *Finegrained Abnormal BEhavior Recognition* (FABER). FABER is a hybrid reasoning framework which relies on medical models describing behavioral modifications that may indicate the early onset of MCI. Clinical models provide us natural language descriptions of fine-grained anomalies and we have used these definitions in FABER to detect abnormal behavior in the daily routine of the subject. The novel aspect of this research is the recognition of fine-grained anomalies from the daily behavior of an elderly. In this chapter, we will explain a general architecture of the proposed model. In Section 4.1, we will present an overview of the methodology adopted to recognize the abnormal behavior. In Section 4.2, we will discuss the architecture in detail along with a brief overview of techniques used to implement the model.

4.1 An overview

In this section, we will briefly summarize our approach to recognize the abnormal behavior. The overall process involves multiple underlying sub-processes. Each sub-process has its own objectives and produces outcomes for the next sub-process.

4.1.1 Identifying target activities

Over the past several years, clinicians and neuro-science experts have put their efforts together to develop functional assessment tools which measure abilities of an elderly person to independently perform routine life activities. These tools are used for the diagnosis of MCI. For example, Katz scale [31] (for ADLs) and Bristol scale [11](for IADLs) are widely used by clinicians for the functional assessment of elderly persons to diagnose MCI. As a matter of fact, due to limited resources, it is difficult to include all these activities in our research. For this reason, our research work includes an excerpt from these scales. Cognitively impaired persons face more difficulties, as compared to cognitively intact persons, in performing routine life activities which are memory dependent and involves executive function [65]. Therefore, in this research, we have considered such routine life activities which are memory dependent and involves executive function. In the rest of the literature, we will use the term *activities* referring both *ADLs* and *IADLs*, unless these terms are used in their explicit meanings.

4.1.2 Modeling of target activities

Our approach to model an activity is based on activity theory [49]. The activity theory describes an activity as a series of interactions between a human and objects in an environment. We have identified different components of target activities such as subject, simple action, and object. In a typical scenario, a *subject* is a person who performs a *simple action* on an *object*. To simplify the model, we have not considered concurrent and interleaved activities in the current design. After identifying all components in target activities, we have represented an activity as a temporal sequence of *simple actions*. In the temporal sequence each simple action occurs at a discrete time instant. The following example describes the activity model.

> **Example 1** Suppose, Anna, the subject, performs an activity preparing meal in her home. In this activity she cooks eggs. In order to model this activity, we identify activity components: *subject* is Anna; *objects* are eggs, fridge, cooking pan, cooking cabinet, and stove; *simple actions* are open, close, turn on, and turn off. After identifying these components, we can represent this activity as a sequence of following simple actions.

```
(Take a food item from fridge)
open fridge at t1
retrieve eggs from fridge at t2
close fridge at t3

(Take a cooking pan from cabinet)
open cooking pot cabinet at t4
retrieve cooking pot cabinet at t5
close cooking pot cabinet at t6

(Use a stove)
turn on stove at t7
turn off stove at t8
```

Let δ is the duration between two consecutive simple actions: $\delta = t2 - t1$. The value of δ is random and depends on physical execution of the activity.

4.1.3 Modeling abnormal behavior

We have modeled the abnormal behavior by identifying possible anomalies that could be found in activities performed by the subject. In order to achieve this objective, we have collaborated with clinicians and neuro-science experts who closely observe cognitively impaired patients on a regular basis. Clinicians and neuro-science experts provide us natural language descriptions of fine-grained anomalies. The fine-grained anomalies, recognized by FABER, allow clinicians to better understand the condition of the subject and also support them to diagnose the stage of the disorder. For example, a fine-grained anomaly occurs if the subject forgets to take meals during a mealtime. Further details of modeling abnormal behavior are given in Chapter 5.

4.1.4 Event sensing and data acquisition

The daily routine of the subject is monitored continuously while the individual performs activities in a smart space. The smart space is equipped with a network of muli-modal sensor nodes. These sensors detect environmental changes and other events that happen when the subject interacts with the smart environment. Depending on a sensor, it either generates analog or digital data. Data are continuously acquired from the smart space and stored in a database. The raw sensor data is further processed to infer semantics of each measured sensor event.

4.1.5 Abnormal behavior recognition

Our proposed abnormal behavior recognition framework is based on two main steps:*activity recognition*, and *anomaly recognition*.

Step 1: Activity recognition In order to recognize the abnormal behavior, the first step is to recognize activities performed by the subject in a smart environment. A human activity may include several simple actions and sensor events, which occur when the subject interacts the smart environment. As a matter of fact, simple actions and sensor events may occur inside or outside of an activity. Therefore, it is necessary to recognize activities from a continuous stream of sensor events. The activity recognition module takes a continuous stream of raw sensor data as an input and process it to detect simple actions (for e.g "opening the fridge door"). The output of the activity recognition module is *recognized activity labels*, *start* and *end time instants* of activities, simple actions and sensor events (bounded by start/end time instants).

Step 2: Anomaly recognition The efforts which have been made during the phase of modeling abnormal behavior result in natural language descriptions describing fine-level details of abnormalities found in the daily routine of MCI patient. After recognizing activities, the next task is to recognize the abnormal behavior according to the provided clinical model. In order to recognize fine-grained anomalies, we have formally represented knowledge provided by the clinical model using artificial intelligent tools. We have used first-order logic to represent knowledge and translated natural language descriptions of fine-grained anomalies into rules. The rule-based reasoning considers several types of facts which are gathered through the smart environment, domain knowledge, and contextual information. Formally, the proposed anomaly recognition method is based on a knowledge-base to infer fine-grained anomalies.

4.1.6 Recognized Fine-grained anomalies

The recognized fine-grained anomalies could be interesting and available for: (1) *clinicians* to support them for a proper diagnosis of cognitive disorder and possible therapeutic interventions to treat the disorder, (2) *family or caregivers* to help them determine the type of support required by their elderly relative and interventions in critical situations , and (3) *the subject* so that he/she can better understand his/her condition to subsist with the disorder. Recognized anomalies are delivered to these recipients thorough a web-based application: a dashboard. The dashboard displays all recognized fine-grained anomalies along with other necessary information such as time at which an anomaly occurs, the nature of the anomaly, the relevant activity, and the frequency of each anomaly in a particular duration (for e.g., one day).

4.2 The Architecture

Figure 4.1 shows the architecture of FABER. The layered architecture is composed of three main modules: smart home, activity recognition, and abnormal behaviour recognition. The working and implementation of these modules is described in the following sections.

4.2.1 Smart home: the sensing infrastructure

Before going into details of the smart home architecture, let us consider the following example which explains concerns of our subject while being monitored through a smart home.

> **Example 2** Clinicians, with the consent of Anna, decided to continuously monitor her daily routine through a smart home. Clinicians have convinced the subject for sensor-based monitoring and she accepts to convert her house into a smart space instrumented with sensors of various modalities. She performs her routine life activities in a smart home. However, while living in the smart home, she has some primary concerns: 1) She feels it difficult to handle latest technology in the form of smart devices (e.g. phone and tablet). 2) She accepts a minimum level of obtrusiveness in her home. 3) She has privacy concerns and does not like to be observed using audio or visual devices.

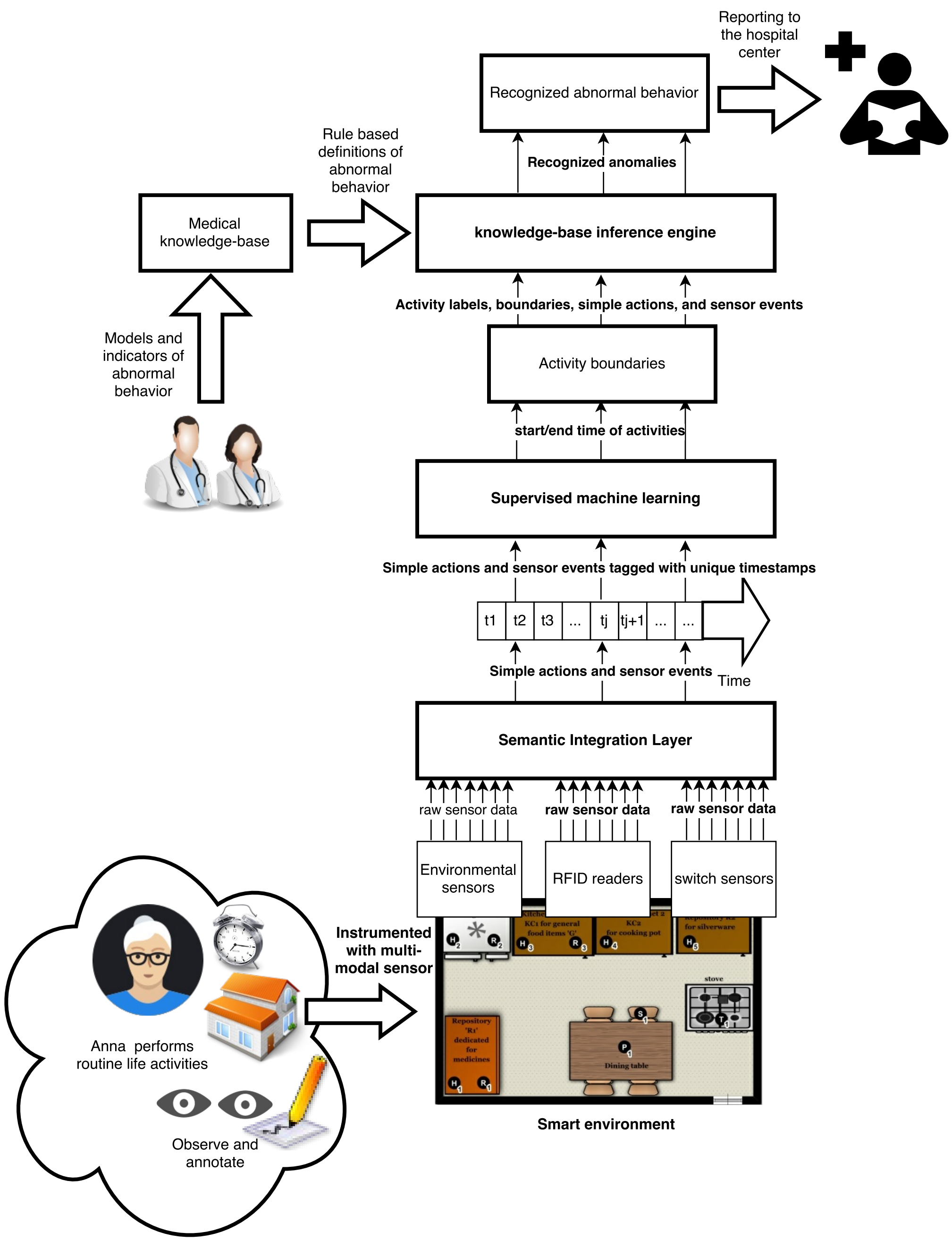

Figure 4.1: The architecture of proposed model

Considering her difficulties, we have aimed to develop a smart home having these features: convenient to handle smart technology, unobtrusive, and maintains necessary privacy of the resident. Therefore, we have relied on unobtrusive ambient sensors which can be deployed in surroundings and avoided wearable sensors. We have also avoided microphones and cameras to maintain the privacy of the resident. In [40], Jacelon and et. al. reported that elderly persons prefer to be monitored by ambient sensors rather than cameras.

As mentioned earlier, in order to design a smart home, our primary objective is to detect simple actions executed by the resident while performing activities. To achieve this objective, we have used various multi-modal sensors which can sense the environmental changes and resident's interaction with the environment. A home environment includes various household articles such as furnishings, electronic appliances, and consumable items. In order to detect simple actions, we have to understand the nature of a human interaction with various household articles. For example, a person can perform two simple actions on a door: "opening the door", and "closing the door". These two simple actions reflect two different states of the door during an activity. Thus, by understanding the nature of these simple actions, we can select a sensor which can detect these simple actions. Here, we are listing down some sensors which we have considered to design a smart environment:

- Switch sensors: There is a wide range of switch sensors available in the market today. A switch sensor produces a binary output, i.e. open switch or close switch. These sensors are particularly useful to detect simple actions which oppositely relate each other. For example, the hall-effect switch sensor deployed on a fridge door can detect two simple actions: "open the fridge door" and "close the fridge door".

- Environmental sensors: These sensors normally produce analog data which can be processed to detect simple actions. A temperature sensor is a typical example of environmental sensors. A temperature sensor can be used to detect stove usage, and can also detect hot water usage in a smart home.

- Motion sensors: A motion sensor is used to detect movements in an environment. In a smart home, a motion sensor is normally used to detect human movements in various regions such as living room, bedroom, and kitchen. Normally, a passive infrared (PIR) sensor is used to detect human movements in an environment. A PIR sensor detects human movements in its surroundings by measuring variations in the spectrum of infra-red waves; emitted by a human body. An alternate of PIR sensor is an ultrasonic sensor which detects human movements in its surroundings by receiving the disrupted reflections of self-generated sound waves.

- Radio Frequency Identification (RFID) technology: The RFID based sensing is typically useful in object-based activity recognition methods [12], which assume that the object usage during an activity provides strong clues about the nature of the performed activity. The RFID sensing setup is based on two components: RFID tags and RFID tag reader. Each RFID tag has a unique identifier which is sensed by an RFID reader; when the tag is brought within the range of RFID reader. There are two types of RFID tags available in market: *passive RFID tags* and *active RFID tags*. A *passive RFID tag* does not have an internal power source and thus unable to transmit its own signal to the RFID reader. It is composed of two components: a microchip and an antenna, together called *RFID inlay*. A passive RFID tag has limited range (normally upto 5cm). On the other hand, an *active RFID tag* has its own internal power source with a small transmitter. The active RFID tag transmits its signal continuously which is received by a nearby RFID reader. The sensing range of an active RFID tag is relatively longer than a passive RFID tag. Our activity model also relies on object usage within an activity. The sensing infrastructure entails RFID sensing to identify contents of consumable items used in an activity. For example, we can attach a passive RFID tag to each medicine placed in a medicine cabinet. While retrieving a medicine from the medicine cabinet, the subject has to bring the RFID tag, attached on the medicine, within the range of RFID reader, so that our system can detect which medicine has been retrieved.

4.2.2 Sensor data acquisition and semantics of raw data

In order to construct a smart home, a wireless sensor network has been deployed in the subject's home. The sensor network includes sensors described above. Raw sensor data acquired from the smart environment are a continuous stream of sensor events. Each sensor event is stored as an entry in a database with its measurement, sensor ID, and the timestamp at which the event occurs. Raw sensor data are processed to infer semantics of events occur in an activity. As shown in Figure 4.1, *Semantic Integration Layer (SIL)* performs this task. It takes raw sensor events as an input and process them to infer meaningful real world events. In particular, we have used rules to express conditions about the type of detected raw events, which determine the recognition of events. These rules may include conditions about the temporal occurrence of raw sensor events. Suppose three sensors are deployed in the smart environment: the first is a *motion* sensor, which detects the *presence* of the person near the sink area; the second is a *water* sensor, which detects *flow* of water through a faucet; and the third is a *temperature* sensor, which measures the *temperature* of water flowing through a faucet. Contextual information received from three different sensors is combined to infer a simple action: if a motion sensor near a faucet detects a presence of the subject*AND* water sensor detects flow of water from the faucet *AND* a temperature sensor detects a rise in the temperature *AND* these three sensor events occur close in time *THEN* the smart home resident performs a simple action "open hot water kitchen faucet".

4.2.3 Temporal model

An individual sensor captures at least one manipulative gesture or movement executed by the subject in an activity. Sensors capture actions and transmit them to a central database system. We adopted a temporal model to represent sensor events. Suppose ε (for e.g., $\varepsilon = door\_is\_open, door\_is\_closed, \ldots$) is a set of all possible events that correspond to various multimodal sensors deployed in the environment. Also, suppose T is a set of all possible timestamps at which a sensor event can occur. For our convenience, we replaced each timestamp with a number which corresponds to the temporal distance (in seconds) between mid-night (12:00 a.m.) and the time instant at which the event occurs. A sequence of events captured by sensors is represented as:

$$S = \langle event(E_1, t_1), event(E_2, t_2), \ldots, event(E_n, t_n)\rangle \tag{4.1}$$

where, the tuple $event(E_i, t_i)$ represents an instance of event type $E_i \in \varepsilon$ occurred at a timestamp $t_i \in T$. We assume that sensor nodes communicate their sensed events in real time to a *gateway*.

4.2.4 Activity boundary detection

An activity consists of multiple simple actions. Note that simple actions are not always part of an activity. For example, "preparing meal" is an IADL in which a person can perform a simple action "open fridge door". However, it is not necessary that the person always performs this simple action inside IADL "preparing meal". For example, the person can "open a fridge door" to take water for drinking at any time in a day. The stream of sensor events includes various simple actions and sensor events which either took place in an activity or independently executed; outside an activity. Therefore, it is necessary to recognize activities which include several simple actions and sensor events.

We have defined $A = \{a_1, a_2, \ldots, a_k\}$ as a set of k activities, for example $A = \{preparingMeal, EatingMeal, takingMedicine\}$. Each activity $a_i \in A$ exists for a particular duration. The boundary of an activity is defined by its *label* and the duration for which it exists. The duration of an activity is defined by two time instants: the timestamp of the sensor event at which the activity *starts*, and the timestamp of the sensor event at which the activity *ends*. Thus we can represent an activity with three variables: label, start time (T_s), and end time (T_e).

Human activities are characterized by wide variability due to different lifestyles, habits, and environmental conditions. A person can adopt various patterns of actions to perform an activity. Moreover, a smart home layout depends on multiple factors: furnishings, quantity and quality of multimodal sensors, deployment scheme, etc. These factors influence sensor activation during an activity, which results in a significantly different sensor activation profile for the same activity performed in smart homes with different layouts. In order to handle such variability, we have exploited techniques which learn patterns of human activities and then detect their boundaries from the stream of sensor events. For this purpose, we have experimented with statistical (supervised machine learning) and hybrid (Markov Logic Network) techniques. The framework based on MLN is called FABER [71] and the framework based on supervised machine learning techniques is called SmartFABER [69]. In order to evaluate the proposed frameworks, we have conducted experiments in two environments: lab environment and real home environment. In fact, experimental evaluation reveals that FABER does not recognize activity boundaries with high accuracy in a real home environment. Therefore, SmartFABER is developed to accurately recognize activities in a real home environment. In the following subsection, we will explain the method used to recognize activity boundaries.

4.2.4.1 FABER: Markov Logic Network (MLN)

As mentioned above, we have considered a hybrid technique –Markov Logic Network (MLN) – to recognize activities from smart home data. This technique is explained in this section.

Due to rich expressiveness, symbolic techniques have been widely used for modeling and reasoning with human activities [68]. However, symbolic techniques do not allow uncertain inference. Therefore, due to this limitation, symbolic techniques are not appropriate to model many real world scenarios. This limitation particularly affects modeling human behaviors which involve temporal sequencing of actions performed in an activity. It is possible that a temporal sequence of actions can belong to multiple or possibly conflicting activities. Another important fact is that the sensed observations are noisy due to inaccurate sensor measurements and unintentional human interaction with the sensing environment. Considering these facts, we needed a framework which allows us to predict various activities with a level of certainty. Consider the following example, which reflects a conflict in recognizing activities using first-order logic.

> **Example 3** Suppose the subject wants to consume a prepared meal. Before eating the meal, the subject performs an activity "SetTheTable", and after finishing the meal the subject performs another activity "ClearTheTable". In both activities the subject accessed some repositories to retrieve or return utensils and silverware. The "silverware_ drawer" keeps the silverware and "utensils_ cabinet" contains utensils such as glasses and plates. In order to recognize these activities, following first-order logic rules might be applicable:

$$\begin{aligned} \forall\ s_i, t_i\ event(s_i, t_i) \wedge event(s_{i+1}, t_{i+1}) \Rightarrow \\ currentActivity(a, t_i)) \end{aligned} \tag{4.2}$$

$$\begin{aligned} \forall\ t\ currentActivity(SetTheTable, t) \Rightarrow \\ \neg currentActivity(ClearTheTable, t)). \end{aligned} \tag{4.3}$$

$CurrentActivity(a, t)$ refers to the fact that an activity a is being carried out at time t. The first rule states that the observation of a sequence of two particular sensor events indicates the execution of a given activity. For example, in case of activity "SetTheTable", at a time instant t_1 the rule 4.2 can be grounded with the following events:

$$\begin{aligned} event(open\_silverware\_drawer, t_1) \wedge \\ event(open\_utensils\_cabinet, t_2) \Rightarrow \\ currentActivity(SetTheTable, t_1) \end{aligned} \tag{4.4}$$

Of course, more complex formulas for *currentActivity* can be defined considering additional combinations of possibly non-consecutive sensor events. The second rule states that the current activity of an individual cannot be "SetTheTable" and "ClearTheTable" at the same time instant. Referring to the first rule, the same sensor sequence $\langle$"*open_silverware_drawer*", "*open_utensils_cabinet*"$\rangle$ can be included in both activities "SetTheTable" and "ClearTheTable". However, the derivation of both activities as instances of *currentActivity* at the same time instant t_i would violate the second rule and makes the model inconsistent.

In order to develop a consistent model, we need a technique which allows us to infer first-order logic rules with a level of certainty, such as Markov Logic Network (MLN) [72]. MLN is a combined representation of first-order logic and probabilistic graphical models. The probabilistic graphical model has the capability to efficiently handle uncertainty, whereas first-order logic allows us to represent knowledge with rich expressiveness. Thus the main idea of MLN is to combine probabilistic inference with the rich expressiveness of knowledge in a single paradigm. MLN allows us to formulate *soft* first-order logic rules. The validity of a soft formula is evaluated according to the probability of being true with respect to gathered facts. Each soft rule is associated to a *weight* that represents the confidence of the validity of the rule. Weights are generally learned from a training set of observations. The main inference task of MLN reasoning is to determine the most probable set of axioms representing the reality that can be inferred based on the defined rules and a set of observations. Intuitively, rules with higher weight will have higher inference in deriving these axioms.

In our model, observable predicates correspond to sensor events. Predicate $nextEvent(t_i, t_{i+1})$ indicates that the sensor event occurred at time t_i and the one occurred at time t_{i+1} are consecutive i.e., the former occurred before the latter, without having any sensor event between them. In our proposed architecture, we have ensured that no more than one sensor event can occur at a given time instant. Hidden predicates correspond to activity boundaries: $startActivity(a, t)$ states that an activity a begins at time t, and $endActivity(a, t)$ states that the activity a ends at time t. The approach used for boundary recognition is to write appropriate *soft rules* to create a correlation between windows of n consecutive sensor events and start/end of activities. For example, in the case of $n = 1$ following soft rules can be used:

- $event(+E_i, t) \rightarrow startActivity(+a, t)$
- $event(+E_i, t) \rightarrow endActivity(+a, t)$

Note that + symbol before a variable means that a *weight* is learned for each grounding of that variable. If we choose $n = 2$ following soft rules can be used:

- $event(+E_1, t_1) \wedge event(+E_2, t_2) \wedge nextEvent(t_1, t_2) \rightarrow$ $startActivity(+a, t1)$
- $event(+E_1, t_1) \wedge event(+E_2, t_2) \wedge nextEvent(t_1, t_2) \rightarrow$ $endActivity(+a, t_2)$

For a couple of consecutive sensor events, the first rule correlates the first event with the *start* of an activity and the second rule correlates the second event with the *end* of the activity. In general, the most effective value of n depends on characteristics of the pervasive system and also on considered activities. Note that in some cases MLN reasoner may not detect the end of an initiated activity. This may happen when a person does not complete that activity due to abnormal behavior. For example, the subject sets up the table but forgets to consume the meal at dinner; we consider the activity having dinner incomplete. In this case, we post-process the MLN results and we consider the activity ended after a maximum time threshold has expired since it starts. Weights of soft rules are learned by using a training set of sensor events acquired during the execution of the considered activities.

4.2.4.2 SmartFABER: Supervised machine learning

We have mentioned above that SmartFABER exploits a state of the art supervised machine learning technique to recognize activities. In fact, SmartFABER uses a time-based learning method which assigns activity class to each pre-processed sensor data instance. We have experimented with several supervised machine learning techniques to detect boundaries of activities. However, decision tree classifiers such as random forests [10] produced the best results for activity recognition. In order to use random forests, we have considered the feature extraction method proposed in [48]. The algorithm is based on segmenting time-sequenced sensor data and then using an exponential function allowing most recent sensor events to contribute more in activity boundary detection for that segment. A possible way of segmenting sensor data is to divide sensor events into windows containing equal number of sensor events. An activity consists of multiple actions which are captured by various sensors at different time instants. The wide spectrum of human activities involves varying rate of sensor firings over different spans of time. For example, the activity "sleeping" involves a few sensor firings over a long span of time, whereas an activity "leaving home" involves rapid firing of sensor events over a short span of time. Hence, it is possible that two sensor events, with a wide temporal gap between them, exist in same window. Intuitively, the recent sensor events in a window define the context of current activity. If each sensor event contributes equally in inferring the current activity, then the unequal distribution of sensor events in various activities can influence the activity recognition process. This problem can be solved by using a time-based weighting schema which determines the relative contribution of each sensor event in the window. In the proposed feature extraction algorithm, a weight is assigned to each sensor event which is relative to the last sensor event in that window. In this way the last sensor events contribute more in defining the label of an activity. Formally, suppose the ith window has the n number of sensor events with the following sequence:

$$\langle event(e_{i-n}, t_{i-n}, ..., event(e_{i-1}, t_{i-1}), event(e_i, t_i)\rangle \tag{4.5}$$

An exponential function has been defined to compute weights, which determine the time-based contribution of a sensor (of a particular type) event in defining the context of the last sensor event:

$$C(i, j) = exp(-\chi(t_i - t_k)) \tag{4.6}$$

Table 4.1: List of extracted features

No.	Feature Name	Description
1 . . . 5	Repository usage	Each of these features measures the temporally-weighted occurrences of usage of an individual repository (fridge, kitchen cabinet, . . .)
6	Stove usage	Measures the temporally-weighted occurrences of stove usage events
7	Cooking pot usage	Measures the temporally-weighted occurrences of cooking pot usage events
8	Food retrieval	Measures the temporally-weighted occurrences of food retrieval events
9	Medicine retrieval	Measures the temporally-weighted occurrences of medicine retrieval events
10	Approaching table	Measures the temporally-weighted occurrences of the event type "approaching kitchen table"
11	Leaving table	Measures the temporally-weighted occurrences of the event type "leaving kitchen table"
12	Start time	Time of the day of the oldest event in the sequence S
13	End time	Time of the day of the most recent event in the sequence S
14	Duration	Difference between end time and start time

Where, t_i is the time instant at which last event occurs in the ith window, t_k is the time instant at which kth sensor event occurs in the ith window, and the factor χ determines the decay rate of the influence. Table 4.1 shows the list of the features which are extracted through this methodology. The value of feature $F_k(S)$ (with $k = 1 \ldots 11$) is computed as:

$$F_k(S) = \sum_{event(E_j,t_j)\in S} w(t_j, t_i) \cdot f_k(event(E_j, t_j)) \tag{4.7}$$

where $f_k(event(E_j, t_j))$ is the time-independent contribution of $event(E_j, t_j)$

to the computation of the F_k value. For instance, when we have consider F_3 that measures the number of events in S related to the usage of the fridge, the value of $f_3(event(E_j, t_j))$ is 1 if E_j corresponds to either "open fridge" or "close fridge"; it is 0 otherwise. The feature vector computed based on S is given as an input to a *supervised machine learning algorithm* to infer the most probable class of the activity instance carried out at t_i. The algorithm is trained using a dataset of activities and feature vectors.

After recognizing activities, in a post-processing phase, an algorithm analyze classified sensor events and tries to fix mispredictions present in it. For this purpose, two aggregation techniques have been proposed: naive aggregation, and smart aggregation. Although these aggregation algorithms are not the contribution of thesis, we briefly explain these algorithms to understand the working of SmartFABER.

Naive aggregation The machine learning technique classify sensor events belonging to various activities. Among these sensor events, some events are correctly classified, while some instances are mispredicted. The naive approach aggregates sensor events which occur close in time and predicted with same activity label. The algorithm is based on a simple aggregation principle: if the machine learning technique predicts two consecutive events, occurred respectively at time instants t_i and t_{i+1}, with the same activity class $A_i = A_{i+1}$, these are considered as observations generated by the same instance of an activity of class A_i. Otherwise, they are considered observations generated by different activity instances.

Smart aggregation The naive aggregation technique does not fix mispredictions. In fact, it only aggregates sensor events belonging to same activity. In order to refine this approach, smart aggregation algorithm is presented which tries to fix mispredictions. The smart aggregation imposes certain conditions on predicted class labels. These conditions are derived separately for each activity. If a predicted class label satisfy imposed conditions, it is correctly predicted. Otherwise, if the predicted class label does not satisfy imposed conditions, it is mispredicted and replaced with a temporally closed correctly predicted class label.

4.2.5 Abnormal behavior recognition: Knowledge-base construction

The orignal contribution of this research is the recognition of fine-grained anomalies found in the daily routine of a smart home resident. We have constructed a knowledge-base to recognize these fine-grained anomalies. Typically, a knowledge-base consists of a set of concepts, instances of concepts, and relationships between different concepts [28]. These knowledge-base ingredients are gathered through various sources: smart environment, subject who is being monitored through smart home, and domain knowledge related to the subject and the smart environment. Domain knowledge is the key ingredient of the knowledge-base and it is either provided by domain experts or based on commonsense knowledge about the subject and the environment. We can divide the process of knowledge-base construction into two important phases: *knowledge acquisition* and *knowledge representation*.

4.2.5.1 Knowledge acquisition

The knowledge acquisition phase includes all practices and processes that are carried out to collect knowledge which is used to recognize fine-grained anomalies. In our model, knowledge is acquired from various sources: domain experts (clinicians and neuro-science experts), caregivers, subject, and commonsense knowledge. Our technique for knowledge acquisition is mainly based on meetings and discussions with domain experts, caregivers, and subject. Meetings with domain experts result in a model of abnormal behavior which is presented in Chapter 5, whereas meetings with caregivers and subject help us to understand the smart home environment. A brief description of the type of knowledge provided by these sources is given as:

- Domain experts: provide the *model* of the abnormal behavior, and other background knowledge which is important from their point of view to recognize the abnormal behavior. For example, medical prescriptions include names and timings of medicines.

- Caregiver/subject: provides knowledge about the subject's personality traits, his/her preferences in the routine life such as preferred mealtimes, and knowledge about the home environment such as names of cabinets according to their use.

- Commonsense: the routine life knowledge such as the food item cannot be consumed without cooking.

4.2.5.2 Knowledge representation

In order to formally represent domain knowledge in our model, we have considered *first-order logic* which is a symbolic language. First-order logic allows us to construct sentences, formally called rules, using various symbols: quantifiers, connectives, predicates, functions, and constants. For example, we can represent a concept that *Anna is a person* using a predicate *person(Anna)*, an activity *brushing teeth* using a predicate *activity(brushing_ teeth)*, and a simple action *open faucet* using predicate *action(open_ faucet)*. In order to recognize fine-grained anomalies, we have translated natural language descriptions of abnormal behavior into first-order logic rules. A rule is an "IF-THEN" structure which has two parts: a condition, and a conclusion. The *condition* part may include several atomic formulas which are connected through various connectives, conjunction and disjunction, to infer the *conclusion*. Anomaly recognition rules include several conditions which are based on indicators of the abnormal behavior provided by domain experts.

> **Example 4** Maintaining personal hygiene is one of the important activities performed by humans in their daily routine. According to neuro-physicians, cognitively impaired persons often face difficulties in carrying out such activities. Consider a scenario in which Anna faces difficulties in performing an activity related to her personal hygiene. Suppose, in a routine life, she wakes up at 7:00 a.m in the morning. She enters washroom at 7:15 a.m to perform hygiene related activities. At 7:20 a.m she starts activity brushing teeth with the following actions: takes her tooth brush, takes tooth paste from the cabinet, brushes her teeth, turns on faucet, and cleans her mouth. Notice that she does not turn off faucet due to forgetfulness. We have proposed the framework with an objective to recognize such fine-grained anomalies. Our proposed model works in the following way to recognize such anomaly:
>
> 1. Sensors deployed in the smart home collects facts about simple actions performed by Anna during an activity. In the given scenario, Anna performs an activity brushing teeth

consisting of some simple actions. Note that we have used a symbolic language (first order logic) to represent facts collected from the smart home:

```
activity: brushing teeth
start
action(take_brush, 7:22:32 a.m)
action(take_toothpaste, 7:22:55 a.m)
action(turnon_faucet, 7:24:10 a.m)
end
```

2. The activity recognition module in the proposed frame work recognizes the activity of brushing teeth. We can represent the recognized using following predicate

$$activity(brushing\_teeth, T_s, T_e)$$

The predicate states that activity brushing teeth starts at $T_s = 7:22:32a.m$ and ends at $T_e = 7:24:10a.m.$

3. The anomaly recognition module recognizes anomaly that faucet is not closed using following rule:

$$\begin{aligned} faucet\_notClosed \Leftarrow & \\ & activity(brushing\_teeth, T_s, T_e) \\ & \wedge action(turnon\_faucet, T_1) \\ & \wedge hold(on, faucet, T_1, T_2) \\ & \wedge T_2 - T_1 > 20 minutes \\ & \wedge \neg action(turnoff\_faucet, T_2). \end{aligned} \tag{4.8}$$

The rule states that the subject turns on faucet during the activity of brushing teeth but it remains on for more than 20 minutes and the subject does not turn it off. The *hold*() predicate is used to calculate temporal distance between two sensor events.

Chapter 5

Abnormal Behavior Recognition

In the previous chapter, we presented the proposed overall framework for abnormal behavior recognition. In this chapter, we will explain the method we have used to recognize the abnormal behavior. The fine-grained anomaly recognition method relies on the medical model of abnormal behavior explained in Chapter 4. The medical model describes the abnormal behavior in natural language. Our proposed anomaly recognition method relies on a symbolic technique to formally represent natural language descriptions into a set of rules. Formally, we have constructed a knowledge-base which contains anomaly recognition rules. These rules automatically infer fine-grained anomalies from the daily routine of a smart home resident by considering various types facts such as performed activities, domain knowledge, and contextual information. The rest of the chapter is structures as follows. In Section 5.1, we list down assumptions which have been made to implement the proposed framework. Section 5.2 describes the construction of knowledge-base for fine-grained abnormal behavior recognition.

5.1 Assumptions to simplify the implementation of the system

In order to effectively implement the proposed model for recognizing fine-grained anomalies, we have made some assumptions which are described below:

1. The subject lives alone in a smart home. A caregiver regularly visits the subject. We have considered single resident scenario, which is quite simple and simplifies the implementation of our model. Otherwise, multi-resident scenario requires a distinction between different activities performed by different residents.

2. We have not considered interleaved and concurrent activities.

3. The subject is continuously monitored through the proposed system and it periodically detects fine-grained anomalies, for example at the end of each day.

4. The stock of consumable items, medicines and food items, is managed by a caregiver. The caregiver regularly visits the smart home and ensures every consumable item is kept at right place and he/she also ensures a continuous supply of these items. The anomaly detection model relies on the utilization of various food items and medicines by the subject. The correct working of the proposed system highly depends on the proper management of these items. Otherwise, the algorithm produces high number of false positives and false negatives.

5. The subject adheres a medication regiment. In this regard, the subject has to take N number of medicines per day according to a prescription provided by a physician. Each medicine has a unique ID such as $(M_1, M_2 M_N)$.

6. Each medicine is kept in a separate box or bottle. Each blistered medicine is kept in a box, whereas a syrup medicine is stored in a bottle. Boxes and bottles are placed inside a "medicine cabinet". An RFID tag is attached to each medicine (box/bottle). The "medicine cabinet" is dedicated for medicines.

7. Food items are divided into two categories: the first is refrigerated food items, and the second is non-refrigerated food items. Refrigerated food items (e.g., butter, milk, cheese etc.) are sensitive to temperature and, therefore, always stored in a refrigerator. Non-refrigerated food (e.g., pasta, rice, sugar etc.) items are stored in a cabinet labeled "non-refrigerated food cabinet". The cabinet is dedicated for non-refrigerated food items.

8. Each food item, refrigerated or non-refrigerated, has a proper packing or kept in a container. RFID tags are attached with each food item to track their usage.

9. Food items, either refrigerated or non-refrigerated, are further categorized depending on their way of consumption. All food items which have to be cooked are categorized as "must be cooked food items". This categorization is done to understand the stove utilization for various food items.

10. Whenever the subject retrieves or returns any consumable item (medicine or food) from a respective repository, he/she has to swipe it through an RFID reader. Note that we are using RFID based tracking of consumable items on experimental basis, therefore, it may result in false positives and false negatives. For example, the subject really takes a medicine but forgets to swipe it is a case of false positive, in which actually an anomaly does not occur but our system detects it. Similarly, the subject can deceive our system by swiping a medicine but actually not consuming it; it is a false negative, in which our system fails to detect the actual anomaly. We consider such scenarios as sensing infrastructure problems, and not the failure of our anomaly recognition method. In fact, we assume that sensing infrastructure always detects a "retrieve" and "return" of a medicine which is actually not true in the current implementation of the system, however, by using more sophisticated sensing systems, we can achieve such an accuracy in our system. Hence, we consider it another research topic, in which efforts should be made to accurately sense "retrieve" or "return" of a medicine: it could be extended to detect even an intake of a medicine.

11. The subject follows a regular timetable for the daily meals: breakfast, lunch and dinner.

5.2 Recognizing fine-grained anomalies

In Chapter 4, we have introduced the clinical model of the abnormal behavior which has been developed in collaboration with neuro-science experts. The modeling of the abnormal behavior results in natural language descriptions of fine-grained anomalies which are usually observed in elderly persons having MCI. The model presents three types of fine-grained anomalies: omissions, omissions, and additions. Fine-grained anomalies are specific deviations normally found in activities performed by an MCI patient. In fact, such deviations are normally not expected in normal aging. Considering the medical model of abnormal behavior, we have defined $L = \{l_1, l_2, \ldots, l_n\}$ as a set of n pre-defined set of anomalies (for example, $L = \{missedMedicine, missedLunch, repeatMedicine\}$). Each anomaly $l_i \in L$ belongs to an activity a which is an instance of a pre-defined set of activities A. In order to automatically infer these anomalies, we have constructed a knowledge-base and the process involves three fundamental tasks: knowledge acquisition, knowledge representation, and formulation of anomaly detection rules in first-order logic.

5.2.1 The rule formulation

In order to formulate fine-grained anomaly recognition rules, we have considered various types of facts. The first type of facts relates to activities A which are performed in the smart environment. Activities are extracted from sensor data using artificial intelligence techniques which are explained Chapter 4. Besides recognized activities, we also need facts which provide us knowledge about the expected normal behavior of the person. The second type of facts is based on domain knowledge. The domain knowledge is mainly based on common sense knowledge and expert knowledge about the smart home and its resident. It includes a variety of information about the subject such as his/her personality traits, lifestyle, habits, and household items used by him/her in the smart home. For example, the subject has to adhere a medication regimen in this case the domain knowledge is a prescription which includes names of medicines and their prescribed timings. The third type of facts relies on contextual information about the environment in which the person performs activities. Humans perform activities in a diversity of spatial, temporal, and environmental contexts [14]. Spatial contexts are related to the location and entities used in the activity. For example, rooms, appliances, and other household articles are spatial contexts. Temporal contexts include information about time and/or duration of an activity. Environmental contexts relate to surrounding conditions in which the activity was performed. Temperature and humidity are examples of environmental contexts. Contextual information is captured through multi-modal sensors. Figure 5.1 illustrates types of facts which have been considered for recognizing anomalies.

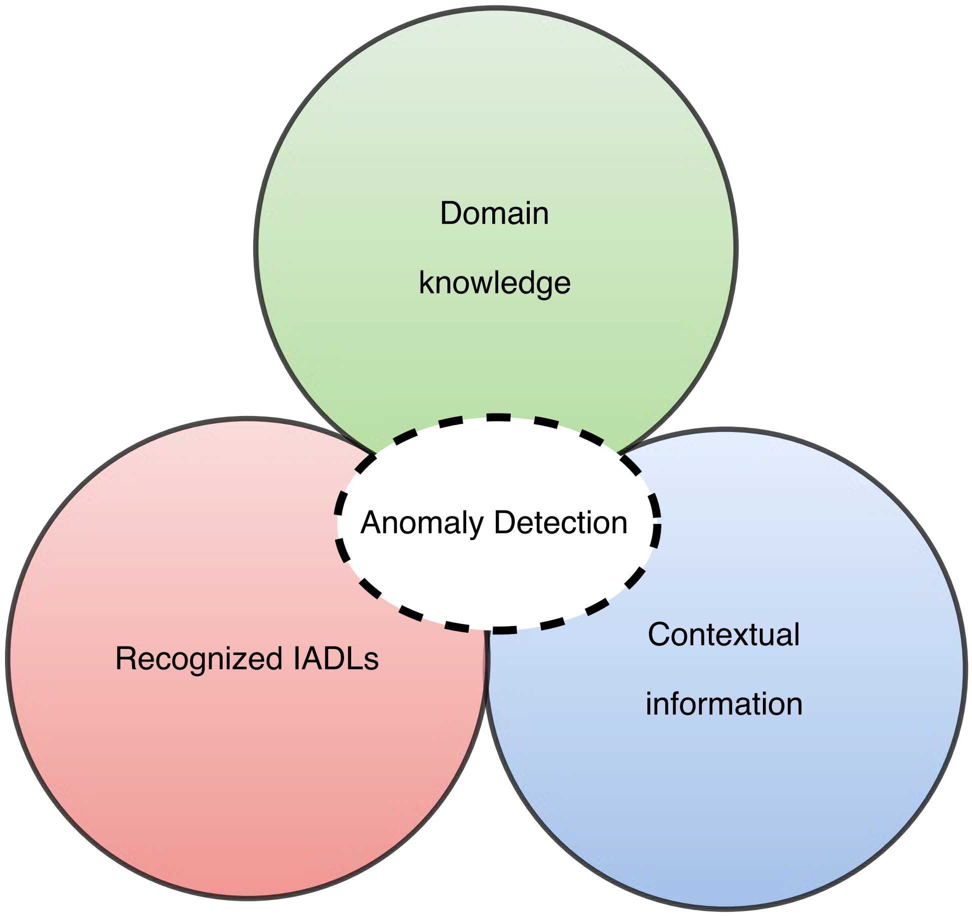

Figure 5.1: Types of facts considered for fine-grained anomaly recognition

In order to recognize fine-grained anomalies, natural language description of abnormal behavior is translated into first-order logic rules. In first-order logic a classification rule is represented with an expression of syntax:

```
if  (Conditions) then L
```

In this expression L is the class label, and *Conditions* are a conjunction of logical tests which describe properties of class label that have to be satisfied for a rule to 'fire'. The class label (L) refers to a predefined set of anomalies. *Conditions* are used to detect the individual anomalies $l_i \in L$ and are derived from various types of facts which are shown in Figure 5.1. The smart home environment provides contextually rich data. Therefore, instead of using propositional logic, we considered to formulate rules in first-order logic. First-order logic is more expressive than propositional logic allows us to represent objects, relations between different objects, and properties of the entire collection of objects using *Quantifiers*. In the knowledge-base, facts are represented using three types of symbols: constants, predicates, and functions [75] . In order to formulate first-order logic rules for detecting anomalies, we have to understand the relation between various types of facts and their logical combinations. The formulated rules are combined together as a rule-set to automatically infer anomalies. The *inference engine* periodically (e.g. end of the day) infers rule-based anomaly definitions.

5.2.2 Logical representation of facts and anomalies

As mentioned earlier, we have considered a symbolic technique — first-order logic — to formulate fine-grained anomaly recognition rules. For this purpose, various types of facts, related to smart home and its resident, have been symbolically represented using three types of logical symbols: constants, predicates, and functions. A constant symbol describes semantics of objects used by a smart home resident. The resident can use numerous household objects such as furniture, electrical appliances, and consumable items. A *predicate* symbol can be used to describes various characteristics of an object along with its semantics and its relation with other objects. For example, the object med_1 is a medicine which can be represented by a predicate in formal logic as $isMedicine(med_1)$. The third type of symbols is a *function* which describe the function of various objects in the domain.

In order to formally represent various facts, we have developed a vocabulary of symbols. Here, a convention is followed that a constant always begins with a *small letter* and a variable always begins with a *capital letter*. Details of these symbols is described as follows:

- Since our objective is to recognize fine-grained anomalies, an anomaly is a *consequent* in every rule. Each anomaly is represented by a standard predicate $anomaly(A, Type, L, O, T_x)$, where A represents a pre-defined set of activities in which a is an individual activity, $a \in A$; $Type$ represents an anomaly type: critical or non-critical; L is a predefined set of anomalies in which l is an individual anomaly, $l \in L$; O is an object involved in the anomaly (e.g., the name of a repository); T is the time instant at which the anomaly occurs.

- Some predicates define characteristics of an object. For example, the predicate $isMedicine(M)$, $isFood(F)$, and $isRepository(R)$ means M is a medicine, F is a food item, and R is a repository, respectively. Note that each variable (capital letter) takes a range of values from its specific domain.

- A simple action is represented by the predicate $action(ACT, O, O', T)$. The predicate states that a person executes an action ACT on object O and O' at a time instant T.

- An activity is represented by the predicate $activity(A, T_s, T_e)$, where A is a pre-defined set of activities, $a \in A$; T_s represents the time instant at which the activity starts; T_e represents the time instant at which the activity ends.

- We have included domain knowledge in our model which enables us to capture the deviation of the human behavior from the normal behavior. The predicate $prescribed(M, Tx, Ty)$ represents information provided by domain knowledge. It states that the person has to take a medicine M between time instants Tx and Ty. Similarly, we have used domain knowledge to categorize food items. For example, the predicate $mustBeCooked(F)$ states that a food item F has to be cooked before consuming it.

- Temporal conditions are expressed by the $hold(S, O, T_1, T_2)$ predicate. The predicate states that the status of an object O has been S from the time instance T_1 to T_2. The predicate is used to measure the temporal distance between two corresponding events, for example the microwave oven has been on from 11:30 a.m. to 11:55 a.m. The temporal expressions that we have used in our rule-based definitions include various temporal measurements such as an interval of time during which an action is performed, the temporal distance between two corresponding actions, the temporal duration of an activity, the temporal order among activities.

5.2.3 Examples of abnormal behavior

Now, we present two scenarios in which the subject exhibits abnormal behavior. These examples explain how we have hypothesized the abnormal execution of an activity. In presented scenarios, Anna performs activities with some anomalies. Afterwards, we show first-order logic rules which automatically detect fine-grained anomalies.

> **Example 5** Anna is living independently in a smart home. A caregiver regularly visits Anna to check her general health condition and also to maintains household essentials. The house is equipped with sensors of various modalities. Doors of rooms (e.g bedroom, living room, kitchen) and repositories (e.g., medicine cabinet, refrigerator, non-refrigerated food storage cabinet) are equipped with magnetic sensors to detect "open" and "close" actions. Based on the contents of food items, these are either placed in a refrigerator or in a non-refrigerated food storage cabinet. RFID tags are attached with each food item (both refrigerated and non-refrigerated) to identify their contents (e.g., rice, milk, coffee, sugar). These tags are used to track the usage of food items. RFID readers are deployed in proximity to cabinets and the refrigerator. RFID readers detect which food item has been retrieved or returned from respective repositories.
>
> In a normal routine, Anna does breakfast between 8:00 a.m and 9:00 a.m. Suppose that at 8:05 a.m Anna opens a "fridge" and "retrieves" a "milk" pack from it. After consuming the milk, she "returns" the pack to a "non-refrigerated food storage cabinet (nrCabinet)"; instead of returning it to the "fridge". Based on sensed events, the following actions, as predicates, are automatically added to the knowledge-base.

```
action(open,door,fridge,8:05:00  a.m)
action(retrieve,milk,fridge,8:05:07 a.m)
action(close,door,fridge,8:05:13 a.m)
action(open,door,nrCabinet,8:10:10 a.m)
action(return,milk,nrCabinet,8:10:15 a.m)
action(close,door,nrCabinet,8:10:20 a.m)
```

Anna commits a critical anomaly, *critical replacement*, as we cannot expect in normal circumstances a person can return an item being retrieved from a fridge to a non-refrigerated food item cabinet. We know through common sense knowledge that milk has to be stored in a fridge. We can represent this knowledge with the predicate $isRefFood(milk)$ which states that milk is a refrigerated food item. Following rule is formulated to detect this anomaly.

General Rule

$$\begin{aligned} anomaly(A, Type, L, O, T_x) \Leftarrow \\ action(return, O, O', T) \wedge \\ isRefFood(O) \wedge \\ isNonRefStorage(O') \wedge \end{aligned} \tag{5.1}$$

Note that this rule can be grounded for the above mentioned scenario:

Grounded Rule

$$\begin{aligned} anomaly(preparingMeal, c, replacement, milk, 8:10:15a.m) \Leftarrow \\ action(return, milk, nrCabinet, 8:10:15a.m) \wedge \\ isRefFood(milk) \wedge \\ isNonRefStorage(nrCabinet) \wedge \end{aligned} \tag{5.2}$$

Example 6 Consider another scenario in which we monitor Anna for adherence to a medication regimen. Suppose Anna has to take some medicines according to a prescription given by her physician . All medicines are placed in a medicine cabinet, labeled "medCabinet", which is dedicated for medicines. Each medicine is kept in a separate box and an RFID tag is attached to each box. An RFID reader is deployed in proximity to the "med-cabinet". The RFID reader detects the medicine which has been retrieved or returned. According to the prescription, Anna has to take a medicine, labeled “med1”, between 3:00 p.m. and 4:00 p.m. One day she forgets to take this medicine during the prescribed time. Therefore, no sensed events are logged in the database about this activity. However, in order to detect this anomaly, we need the prescription. The prescription is stored in the knowledge-base with the following predicates:

```
prescribed(med1, 3:00 p.m, 4:00 p.m)
isMedicine(med1)
```

We can formulate the following rule to detect this anomaly:

General Rule

$$\begin{aligned} anomaly(A, Type, L, O, T_x) \Leftarrow \\ prescribed(med1, T_1, T_2) \\ not((action(retrieve, med1, medCabinet, T) \wedge \\ (T > T_1) \wedge \\ (T < T_2)) \wedge \\ isMedicine(med1) \wedge \\ isMedicineCabinet(medCabinet). \end{aligned} \tag{5.3}$$

Since no actions are found in the database, it is assumed that the subject has forgotten to take the prescribed medicine. It is a critical omission (o). The rule can be grounded with factual information for this particular scenario.

Grounded Rule

$$\begin{aligned} anomaly(takingMedicine, c, omission, med1, 4:00p.m) \Leftarrow \\ prescribed(med1, 3:00p.m, 4:00p.m) \\ not((action(retrieve, med1, medCabinet, T) \wedge \\ (T > 3:00p.m) \wedge \\ (T < 4:00p.m)) \wedge \\ isMedicine(med1) \wedge \\ isMedicineCabinet(medCabinet). \end{aligned} \tag{5.4}$$

Note that in the grounded rule T is a variable and according to the temporal model defined in Chapter 4 each sensor event occurs at a unique timestamp. Therefore, T can be any timestamp which exists between the start of prescribed interval T_1 and the end of prescribed interval T_2.

5.3 Knowledge-base specifications

In Section 5.2.1, we have introduced the technique to formulate fine-grained anomaly detection rules. In this section, we will formally present rules to infer various anomalies which reflect behavioral changes in the daily behavior of the subject. In each rule, *antecedents* are derived from descriptions of abnormal behavior provided by clinicians and neuro-science experts. In this work, we have considered three activities recommend by clinicians from the Institute Fatebenefratelli, Lombardy. These activities are: eating meal (ADL), preparing meal (IADL), and adherence to a medication regimen (IADL). In general, for the activity preparing meal the anomaly recognition system checks the correct execution of activity during regular mealtimes. We equipped the cooking area with various sensors to detect actions performed by the subject while preparing a meal. The second activity is eating meal in which the system recognizes the consumption of regular meals during mealtimes. In case of MCI patients, a common example of abnormal behavior is skipping regular meals. For example, an anomaly occurs when the subject prepares a meal, but forgets to consume it. The third activity is compliance to a medical prescription. In this activity, we construct rules which check various aspects of compliance such as missing a prescribed medicine, taking a medicine at a wrong time, and repeating a prescribed medicine within the prescribed time. Further details of these anomalies are provided within the rule definitions of anomalies in the following subsections. Table 5.1 describes all constant and variable symbols which we are used to formulate rules. These symbols include anomaly types, anomaly labels, activity labels, actions, names of items, time instants, and intervals. Note that a symbol beginning with a *small letter* is a constant, whereas a symbol beginning with a *capital letter* is a variable, which takes a range of values from a specific domain.

Table 5.1: Constants and variable symbols in anomaly recognition rules

No.	Symbol	Description
Anomaly types		
1	*c*	Critical anomaly
2	*nc*	Non-critical anomaly
Anomaly Labels		
3	*o*	Omission
4	*rpt*	Repeat
5	*ia*	Improper activity
Activity Labels		
6	*tm*	Taking medicines
7	*pm*	Preparing meal
8	*em*	Eating meal
Actions		
9	*retrieve*	The person retrieves an item from a repository
10	*return*	The person returns an item from a repository
11	*open*	The person opens a repository
12	*close*	The person closes a repository
13	*turnOn*	The person turns on a stove burner
14	*turnOff*	The person turns off a stove burner
Items		
15	*medCab*	A medicine cabinet dedicated for medicines
16	*fridge*	A refrigerator
17	*nrCab*	A cabinet dedicated for non-refrigerated food items
18	*cpCab*	A cabinet which keeps utensils used for cooking food
19	*swCab*	A cabinet which keeps silverware
20	*door*	The door of a repository
21	*stove*	A stove used in the kitchen for cooking food
22	*burner*	A burner on the stove
23	*M*	A variable takes names of medicines
24	*FI*	A variable takes names of food items
Time instants and intervals		
25	*Ts*	The time instant at which an activity starts
26	*Te*	The time instant at which an activity ends
27	*Tx*	The beginning of an interval
28	*Ty*	Th ending of an interval
29	*Tr*	The time instant of a repeating action

5.3.1 Anomaly detection rule for medication adherence

MCI patients as well as cognitively intact elderly persons often face difficulties in adherence to a medication regimen. Adherence to the medication regimen involves cognitive skills which depend on executive function and working memory [39]. In order to comply with a medication regimen, the person has to remember names of medicines and their dosage timings. However, due to the decline in cognitive abilities, the person can forget physician's instructions or other related information which may lead to medication non-adherence. Medication non-adherence is a serious issue as the failure to take a medicine within the prescribed time can increase the risk of hospitalization in elderly people or it can be critical in certain chronic diseases such as hypertension. As mentioned earlier, we have formulated rules to cover various aspects of medication non-adherence such as missing a prescribed medicine (rule 5.5), taking a wrong medicine (rule 5.6), and repeating a medicine (5.7). We have taken into account the prescription, as domain knowledge, to detect the anomalous behavior of the subject.

Missed medicine The subject forgets to take a prescribed medicine.

$$\begin{aligned} &anomaly(tm, c, o, M, T_y) \Leftarrow \\ &\qquad prescribed(M, T_x, T_y) \\ &\qquad \wedge isMedicine(M) \\ &\qquad \wedge not((action(retrieve, M, medCab, T) \\ &\qquad \wedge (T \geqslant T_x) \wedge (T \leqslant T_y))). \end{aligned} \tag{5.5}$$

Wrong Medicine The subject takes a wrong medicine.

$$\begin{aligned} &anomaly(tm, c, ia, M, T) \Leftarrow \\ &\qquad isMedicine(M) \\ &\qquad \wedge action(retrieve, M, medCab, T) \\ &\qquad \wedge not((prescribed(M, T_x, T_y) \\ &\qquad \wedge (T \geqslant T_x) \wedge (T \leqslant T_y))). \end{aligned} \tag{5.6}$$

Repeat Medicine The subject repeats a medicine dosage within the prescribed time.

$$\begin{aligned} anomaly(tm, c, rpt, M, T_r) \Leftarrow \\ & isMedicine(M) \\ & \wedge prescribed(M, T_x, T_y) \\ & \wedge action(retrieve, M, medCab, T) \\ & \wedge action(retrieve, M, medCab, T_r) \\ & \wedge (T \geqslant T_x) \wedge (T \leqslant T_y) \\ & \wedge (T_r \geqslant T_x) \wedge (T_r \leqslant T_y) \\ & \wedge (T_r > T). \end{aligned} \tag{5.7}$$

Medicine not returned to repository Besides taking a medicine within the prescribed time, it is also important that the subject must return a retained medicine to the medicine cabinet after taking its required dosage. Otherwise, the subject is unable to find it in the medicine cabinet (medCab) for the next dosage. We have used *hold*() predicate to formulate the temporal distance between a "retrieve" action and its corresponding "return" action for all items which the subject retrieves (medicine in this case) from their respective repositories. Based on this temporal distance, we have formulated following two rules which recognize this anomaly. The first rule 5.10 states that the subject retrieves a medicine and fails to return it within *30 minutes*. The second rule 5.11 states that the subject fails to return the medicine within the activity.

$$\begin{aligned} holds(isRetrieved, M, T, T) \Leftarrow \\ & action(retrieve, M, medCab, T). \end{aligned} \tag{5.8}$$

$$\begin{aligned} holds(isRetrieved, M, medCab, T_1, T_j) \Leftarrow \\ & nextevent(T_i, T_j) \\ & \wedge holds(isRetrieved, M, medCab, T_1, T_i) \\ & \wedge not(action(return, M, medCab, T_i)). \end{aligned} \tag{5.9}$$

$$
\begin{aligned}
&anomaly(tm, c, o, M, T_e) \Leftarrow \\
&\qquad activity(tm, T_s, T_e) \\
&\qquad \wedge\, isMedicine(M) \\
&\qquad \wedge\, holds(isRetrieved, M, medCab, T_x, T_y) \\
&\qquad \wedge\, (T_x \geqslant T_s) \wedge (T_x \leqslant T_e) \\
&\qquad \wedge\, (T_y \geqslant T_s) \wedge (T_y \leqslant T_e) \\
&\qquad \wedge\, ((T_y - T_x) > 30 minutes).
\end{aligned}
\tag{5.10}
$$

$$
\begin{aligned}
&anomaly(tm, c, o, M, T_e) \Leftarrow \\
&\qquad activity(tm, T_s, T_e) \\
&\qquad \wedge\, isMedicine(M) \\
&\qquad \wedge\, holds(isRetrieved, M, medCab, T_x, T_y) \\
&\qquad \wedge\, (T_x \geqslant T_s) \wedge (T_x \leqslant T_e) \\
&\qquad \wedge\, (T_y \equiv T_e) \\
&\qquad \wedge\, not(action(return, M, medCab, T_e)).
\end{aligned}
\tag{5.11}
$$

5.3.2 Anomaly detection rules for Preparing meal

Taking meals at regular timings ensures a healthy lifestyle. The subject can consume ready-made meals, however, the activity preparing meal indicates the level of activeness of a person in old age. The continuous skipping of this activity may indicate serious issues such as physical health problems, depression, isolated lifestyle, and most importantly decline in cognitive abilities. For example, it is a high alert for clinicians if an elderly person is not preparing meal from continuously three days. Similarly, it is also an alert if the subject is continuously taking cold meals, even at the time of lunch and dinner when usually people prefer to prepare a hot meal. Therefore, we have covered different aspects of this activity, which include skipping of the activity “preparing meal”, stove utilization, and a proper cooking of food items.

Missed Preparing meal As mentioned earlier, activities are recognized from a continuous stream of sensor events. In order to formulate a rule which detects a missed meal, we have considered different types of facts: domain knowledge, mealtimes according to the subject's habits, and recognized activities with their start and end timestamps.

$$\begin{aligned} anomaly(pm, c, o, meal, T_y) \Leftarrow \\ & mealTime(Meal, T_x, T_y) \\ & \wedge not((activity(pm, T_s, T_e) \\ & \wedge (T_s \geqslant T_x) \wedge (T_s \leqslant T_y) \\ & \wedge (T_e \geqslant T_x) \wedge (T_e \leqslant T_y))). \end{aligned} \tag{5.12}$$

Stove usage It is one of the most common anomalies observed in MCI patients that they forget to attempt important and familiar steps in an activity such as forgetting to turn off the stove after using it. Again, we have used *hold*() predicate to calculate the temporal distance between the time instant when the person turns on the stove burner and the time instant when the person turns it off. *holds*() predicate initializes a duration starting when the person turns on the stove burner and continuously updates it until the stove is not turned off. Formally, the rule 5.15 states that the subject has turned on the stove burner during the activity "preparing meal", but forgets to turn it off after finishing it.

$$\begin{aligned} holds(isOn, stove, T, T) \Leftarrow \\ & action(turnOn, burner, stove, T). \end{aligned} \tag{5.13}$$

$$\begin{aligned} holds(isOn, burner, stove, T_1, T_j) \Leftarrow \\ & \wedge nextevent(T_i, T_j) \\ & \wedge holds(isOn, burner, stove, T_1, T_i) \\ & \wedge not(action(turnOff, burner, stove, T_i)). \end{aligned} \tag{5.14}$$

$$
\begin{aligned}
anomaly(pm, c, o, stove, T_e) \Leftarrow & \\
& activity(pm, T_s, T_e) \\
& \wedge holds(isOn, burner, stove, T_x, T_y) \\
& \wedge (T_x \geqslant T_s) \wedge (T_x \leqslant T_e) \\
& \wedge (T_y \equiv T_e) \\
& \wedge not(action(turnOff, burner, stove, T_e)).
\end{aligned} \tag{5.15}
$$

Improper preparing meal It is a normal behavior that whenever a person retrieves a cooking pan along with a food item which has to be cooked then he/she must use a stove to cook the food item. However, a forgetful MCI patient may has an intention to cook the raw food item, but due to cognitive decline the subject forgets to use the stove in the activity. Following rule 5.16 is formulated to detect such a situation.

$$
\begin{aligned}
anomaly(pm, c, o, stove, T_e) \Leftarrow & \\
& activity(pm, T_s, T_e) \\
& \wedge mustBecooked(FI) \\
& \wedge action(retrieve, FI, nrCab, T_1) \\
& \wedge (T_1 \geqslant T_s) \wedge (T_1 \leqslant T_e) \\
& \wedge not((action(turnOn, burner, stoveT) \\
& \wedge (T \geqslant T_s) \wedge (T \leqslant T_e))).
\end{aligned} \tag{5.16}
$$

5.3.3 Anomaly detection rules for Eating meal

Eating is a vital activity for all human beings. Researchers have indicated several symptoms of eating disturbances which occur with progression in cognitive impairment. These symptoms include swallowing disturbance, change of appetite, change of eating habits, consumption of inedible objects, and difficulty in distinguishing utensils [44]. Eating disturbances may lead to the habit of skipping meals which result in malnutrition, decline in physical health, and weight loss. An anomaly “missed eating meal” occurs if a person forgets to take a meal in the preferred mealtimes. We can get information about preferred mealtimes from the subject or from his/her caregiver and use this domain knowledge to detect the anomalous behavior. However, in some situations the subject attempts the activity in an improper way. For example, the subject forgets to take the silverware for eating a meal. The following rules recognize anomalies related to activity "eating meal".

Missed eating meal The rule 5.17 states that an anomaly occurs if the subject fails to take his/her meal in the preferred mealtimes. Note that variables T_x and T_y represent the beginning and the end of an interval in which the subject normally takes his/her meals. For example, the subject normally takes his/her breakfast between $7:30am$ and $9:00am$. So, in this case the value of T_x is $7:30am$ and the value of T_y is $9:00am$.

$$
\begin{aligned}
&anomaly(em, c, o, meal, T_y) \Leftarrow \\
&\qquad \wedge\, mealTime(Meal, T_x, T_y) \\
&\qquad \wedge\, not((activity(em, T_s, T_e) \\
&\qquad \wedge\, (T_s \geqslant T_x) \wedge (T_s \leqslant T_y) \\
&\qquad \wedge\, (T_e \geqslant T_x) \wedge (T_e \leqslant T_y))).
\end{aligned}
\tag{5.17}
$$

Silverware MCI patients may intend to eat a meal, however, he/she does not fulfill its basic requirements such as taking silverware for eating the food. A cabinet ($swCab$) is dedicated for silverware. The rule 5.18 states that an anomaly occurs if the subject does not *open* this cabinet within the activity "eating meal".

$$
\begin{aligned}
&anomaly(em, c, o, silveware, T_e) \Leftarrow \\
&\qquad activity(em, T_s, T_e) \\
&\qquad \wedge\, not((action(open, door, swCab, T) \\
&\qquad \wedge\, (T \geqslant T_s) \wedge (T \leqslant T_e))).
\end{aligned}
\tag{5.18}
$$

5.3.4 Non-critical anomalies

As discussed earlier, non-critical anomalies are weak indicators of behavioral modifications. However, it is important to track such anomalies so that clinicians can differentiate between normal lifestyle of the person and behavioral changes. For example, a history of an elderly person tells us that he/she has a habit to close a repository after retrieving an item from it. It is possible that he/she occasionally left the repository open due to hastiness and negligence. However, after some time (possibly months or years) this habitual trend starts changing and the person is no more careful to close repositories after using them. This diverging trend can alert clinicians to further investigate reasons of this behavioral change. The following rules recognize the non-critical anomaly: the repository is not closed after using it. The rule 5.21 states that an anomaly occurs if the subject opens a repository and does not close it within *20 minutes*. The rule 5.22 detects that the subject forgets to close a repository in an activity. *hold*() predicate calculates the temporal distance between an event *open a repository* and the corresponding event *close the repository*.

$$holds(isOpen, Repository, T, T) \Leftarrow \\ action(open, Repository, T). \tag{5.19}$$

$$holds(isOpen, Repository, T_1, T_j) \Leftarrow \\ nextevent(T_i, T_j) \\ \wedge holds(isOpen, Repository, T_1, T_i) \\ \wedge not(action(close, door, Repository, T_i)). \tag{5.20}$$

$$anomaly(A, nc, o, Repository, T_s) \Leftarrow \\ activity(A, T_s, T_e) \\ \wedge holds(isOpen, Repository, T_x, T_y) \\ \wedge (T_x \geqslant T_s) \wedge (T_x \leqslant T_e) \\ \wedge (T_y \geqslant T_s) \wedge (T_y \leqslant T_e) \\ \wedge ((T_y - T_x) > 20 minutes). \tag{5.21}$$

$$
\begin{aligned}
anomaly(A, nc, o, Repository, T_s) \Leftarrow \\
& activity(A, T_s, T_e) \\
& \wedge holds(isOpen, Repository, T_x, T_y) \\
& \wedge (T_x \geqslant T_s) \wedge (T_x \leqslant T_e) \\
& \wedge (T_y \geqslant T_e) \\
& \wedge not(action(close, door, Repository, Te)).
\end{aligned} \tag{5.22}
$$

Chapter 6

Automatic Induction of Abnormal Behavioral Patterns

In Chapter 5, we have described the specifications of the knowledge-base used to recognize rule-based descriptions of anomalies. The knowledge-base relies on factual information gathered through the sensing infrastructure and domain knowledge. In order to construct the knowledge-base, we have manually translated natural language definitions of the abnormal behavior into first order logic rules. However, there are some design constraints involved in the manual construction of the knowledge-base. In this chapter, we will address those design constraints and introduce a rule learning based method which automates the process of rule generation for anomaly detection. In fact, the automatic rule generation for fine-grained anomaly recognition is the most novel aspect of this thesis. The rest of the chapter is structured as follows. In Section 6.1, we will explain the importance of rule learning along with an example which highlights the limitations of manual rule formulation. In Section 6.2, we present the basic working principle of various rule learning techniques along with a brief overview of few algorithms. In Section 6.3, we describe InductiveFABER which is a revised version of FABER and relies on a rule induction algorithm (RIPPER) for automatic rule generation. Finally, in Section 6.4, we present rules which have been learned during experiments.

6.1 Motivation

In order to construct a knowledge-base for recognizing the abnormal behavior, the primary task is to represent knowledge as first order logic rules. However, the process of rule formulation involves a deep and complex understanding of *relationships* between different types of facts acquired from smart home and abnormal behaviors exhibited by the subject. These *relationships* are influenced by several *factors*, including the home environment, sensing infrastructure, personal habits, and physical health status of the senior. It is not a trivial task for a knowledge engineer to acquire detailed information of these *factors* and their influence on the process of rule formulation. For example, the sensing infrastructure in a smart home involves several *design intricacies* such as types of multi-modal sensors used in the design, the quantity of individual sensors deployed in the smart environment, and locations at which sensors are deployed. Considering all these factors, the process of rule formulation becomes a challenging and arduous task. Moreover, manual rules are formulated while considering a specific person and a specific smart home environment. Thus manually formulated rule-set is not seamlessly portable to different environments and it makes the overall process more challenging because the knowledge engineer may has to repeat the whole process for a different person living in a different smart environment. Consider the following example, which elaborates above mentioned limitations through a practical scenario.

> **Example 7** Continuing the example of Anna, who is an elderly woman living in a smart home and monitored through FABER. Besides Anna, clinicians are now interested to monitor another senior citizen, Bob, who also has a tendency of cognitive impairment. Comparing to Anna, Bob has several severe comorbidities which affects his routine life activities and therefore his lifestyle is different as compared to Anna. Both subjects live independently in their own smart homes, which are equipped with different sensors. Due to different smart home layouts and physical conditions, same activity executed by Anna and Bob results in different sensors activation; therefore, different sequences of sensor events. Hence, the same anomaly may exhibit different patterns of actions and events, which are very hard to capture manually. Furthermore, in order to recognize anomalies, the knowledge en-

gineer has to develop two separate rule-sets, while considering individual cases of Anna and Bob.

Solution In order to address problems faced in the process of manual rule formulation, we have revised our methodology of knowledge-base construction to achieve the following objectives:

- development of a flexible and scalable model.
- portability of the model to other smart environments.
- rapid construction of rule-sets for different environments.

In the revised methodology, we have considered anomaly recognition as a pattern identification problem and proposed to use adaptive and non-parametric learning techniques such as *rule induction* for anomaly recognition. Rule induction techniques are used to learn rules through a set of distinctive features which are extracted from a dataset. In the following section, we will give a brief overview of rule induction methods along with the basic learning principle followed by different rule learners.

6.2 Rule induction

Rule Induction is a special paradigm of supervised machine learning algorithms. Adistinctive feature of rule induction algorithms is that they automatically generate propositional logic rules to classify data. In order to learn rules, the data acquired from smart home should be represented in the form of independent features, which distinctively characterizes each target class. Rule induction algorithms have been widely used for modeling and analyzing data in various data mining applications [5], [50]. A few prominent examples of such application are: medical data for diagnosis of an illness [21], financial data in banking and fraud detection [9], and policy and claim data in insurance [4]. Rule induction algorithms are useful in applications involving classification problems with big data volumes, having distinctive attributes for each class. In such cases, it is normally difficult for a human expert to understand relationships between various attributes for classifying data instances. Applications involving the processing of events, detected by a large number of sensors, for identifying a situation of interest are of similar nature.

Therefore, we have proposed to use a rule induction algorithm for automatic rule generation by finding the hidden relationship between different data attributes (or features) extracted from the sensor data and the corresponding class.

As described earlier, a rule has two parts: the first is *condition* or antecedent, and the second is *conclusion* or consequent. The condition part of a rule is composed of logical conjunctions of different features extracted from a dataset. A rule learner tests a combination of these features in the condition part to discern specific properties of a class in a given classification example. In order to learn a rule, the rule learner generally follows two main approaches: the first is top-down approach, and the second is bottom-up approach. In the top-down approach, a rule learner starts with a most general rule and recursively refines itself by appending more logical conjunctions in the *condition* part, until the required classification is achieved. At the end of each iteration, the new rule is more specific than its earlier version. In the bottom-up approach, the rule learner starts from the most specific rule and generates a more general rule by recursively relaxing the *conditions*. At the end of each iteration, the new rule is more general than its earlier version.

The working of the most of rule induction algorithms is based on the *covering algorithm*. The covering algorithm uses *separate-and-conquer* approach to produce a rule-set for classifying instances. The strategy is to divide a training set into different classes, and learn new rules for each class of training examples. Suppose, the given training set covers examples of a set of classes C. The objective is to develop a set of rules which can classify each member $c_i \in C$. The algorithm learns an individual rule R_i, which covers a part of training examples (a particular class). After R_i has been learned, the rule learner removes *(the separate part)*, already covered examples from the training set, and recursively learn a new rule R_j which covers some of the remaining training examples. The algorithm proceeds in this way until it covers all training examples or meet any other stopping criteria. The term *separate-and-conquer* was introduced by *Pagallo and Haussier* in 1990 [58]. A variety of rule learning algorithms are available today, which have been developed over the past few decades. Most of the rule learning algorithms are based on the *covering algorithm*. One of the initial works in this domain is *AQ algorithm* which is based on covering algorithm [56]. In [15], authors presented *CN2 algorithm* which is based on *AQ* algorithm[56] and *ID3 algorithm*[63]; a decision tree learning algorithm. Similarly, CN2 algorithm was the first work which addressed overfitting problem by handling noisy data.

Another powerful rule learning algorithm was presented by Cohen which is called *Repeated Incremental Pruning to Produce Error Reduction(RIPPER)* [16] and it solves the problem of overfitting in a more effective way. RIPPER algorithm is based on *Incremental Reduced Error Pruning (IREP)* approach presented in [32]. RIPPER algorithm includes a post processing phase, in which the algorithm relearns each rule for a refinement. During the relearning phase, each rule is considered not only in the context of already derived rules, but also considering subsequent rules to improve the accuracy. In the current implementation of our method, we used RIPPER algorithm; however, different rule learning algorithms can be used without modifying the core of our technique.

6.3 Anomaly recognition framework with Rule induction

As a review, the architecture of FABER is based on two main modules: *activity recognition*, and *anomaly recognition*. The activity recognition module acquires sensor data and process it to detect simple actions (e.g., opening a repository door). Simple actions are processed to detect the start- and end-time of activities. The activity recognition module is based on supervised learning. The inference of the activity recognition module, along with sensor data, is delivered to the anomaly recognition module, which adopts rule-based reasoning to infer occurred anomalies. In FABER, we have manually translated natural language description of anomalies into first order logic rules. In Section 6.1, we have described difficulties and limitations involved in the manual construction of knowledge-base. In this section, we describe the revised version of FABER with rule induction, which is called *InductiveFABER*. *InductiveFABER* exploits a rule learning technique to automatically generate rules for fine-grained anomaly recognition. The overall methodology of fine-grained anomaly recognition remains the same in InductiveFABER with the exception of using a rule induction algorithm to learn fine-grained anomaly definitions.

Figure 6.1 shows the block diagram of InductiveFABER [42]. The revised version relies on the same clinical model of the abnormal behavior which has been discussed in Chapter 2. As shown in the block diagram, both subjects live independently in their smart homes and perform routine life activities.

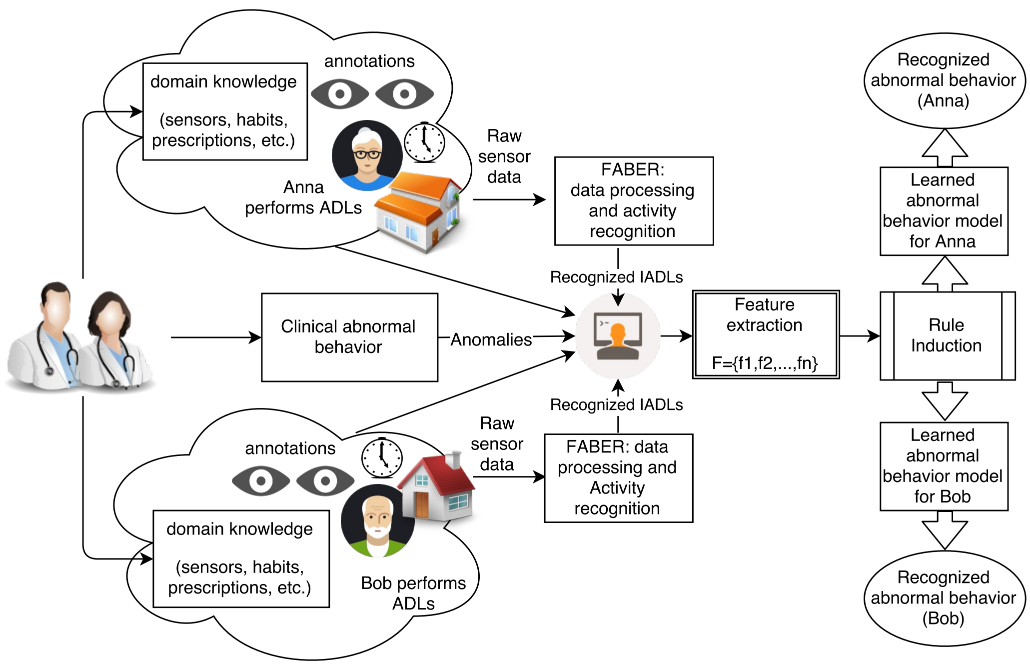

Figure 6.1: Anomaly recognition for different persons living in different homes

In order to generate a *training set* for a rule learner, a human observes the behavior of subjects while they perform activities and takes necessary annotations for various activities and anomalies executed by them. Domain knowledge is acquired from various sources: the expert knowledge which is based on clinical knowledge, such as prescriptions and details of anomalies; caregivers provide personal knowledge about their subject, such as preferred mealtimes; and technicians provide knowledge about the sensing infrastructure, such as types of multi-modal sensors deployed in the smart environment. The domain knowledge along with the training data is provided to a knowledge engineer who uses it to generate fine-grained anomaly recognition rules for the knowledge-base.

The classification rule learner takes *training data* as input and generates rules satisfying the training data. Note that each smart home produces its own training data for the subject living in it. Typically, a smart home training data are represented as a feature set (data attributes) and corresponding feature values (instances) to train a rule learner. For the training purpose, instances of the feature set are labelled with a known class label using annotations made by an observer. The training data include a set of both *positive* and *negative* examples. A dataset of *positive examples* includes all instances for which it is known that they belong to the target class. A dataset of *negative examples* includes all instances for which it is known that they do not belong to the target class. In our model, the target class is an individual fine-grained anomaly l_i which belongs to the predefined set of fine-grained anomalies L.

After the training session, the rule learner generates separate rule-sets for individual subjects living in separate homes. Each rule-set should have two basic properties: (1) it should uncover the hidden relationship between different feature instances and corresponding target classes; (2) it should be generalized and able to classify previously unseen examples.

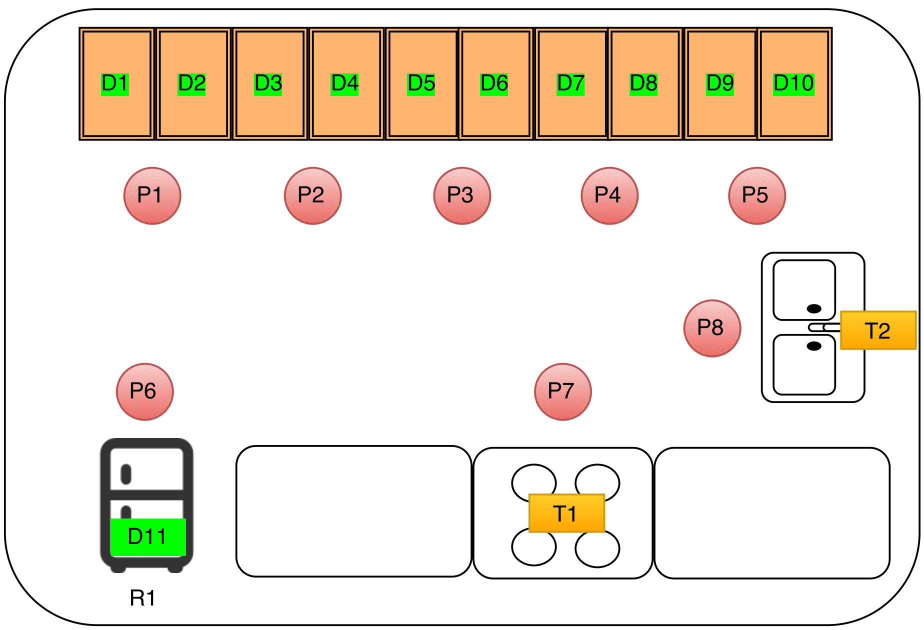

Figure 6.2: A's home: kitchen map with sensors

Example 8 In order to further explain the importance of rule learning, consider a scenario in which Anna and Bob performs an activity preparing meal in their smart homes. Suppose their

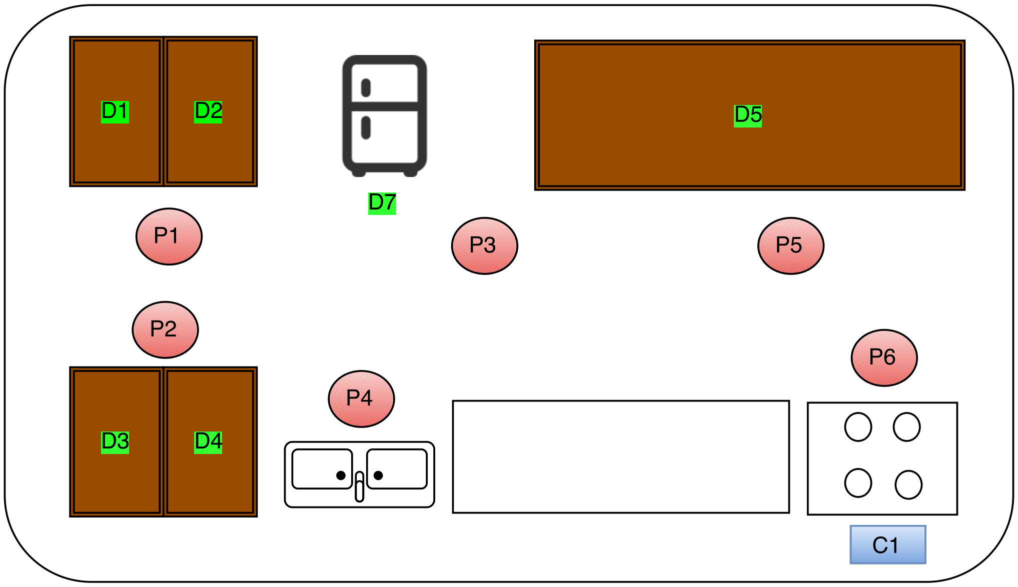

Figure 6.3: B's home: kitchen map with sensors

kitchens are equipped with various multi-modal sensors to detect fine-grained anomalies. Layouts of both smart environments are shown in Figure 6.2(Ann's home) and Figure 6.3 (Bob's home). Details of the sensing infrastructure is given as:

- RIF tags: a single RFID tag is attached with each food item to identify their contents for cooking. For example, rice has to be cooked before consuming it, whereas a fruit juice does not need cooking.
- Motion: several sensors are deployed to detect the presence of the subject in various regions of the kitchen (for e.g., near the stove). Motion sensors are labelled with a capital letter "P" in layouts.
- Door: several switch sensors are deployed on doors of cabinets and fridge to detect open/close events. Door sensors are labelled with a capital letter "D" in layouts.
- Temperature: Anna has a gas stove in her kitchen, so a temperature sensor is deployed on her stove to detect the stove usage. The sensor is labelled with a capital letter "T"

in the layout.

- Current: Bob has an electric stove in his kitchen, so a current sensor is deployed on the plug of his electric stove to detect its usage. The sensor is labelled with a capital letter "C" in the layout.

In order to recognize activities and fine-grained anomalies, the smart home data has been annotated to get a training set for the rule induction algorithm. For automatic rule induction, we have to provide a feature set to the rule learner. Referring to the general architecture of FABER shown in Figure 4.1 in Chapter 4, note that the input of the anomaly recognition module is recognized activities: their start and end time instants along with simple actions and sensor events bounded by these time instants. Therefore, for automatic rule induction, we have extracted a feature set from sensor data which belong to recognized activities. In fact, activity labels along with their start and end time instants are individual features. Having the sensing infrastructure described above, we can extract some other unique features: a count of individual motion sensor events, for example total_ events _ P1, total_ event_ p2, and so on; a count of individual door sensor events, for example total _ events _ D1, total_ events _ D2, and so on; and stove usage, for example stove usage=yes/no. Suppose both the subjects commit same anomaly i.e, forget to retrieve a cooking pan in the activity "preparing meal". The scenario is elaborated below:
The subjects retrieve a food item that must be cooked. Afterwards they turned on the stove, but forgot the cabinet in which cooking pans are placed. They search for cooking pans, but could not find it and at last they left the activity incomplete. In this scenario, the activity recognition module detects the performed activity is "preparing meal". Considering extracted features, the rule induction algorithm generates individual rules for both smart environments by finding the hidden relationship between the anomaly label and corresponding features extracted from the sensor data. The rules are shown as:

Rule for Anna's home:

$$\begin{aligned} cookingPan\_notRetrieved &\Leftarrow \\ isRetrieved\_mustBeCookedFood &= yes \\ \wedge isUsed\_stove &= yes \\ \wedge total\_events\_D9 &\equiv 0 \\ \wedge total\_events\_D10 &\equiv 0 \\ \wedge total\_events\_P5 &\equiv 0 \end{aligned} \tag{6.1}$$

Rule for Bob's home:

$$\begin{aligned} cookingPan\_notRetrieved &\Leftarrow \\ isRetrieved\_mustBeCookedFood &= yes \\ \wedge isUsed\_stove &= yes \\ \wedge total\_events\_D5 &\equiv 0 \\ \wedge total\_events\_P6 &\equiv 0 \end{aligned} \tag{6.2}$$

In case of Anna's home, the learned rule 6.1 shows that the anomaly occurs because she did not open cabinet doors $D9$ and $D10$ ($D9 = 0 and D10 = 0$) during the activity of "preparing meal" and on investigation it is revealed that these are the doors of cooking pan cabinet. Similarly, the induced rule for Bob's home 6.2 shows that he did not open door $D5$ during the activity of "preparing meal" and on investigation it is revealed that $D5$ is the door of cooking pan cabinet.

6.3.1 Learning process

We have divided the learning process into the following two steps:

6.3.1.1 Feature extraction

The rule induction algorithm learns the rules from a set of N distinctive features. We can represent a feature set as $F = \{f_1, f_2, \ldots, f_N\}$. We consider the facts collected from various sources: sensing infrastructure, activity recognition module, and domain knowledge. We assume that an activity instance χ is composed of a sequence of κ actions, which correspond to given

Table 6.1: List of extracted features for rule learning

No.	Feature Name	Description
1	Activity Label	The activity label output by the activity recognition module.
2-6	Repository use	Each of these features refers to a single repository (fridge, kitchen cabinet, etc.). Each feature has a binary value. The value is 1 if the repository has been used at least once; 0 otherwise.
7	Total repository events	The cumulative sum of the number of access events (open / close) of repositories.
8	Repository status difference	Difference between the total number of close events and the total number of open events over all repositories.
9	Maximum duration repository left open	The maximum time duration during which a repository remained open.
10	Stove usage	A binary feature: true if the stove was used; false otherwise
11	Retrieval of a food item that must cooked	A binary feature: true if at least one food that needs to be cooked has been retrieved; false otherwise.
12	Presence in dining area	A binary feature: true if the person has been in the dining area; false otherwise.
13	Maximum duration a medicine is retained	The maximum time duration between retrieving and returning a particular medicine (used during the activity of taking medicines).
14	Anomalies	The label identifying the anomaly occurred during the activity; its value is *null* if no anomaly occurred.

sensor events. We define E as the set of all the considered event types (e.g., $E = \{\text{FridgeDoorIsOpened, FridgeDoorIsClosed}, \ldots\}$), and T as the set of time instants at which the events can occur. We represent each activity χ as the temporal sequence of the occurred events:

$$\chi = \langle event(E_s, t_s), ..., event(E_e, t_e)\rangle$$

where $E_i \in E$, $t_i \in T$, t_s and t_e are the time instants of *start* and *end* of χ, respectively. For each temporal sequence χ we extract an N-dimensional feature vector F_χ:

$$F_\chi =< f_1(\chi), f_2(\chi), ..., f_N(\chi) >,$$

where $f_i(\chi)$ is the value of the i-th feature, extracted applying a statistical or boolean function f_i to χ. Table 6.1 shows the list of features used in our testbed. For example, the boolean feature value $f_2(\chi)$ returns 1 when χ includes at least one event of type "open_fridge" or "close_fridge"; it returns 0 otherwise:

$$f_2(\chi) = \begin{cases} 1 & \text{if } \exists\, event(E_i, t_i) \in \chi : E_i = \text{“open\_fridge”} \\ & \vee\ E_i = \text{“close\_fridge”}; \\ 0 & \text{otherwise.} \end{cases}$$

While constructing the training set, each feature vector extracted from recognized activities is labeled either with a *null* class value (if no anomaly occurred during the execution of that activity) or with an anomaly label l_i belonging to a predefined set of anomalies L. In the training phase, the rule induction algorithm takes the feature set as input and learns a set of rules for anomalies in L.

6.3.1.2 Rule induction

The rule induction algorithm finds a rule for an anomaly by heuristically looking for a conjunction of conditions on feature values that provides a reliable prediction rate for that anomaly. In order to execute this function, different existing rule induction methods can be used [37]. The general representation of a learned rule is:

$$a \Leftarrow c_{j_1}\big(f_{i_1}(\chi)\big) \wedge ... \wedge c_{j_k}\big(f_{i_k}(\chi)\big),$$

where $f_{i_l}(\chi)$ is the value of the feature $f_{i_l} \in F$ computed on χ, c_{j_l} is a condition on the value of $f_{i_l}(\chi)$, and $a \in A$ is a specific kind of anomaly.

6.4 Learned rules

In this section, we will list down rules which have been learned through a dataset acquired from our implementation of a smart home lab prototype. The prototype of sensing infrastructure is explained in Chapter 7.

Food is not cooked Rule 6.3 states that the subject has retrieved a food item which has to be cooked, however, the subject has never used the stove in the activity, preparing meal, to cook the food item.

$$\begin{aligned} foodNotCooked &\Leftarrow \\ isRetrieved\_mustBeCooked\_FoodItem &\equiv yes \\ \wedge Stove\_used &\equiv no \end{aligned} \tag{6.3}$$

Medicine is not returned Rule 6.4 states that the subject has retrieved a medicine from the medicine cabinet and retains it for more than 30 minutes. If the medicine is not returned within 30 minutes after its retrieval then it is assumed that the subject forgets to return the medicine.

$$\begin{aligned} isNotReturned\_medicine &\Leftarrow \\ medicine\_retained\_max\_duration &\geqslant 30minutes \\ \wedge activity\_label &\equiv takingMedicines \end{aligned} \tag{6.4}$$

Silverware is not retrieved Silverware is kept in a drawer which is dedicated for it. Rule 6.5 states that if during the activity "eating meal", the total repository access events are 0, then the subject has forgotten to retrieve silverware.

$$\begin{aligned} isNotRetrieved\_Silverware &\Leftarrow \\ total\_Repository\_Access\_events &\equiv 0 \\ \wedge activity\_label &\equiv eatingMeal \end{aligned} \tag{6.5}$$

Cooking pan is not retrieved Suppose the subject retrieves a food item from the cabinet which contains non-refrigerated food items. The cabinet only contains food items that must be cooked. The subject also turns on the stove burner, however, there is no event of accessing a cooking pan from the corresponding cabinet. Rule 6.6 detects an anomaly because the person initiated the activity "preparing meal" but forgets to retrieve the cooking pan.

$$\begin{aligned} isNotRetrieved\_CookingPan \Leftarrow \\ isUsed\_NonRefrigeratedFoodItemCabinet \equiv yes \\ \wedge isUsed\_CookingPanCabinet \equiv no \\ \wedge isUsed\_Stove \equiv yes \end{aligned} \tag{6.6}$$

Repository door is not closed In normal circumstances, it is expected that the subject should close a repository after retrieving an item from it. Rule 6.7 states that if 20 minutes have been passed and the repository door is still open then the person has forgotten to close the door.

$$\begin{aligned} anomaly = isNotClosedRepository\_Door \Leftarrow \\ Maximum\_duration\_Repository\_left\_open \geqslant 20.31 minutes \\ \wedge total\_Difference\_Repository\_Open\_Close\_events \geqslant 0 \end{aligned} \tag{6.7}$$

Chapter 7

Experiments and Framework Evaluation

In order to evaluate the proposed framework, we have performed experiments in a lab setup and also in a real patient's home. We have acquired two large annotated datasets for both normal and abnormal behaviors. The first tesbed is a smart home kitchen lab environment in which data is acquired through 21 volunteer actors who simulated the behavior of cognitively impaired and cognitively intact persons. The second testbed is a real home kitchen environment in which an elderly woman, an MCI patient, performs her routine life activities. In this chapter, we will describe the approach that we have used to evaluate our proposed framework. Section 7.1 explains the sensing infrastructure which we have developed for the experimentation. Section 7.2 describes the datasets which we have acquired from the sensing infrastructure after performing the experiments. In Section 7.3, we present the experimentation results along with discussion on these results.

7.1 Prototype development

The smart home prototype testbeds have been developed within the SECURE project. The construction of prototype involves several tasks which have been carried out by different academic and industrial partners working in SECURE project. A brief description of these tasks is given as follows:

7.1.1 The sensing infrastructure

The sensing infrastructure has been implemented using various off-the-shelf sensor motes available in the market. These sensing motes having multi-modal sensors detect human actions and deliver the data to a local database using Zigbee protocol. In particular, we have considered *Waspmotes* from *Libelium* [1] which offers a wide range of low power sensing devices. Libelium sensing devices are programmed in C/C++ and can be deployed easily in a home environment. Libelium also offers a multi-protocol router and gateway named *Meshlium*. Meshlium collects data from sensing motes using Zigbee protocol and it also has a Wifi interface enabling to conveniently transfer acquired data to a local server.

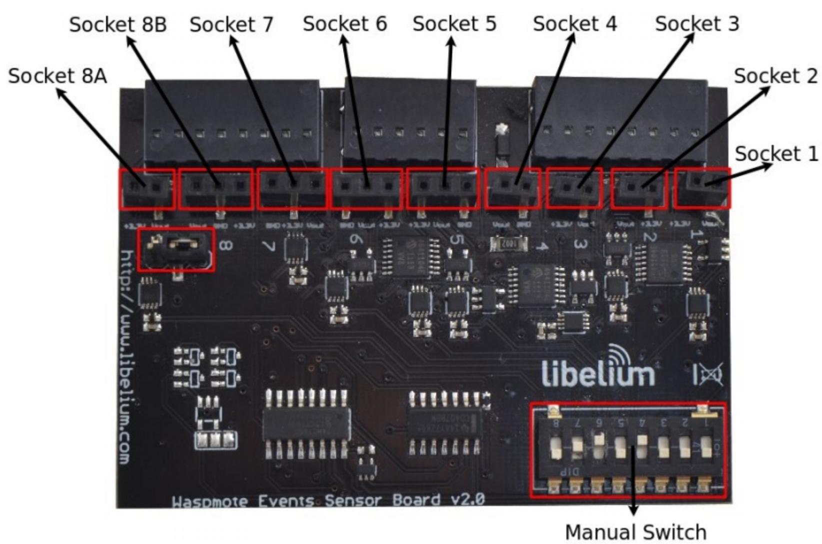

Figure 7.1: Libelium event sensor board

Figure 7.1 shows an *event sensor board* from Libelium. It has several sockets which are used to connect different sensors. Our objective is to develop a sensing infrastructure which can detect atomic steps performed in an activity. In order to achieve this objective, we have considered the following sensors which connect with a Waspmote event sensor board and detect atomic steps when a person interacts smart environment.

[1] Libelium: `www.libelium.com/`

- Hall effect: It is a magnetic switch sensor based on hall effect principle. The switch remains in a *close* state in the presence of magnetic field, otherwise it is in an *open* state.The sensor can be deployed on doors (or drawers) of various repositories (e.g., medicine cabinet, fridge, silverware drawer) to detect the open and close events.

- Presence: It is a *Passive Infra-Red (PIR)* sensor and detects movements of a person in its range. We are using this sensor to detect movements of a person in the dinning area during the activity of eating meal.

- Pressure: It is a *Flexiforce* pressure sensitive resistive sensor. The resistance between terminals varies when a force (or pressure) is exerted on it. The pressure sensor can be deployed on a dinning chair to detect *sitting* events during the activity eating meal. A *sitting* event is detected if the measured pressure is above than a certain threshold value. The threshold value can be obtained empirically.

- Temperature: It is an analog sensor and it measures the temperature of surrounding environment. It converts a measured environmental temperature value into a proportional analog value. The temperature sensor can be used to detect stove related events during the activity of preparing meal. The sensor can be deployed near a stove burner. When a person turns on a stove burner, the temperature of its surroundings rises and we can detect a stove usage. Similarly, when the person turns off the stove burner the temperature drops and we can detect that the person has stopped using the stove.

- RFID: RFID readers can be deployed in proximity to repositories. The RFID tags can be attached with medicines and food items. We expect the person swipes RFID tagged item every time he/she retrieves or returns a tagged item from the respective repositories. During experiments, we have given instructions to the elderly about using RFID technology. Although it is obtrusive for an elderly person to swipe a tagged item, we are looking for more sophisticated sensing technologies which can eliminate such swiping. For example, we can alternatively use active RFID tags with a longer range so that the subject can conveniently perform a "retrieve" and "return" actions.

7.1.2 Software implementation

A prototype implementation of the whole system has been done within the activities of SECURE project. Since a mobile device runs FABER (as an application) at the subject's home, core software modules have been implemented in Java for Android platform. Figure 7.2 shows FABER running on a mobile phone. In order to implement the technique for activity recognition, we have used machine learning libraries of Weka[2]. For the evaluation of rule-based definitions of fine-grained anomalies, we have used Java APIs of TuProlog [27]; a lightweight Java implementation of an inference engine for the well-known Prolog logic programming language.

7.1.3 Data logging

In the prototype implementation, sensor data is continuously acquired through a smart home and logged in a local sever database through the Wifi interface of Meshlium gateway. Each sensor event is stored with multiple fields: a unique event ID, an event label, sensor state (binary sensors), and a unique timestamp at which the event occurs. A C++ application running on the gateway is in charge of these tasks: receiving data from the sensing infrastructure, assigning unique timestamps, locally storing the data in a PostgreSQL database, and periodically communicating data to the Android application.

7.1.4 Dashboard

A web-based dashboard has been developed with in SECURE project. Activities and anomalies are periodically recognized from sensor data in a fixed time window. In our current implementation, the window size is one day i.e., starting from one mid-night to the succeeding mid-night. Recognized activities and anomalies are displayed on the dashboard with their labels and timestamps. The dashboard is accessible by clinicians and caregivers who can visualize the history and trends of performed activities and corresponding fine-grained anomalies, and then accordingly intervene to assist the subject. Figure 7.3 shows a snapshot of the dashboard which presents fine-grained anomalies and recognized activities from the real-patient dataset. Types of fine-grained anomalies (Red, Green, and Yellow) will be explained later in this chapter.

[2] `http://www.cs.waikato.ac.nz/ml/weka/`

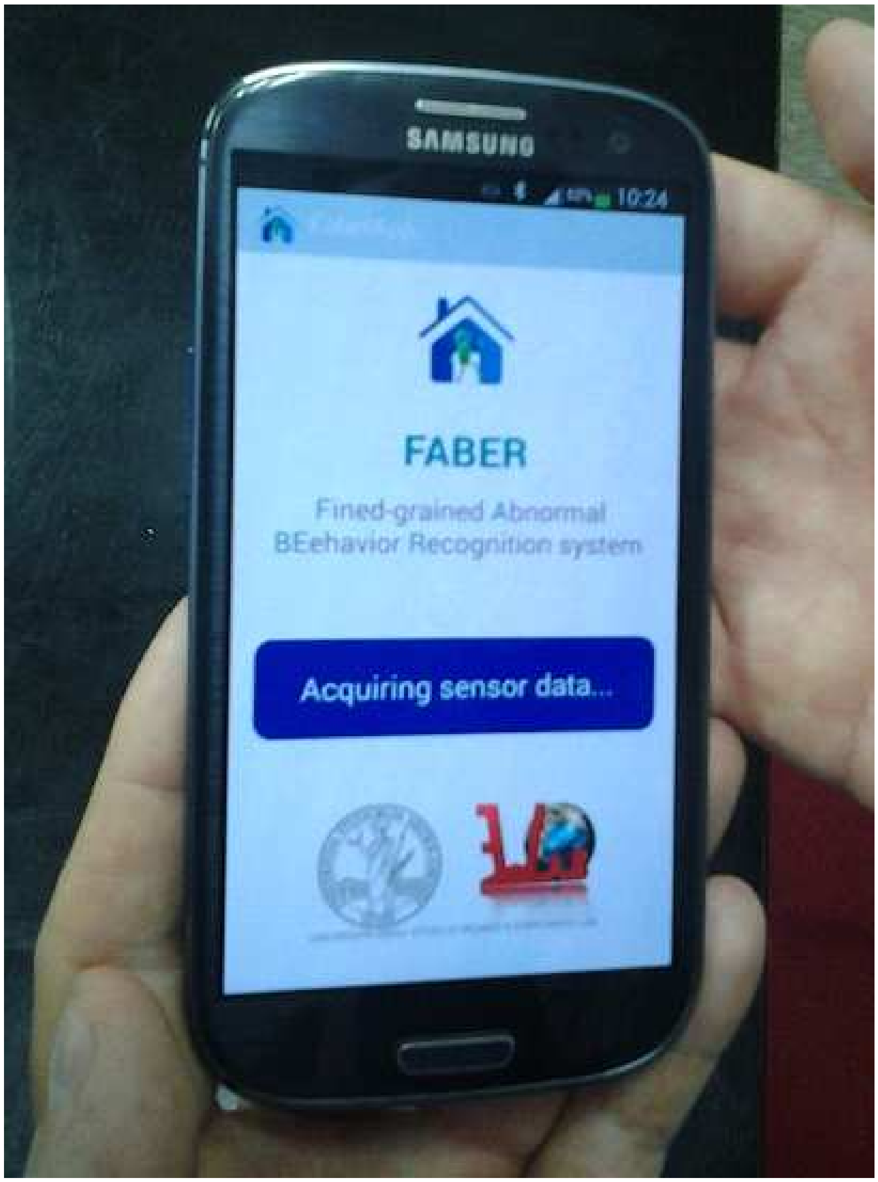

Figure 7.2: FABER android application
[69]

Type	Occurences in last 7 days	Occurences in last 30 days	Occurences in last 90 days
Red (most important)	6	23	44
Yellow	14	41	74
Green (less important)	13	49	97

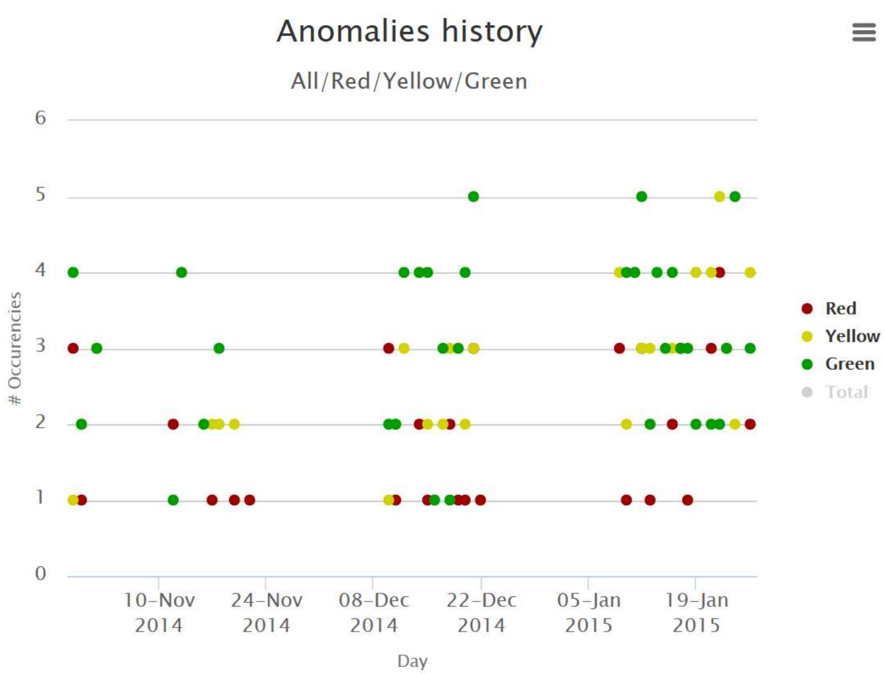

Figure 7.3: FABER dashboard for clinicians
[69]

7.2 Datasets

In order to experimentally evaluate the proposed model, we have acquired two datasets from the smart home prototype testbeds. One dataset has been acquired from a smart home laboratory, and the other dataset has been acquired from the instrumented home of a senior having MCI.

(a) Magnetic sensor attached to a drawer

(b) Presence sensor above the kitchen table

(c) RFID reader for medicine boxes and food items

Figure 7.4: Some sensors used in the smart home lab.

7.2.1 Smart home lab dataset

The lab dataset has been acquired through voluntary actors who simulated the daily routine of 21 elderly persons residing in a smart home. Volunteers have considered the clinical model to simulate the abnormal behavior of both cognitively intact and cognitively impaired elderly persons. The clinical model has been explained in Chapter 2. The data is acquired for two groups: 7 healthy seniors (group 1), and 14 elderly persons with early symptoms of MCI (group 2). We assume that individuals of both groups live alone and independently in their respective homes. During their one-day routine, individuals in *group 1* do not execute any *critical anomaly*, but may execute a few non-critical ones. Individuals in group 1 are mainly used to evaluate the number of *false positives* produced by our anomaly recognition method. Group 2 individuals may perform several non-critical and critical anomalies during the day.

During the execution of the daily routines, we have acquired the timestamped data coming from sensors deployed in the smart home and manually annotated the dataset with the start- and end-time of specific activities and anomalies. We have selected the following activities to validate our proposed method:

- Preparing meal: the subject has to prepare daily meals (breakfast, lunch, dinner) at appropriate times.
- Eating meal: when the subject prepares a meal, he/she has to consume it within a reasonable time period.
- Taking medicines: the subject has to take prescribed medicines in the due time. We assume that no smart dispenser is used; instead, we assume that the subject keeps all medicines in a dedicated cabinet.

We have considered the following fine-grained anomalies:

- Non-critical anomalies: These anomalies happen when the subject: (NC1) forgets to close a repository; (NC2) does not return a medicine to its cabinet; (NC3) retrieves a food item which must be cooked, but does not use a stove burner; (NC4) does not prepare a meal.
- Critical anomalies. These anomalies happen when the subject: (C1) does not retrieve a prescribed medicine in the due time; (C2) takes a medicine that is not prescribed; (C3) takes a prescribed medicine in the due time, but multiple times, resulting in an inappropriate dosage; (C4) does not turn off the stove burner after preparing a hot meal; (C5) does not take silverware before consuming meal; (C6) does not consume a prepared meal; (C7) turns on a stove burner, but does not take any cooking pan.

Overall, our dataset contains 21 days of activities and fine-grained anomalies. Group 1 individuals did 7 non-critical and 0 critical anomalies; group 2 individuals did 24 non-critical anomalies and 36 critical anomalies.

7.2.1.1 Real home dataset

As a first step towards the evaluation of our proposed method in the actual home of elderly persons, we have taken an advantage of our cooperation with

(a) Magnetic contact sensor on the fridge door

(b) Passing a tagged medicine box over the RFID reader

(c) A board with temperature sensor over the stove

(d) Passive infrared presence sensor over the kitchen table

Figure 7.5: Part of the sensors deployed at the elderly's home

a medical institution and a tele-medicine company as partners in SECURE project, and deployed our prototype inside a home of an elderly woman aged 74, who lives alone, with a diagnosis of MCI and medical comorbidities. We will call her Mary in the following text. Details about the technical implementation of the system in Mary's home are reported in [70].

We have acquired a dataset consisting of 55 days of activities performed by Mary. In that period of time, we have collected data for about 200 instances of activities. We have considered same type of activities as for the smart home lab dataset. For this experimentation, clinicians provided us with a set of fine-grained anomalies to be detected, together with Mary's prescriptions for meals (i.e., breakfast, lunch, and dinner) and medicines. According to the recommendations of clinicians, we have divided fine-grained anomalies into three levels of seriousness:

- Green anomalies (low level). This type of anomalies occurs when the individual: prepares (G1) or consumes (G2) a meal at a different time than prescribed mealtime.

- Yellow anomalies (medium level). This type of anomalies occur when the individual: misses to consume (Y1) or prepares (Y2) a meal; takes a prescribed medicine outside the prescribed time (Y3); consumes (Y4) or prepares (Y5) the same meal multiple times during the same day.

- Red anomalies (high level). This type of anomalies occur when the individual: takes a medicine that was not prescribed (R1); does not take a prescribed medicine (R2).

Totally, 605 anomalies were detected during experiments, most of them being green and yellow ones. For the sake of this project, it was not feasible to directly observe the execution of activities, except for limited periods of time during the setup of the system, due to obvious privacy reasons. Hence, we manually labeled most of activities offline, based on the observation of raw sensor data; it was possible since the considered activities are relatively easy to distinguish by a human observer based on the collected sensor readings. We labeled anomalies by executing their respective rule-based definitions on the dataset of sensor events and labeled activities.

7.3 Experimental results

As described earlier, the proposed framework for abnormal behavior recognition is based on two main modules: activity recognition and anomaly recognition. In fact, the performance of anomaly recognition module directly depends on the performance of activity recognition. It means that if proposed method detects activity boundaries with high accuracy, consequently the anomaly recognition rate will also increase. In this section, we will present results of activity and anomaly recognition methods. First we describe the evaluation method and the metrics used to represent results.

7.3.1 Validation method

We have used supervised machine learning methods in our model, therefore, we have evaluated the performance of modules (activity and anomaly recognition) through unseen examples. In this regard, we have divided acquired data into two parts: a training dataset, and a testing dataset. The training dataset is used to learn an unknown model by training a supervised machine learning algorithm through examples, and the testing dataset is used to predict the accuracy of the learned model. We have considered *k-fold cross validation* to define the testing dataset. In k-fold cross validation, the dataset is randomly partitioned into k equal sized parts.The process of validation is then repeated for k times, and in each iteration exactly one part serves as testing data, while rest $k-1$ parts are used for training purpose. At the end of all iterations, a single estimation of a particular parameter is calculated by taking the average of predicted values from all iterations for that particular parameter. In our case, we have divided the dataset into equal sized parts in which one part is the smart home data acquired in one day. In this way, in each iteration, exactly one day of the acquired data serves as testing dataset and the rest of the days serves as training data.

7.3.2 Evaluation metrics

The quality of prediction's is evaluated in terms of three standard measures: precision, recall, and f-measure(F1). In general, precision measures the exactness or quality of the predicted values, recall measures the completeness or quantity of the predicted values, and f-measure is a relation between precision and recall values. These measures are calculated using the following equations:

$$\text{precision } (p) = \frac{TP}{TP + FP}$$

$$\text{recall } (r) = \frac{TP}{TP + FN}$$

$$F_1 = \frac{2 \cdot p \cdot r}{p + r}$$

In above equations, TP, FP, and FN are defined as *true positive, false positive, and false negative*, respectively. These are standard measurements used in classification tasks, which compare predicted values with actual values. In our model, a TP value represents the number of activities (and anomalies) which are correctly recognized by the proposed framework; an FP value represents the number of activities (and anomalies) which are not annotated by an observer, but recognized by our proposed framework; and an FN value represents the number of activities (and anomalies) which are annotated by an observer, but our proposed framework fails to recognize them.

As we have mentioned earlier, the proposed framework predicts activity boundaries in terms of three parameters: the label of an activity, the start time of the activity (T_s, and the end time of the activity (T_e). Since the model involves temporal predictions, it is possible that values of T_s and T_e are predicated approximately, and there may exist a small time difference between predicated values and actual values; when the activity was actually started or ended in annotations. For this reason, we have introduced a flexibility factor α in these measurements, which reduces the rate of false predictions and allows us to see the real performance of the proposed model. For instance, in these predictions, the factor α approximates the actual start time as $T_s - \alpha$ and $T_s + \alpha$. It means that an activity is considered to be correctly recognized if the predicted T_s value of an activity lies within the range defined by the flexibility factor α. The same concept of flexibility factor is also applied on the end time of an activity T_e. For the sake of these experiments, the value of α is taken as 15 minutes.

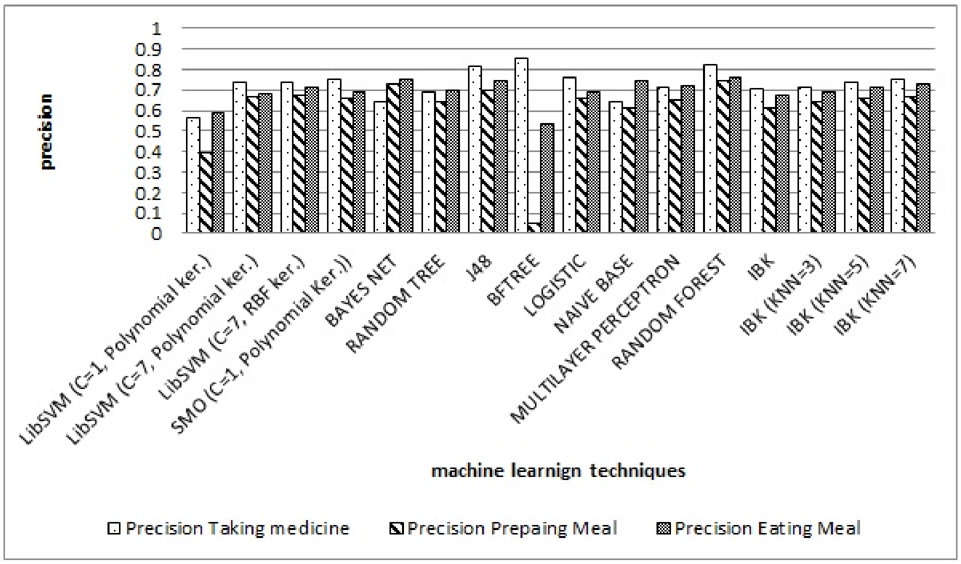

Figure 7.6: A comparison of precision values for activity boundary detection using supervised machine learning algorithm on real home dataset

7.3.3 Fine-grained anomaly recognition

The architecture of the proposed model has been presented in Chapter 4. As discussed earlier in Chapter 4 and Chapter 5, the performance of anomaly recognition method strongly depends on the performance of activity recognition method. Therefore, first we briefly discuss the results of activity recognition method which helps us to understand the performance of anomaly recognition method. We have already mentioned in Chapter 4 that two approaches have been adopted to recognize activity boundaries: Markov logic network (MLN) and supervised machine learning. Table 7.1 shows results of MLN based activity recognition method used in FABER. The variable n represents the window size and its value is based on the temporal sequence of the most recent sensor events used for recognizing an activity. In case of smart home lab dataset, MLN performs well and the highest recognition rate is achieved with $n = 3$ (f-measure=0.968). The value of n shows that the temporal sequence of the 3 most recent sensor events can reliably detect the *start* and the *end* time of an activity. On the other hand, MLN shows a poor performance on real home dataset and the highest recognition rate is achieved

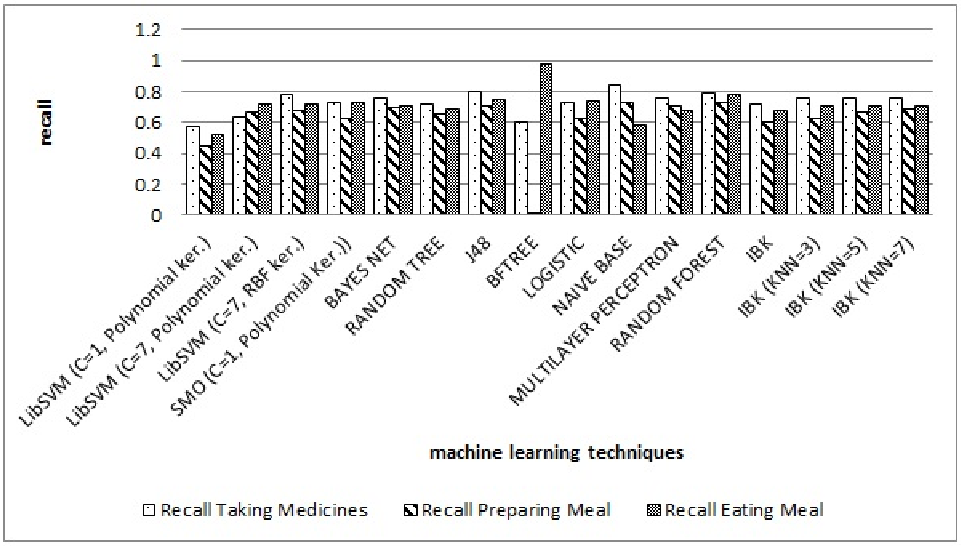

Figure 7.7: A comparing of recall values for activity boundary detection using supervised machine learning algorithm on real home dataset

with $n = 4$ (f-measure=0.617). It is possibly due to the variability involved in the real life human activities, which of course is not present in the smart home lab dataset. In order to improve the activity recognition rate, we have considered supervised machine learning techniques. We have experimented with various supervised machine learning techniques to select the one which produces highest activity recognition rates in our model. Results of these experiments are shown in terms of precision, recall, and f-measure in Figure 7.6, Figure 7.7, and Figure 7.8, respectively. As we can see in these results, on average Random Forest [10] performs the best on the real home dataset. To further improve the activity recognition rate, two algorithms have been developed and names as *naive aggregation* and *smart aggregation*. These algorithms are described in [69] and this improved version of FABER is called *SmartFABER*. Table 7.2 shows the activity recognition results using naive aggregation. The performance of naive aggregation ($f\text{-}measure = 0.966$ and $n = 3$) and MLN is almost the same for the smart home lab data set, whereas naive aggregation performs significantly better than MLN for the real home dataset with $f\text{-}measure = 0.716$ and $n = 3$. Table 7.3 shows results of activ-

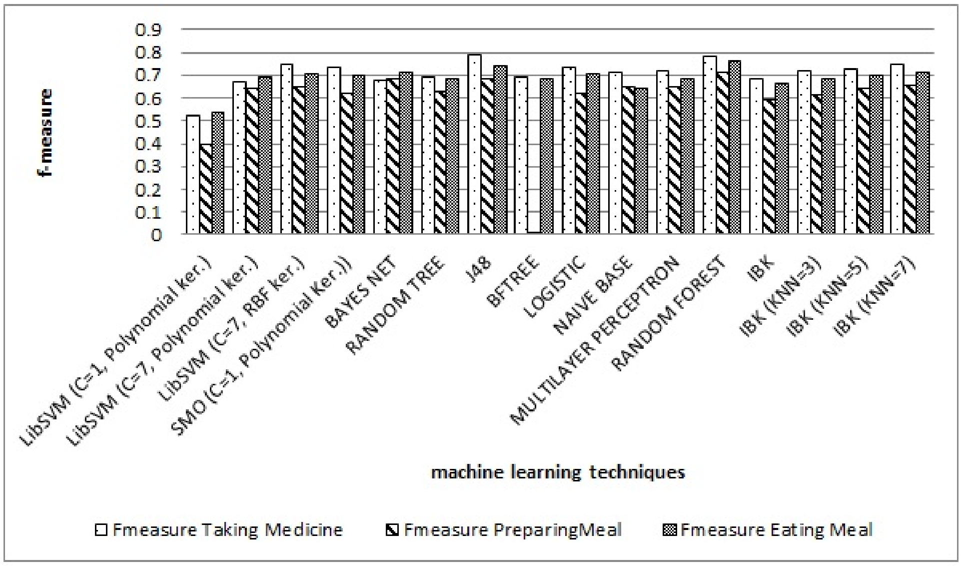

Figure 7.8: A comparison of f-measure values for activity boundary detection using supervised machine learning algorithm on real home dataset

ity recognition using smart aggregation in SmartFABER. Again, in the case of smart home lab dataset, results show that the activity recognition rates of smart aggregation are comparable with MLN. However, in case of real home dataset, the smart aggregation outperforms both naive aggregation and MLN with $f\text{-}measure = 0.802$ and $n = 3$.

Table 7.1: Evaluation of FABER for activity boundary detection using MLN method on smart home lab dataset and real home dataset

	Smart home lab dataset			Real home dataset		
Window size (n)	Recall	Precision	F-measure	Recall	Precision	F-measure
1	0.658	0.739	0.693	1	0	0
2	0.785	0.799	0.79	0.883	0.209	0.338
3	0.965	0.974	0.968	0.734	0.425	0.539
4	0.968	0.962	0.964	0.749	0.525	0.617

Fine-grained anomalies are recognized using the knowledge-base presented in Chapter 5. The knowledge-base takes the temporal sequence of sensor

Table 7.2: Evaluation of smartFBER for activity boundary detection using naive aggregation method on smart home lab dataset and real home dataset

	Smart home lab dataset			Real home dataset		
Window size	Recall	Precision	F-measure	Recall	Precision	F-measure
1	0.864	0.987	0.921	0.499	0.954	0.655
2	0.941	0.985	0.963	0.558	0.942	0.7
3	0.947	0.985	0.966	0.59	0.91	0.716
4	0.915	0.98	0.946	0.576	0.901	0.702
5	0.934	0.966	0.95	0.545	0.854	0.665

Table 7.3: Evaluation of smartFABER for activity boundary detection using smart aggregation method on smart home lab dataset and real home dataset

	Smart home lab dataset			Real home dataset		
Window size	Recall	Precision	F-measure	Recall	Precision	F-measure
1	0.957	0.984	0.97	0.826	0.731	0.775
2	0.957	0.989	0.973	0.843	0.743	0.791
3	0.956	0.989	0.972	0.862	0.75	0.802
4	0.956	0.974	0.965	0.855	0.771	0.811
5	0.959	0.963	0.961	0.841	0.766	0.802

events as input along with the detected activity boundaries and infers fine-grained anomalies which reflects the abnormal behavior. In order to recognize anomalies, we have conducted experiments on both datasets using activity recognition techniques implemented in FABER (MLN) and SmartFABER (naive and smart aggregation) with an optimum value of n. The recognition results of each anomaly are described using three parameters: true positive (TP), false positive (FP), and false negative (FN). The *TP* number represents anomalies which are correctly recognized by the system; annotated anomalies. The *FP* number represents anomalies which are recognized by the system, but these anomalies were not actually occurred. The *FN* number represents anomalies which were actually occurred during experiments, but the system fails to recognize them. Fine-grained anomaly recognition results of both dataset are explained in the following subsections.

Table 7.4: Smart home lab dataset. Accuracy of abnormal behavior recognition with FABER

ANOMALY	GROUP 1			GROUP 2		
	TP	FP	FN	TP	FP	FN
NC1: Repository left open	5	0	2	18	0	0
NC2: Medicine not returned	0	0	0	4	0	0
NC3: Food item not cooked	0	0	0	2	0	0
NC4: Meal not prepared	0	2	0	0	1	0
C1: Missed a prescribed medicine	0	2	0	10	0	0
C2: Took a wrong medicine	0	0	0	7	0	0
C3: Repeated medicine intake	0	0	0	3	0	0
C4: Stove burner left on	0	0	0	0	0	0
C5: Had meal with no silverware	0	0	0	7	0	0
C6: Prepared meal not consumed	0	0	0	1	1	0
C7: Burner turned on by mistake	0	0	0	8	0	0
TOTAL	5	4	2	60	2	0

7.3.3.1 Fine-grained anomaly recognition using smart home lab dataset

Tables 7.4 and 7.5 show results of experiments which have been conducted on smart home lab dataset using FABER and SmartFABER, respectively. Each row in these tables corresponds to a specific fine-grained anomaly which is

Table 7.5: Smart home lab dataset. Accuracy of abnormal behavior recognition with SmartFABER and *smart aggregation*

ANOMALY	GROUP 1			GROUP 2		
	TP	FP	FN	TP	FP	FN
NC1: Repository left open	7	0	0	18	1	0
NC2: Medicine not returned	0	0	0	4	0	0
NC3: Food item not cooked	0	0	0	2	0	0
NC4: Meal not prepared	0	0	0	0	0	0
C1: Missed a prescribed medicine	0	0	0	10	0	0
C2: Took a wrong medicine	0	0	0	7	0	0
C3: Repeated medicine intake	0	0	0	3	0	0
C4: Stove burner left on	0	0	0	0	0	0
C5: Had meal with no silverware	0	0	0	7	0	0
C6: Prepared meal not consumed	0	0	0	1	0	0
C7: Burner turned on by mistake	0	0	0	8	1	0
TOTAL	7	0	0	60	2	0

Table 7.6: Smart home lab dataset. Results of fine-grained abnormal behavior recognition based on different boundary detection methods

TECHNIQUE	PRECISION	RECALL	F1 SCORE
FABER (MLN)	0.915	0.97	0.942
SmartFABER-SmartAggregation	**0.971**	**1**	**0.985**

either *critical (C)* or *non-critical(NC)*. As described earlier, the smart home dataset includes two groups of individuals: *group 1* includes cognitively intact elderly persons, and *group 2* includes cognitively impaired elderly persons. As expected, cognitively intact persons execute less anomalies which include few non-critical anomalies and no non-critical anomaly. In total, individuals in group 1 executed 7 non-critical anomalies: repository left open. Among them 5 anomalies are correctly recognized by FABER ($TP = 5$) and it fails to recognize 2 anomalies ($FN = 2$). In fact, FABER fails to recognized these anomalies because the activity recognition technique fails to detect boundaries of activities in which these anomalies occurred. There are 4 anomalies which are recognized by FABER ($FP = 4$), but do not occur in reality. Two of these anomalies are "meal not prepared" and the other two are "missed a prescribed medicine". The false positives show that the MLN based activity recognition algorithm fails to recognize the relevant activities i.e., two times the activity "preparing meal" is not recognized and two times the activity "taking medicine" is not recognized by the system. Comparing results of FABER with SmartFABER for group 1, SmartFABER with smart aggregation recognizes all anomalies correctly without producing any FP and FN. It clearly shows that SmartFABER with smart aggregation recognizes activities with more accuracy.

In group 2, cognitively impaired individuals executed several anomalies; both critical and non-critical anomalies. Considering FABER, in total 60 anomalies were executed by cognitively impaired individuals in 14 days and all of these anomalies are correctly recognized by FABER i.e, $FN = 0$. Similarly SmartFABER with smart aggregation also recognizes all anomalies.However, both FABER and SmartFABER recognizes 2 extra anomalies ($FP = 2$). Again, the reason of these false positives is the same i.e., mispredictions by activity boundary detection technique.

Note that, results of SmartFABER with naive aggregation are identical to SmartFABER with smart aggregation. In conclusion, this dataset (group 1 and 2 together) contains 150 activity instances with 67 anomalies in 21 days. FABER correctly recognizes 65 anomalies, whereas it produces 2 false negatives and 6 false positives. It clearly shows that FABER recognizes anomalies with less precision but higher recall. On the other hand, SmartFABER with smart aggregation correctly recognizes all of the 67 anomalies while producing only 2 false positives. Thus the overall performance of both frameworks is comparable which is probably due to the absence of variability and noise present in the real home dataset. Table 7.6 presents a summary of these results. Since the performance of both techniques is same in case of smart home lab data, we cannot generalize these results to conclude which technique is better to handle variability and noise. Therefore, the difference in these results does not seem to be statistically significant.

7.3.3.2 Fine-grained anomaly recognition using real home dataset

For this dataset, our objective is to recognize three types of anomalies: Green, Yellow, and Red. These color codes represent the seriousness level of an anomaly and also help clinicians to conveniently visualize and differentiate between recognized anomalies. Like smart home lab dataset, we have conducted experiments with FABER and SmartFABER using optimum values of n.

Table 7.7: Real home dataset. Accuracy of abnormal behavior recognition with FABER

ANOMALY	CODE	TP	FP	FN	PREC.	REC.	F1
Prepared meal at unusual time	G1	37	10	68	0.787	0.352	0.487
Meal eaten at unusual time	G2	36	21	51	0.632	0.414	0.5
Meal not eaten	Y1	60	46	7	0.566	0.896	0.694
Meal not prepared	Y2	41	69	0	0.373	1	0.543
Took a medicine outside prescribed time	Y3	73	4	15	0.948	0.83	0.885
Repeated preparing meal	Y4	1	3	5	0.25	0.167	0.2
Repeated eating meal	Y5	0	2	0	0	/0	/0
Took a wrong medicine	R1	29	4	14	0.879	0.674	0.763
Missed a prescribed medicine	R2	164	16	4	0.911	0.976	0.943
TOTAL		441	175	164	0.716	0.729	0.722

Tables 7.7, 7.8, and 7.9 show anomaly recognition results of MLN, naive aggregation, and smart aggregation, respectively. According to these results: around 74% of fine-grained anomalies are correctly recognized using MLN-based FABER, around 87% of fine-grained anomalies are correctly recognized using naive aggregation based SmartFABER, and around 81% of fine-grained anomalies are correctly recognized using smart aggregation based SmartFABER. Although naive aggregation technique has correctly recognized more anomalies as compared to smart aggregation technique, the naive aggregation technique produces large number of false positives as compared to smart aggregation technique. In fact, naive aggregation technique has produced around 48% more false positives as compared to smart aggregation technique. Hence, these facts prove that the naive aggregation technique is less precise than the smart aggregation technique. Table 7.10 shows the overall performance of three techniques in terms of precision, recall, and f-measure values. It can be clearly seen that SmartFABER with smart aggregation produces the highest f-measure score i.e., 0.785 with precision and recall measures are well balanced. In case of naive aggregation technique, the precision and recall measures are less balanced which is obviously due

Table 7.8: Real home dataset. Accuracy of abnormal behavior recognition with SmartFABER and *naive aggregation*

ANOMALY	CODE	TP	FP	FN	PREC.	REC.	F1
Prepared meal at unusual time	G1	81	22	24	0.786	0.771	0.779
Meal eaten at unusual time	G2	64	54	23	0.542	0.736	0.624
Meal not eaten	Y1	57	9	10	0.864	0.851	0.857
Meal not prepared	Y2	29	8	12	0.784	0.707	0.744
Took a medicine outside prescribed time	Y3	84	3	4	0.966	0.955	0.96
Repeated preparing meal	Y4	5	182	1	0.027	0.833	0.052
Repeated eating meal	Y5	0	40	0	0	/0	/0
Took a wrong medicine	R1	40	1	3	0.976	0.93	0.952
Missed a prescribed medicine	R2	167	3	1	0.982	0.994	0.988
TOTAL		527	322	78	0.621	0.871	0.725

to large number of false positives. It means that naive aggregation produces several false predictions about anomalies, when these anomalies are actually not occurred. It can be particularly observed in the case of anomalies related to the repetition of activities (Y4 and Y5).

7.3.4 Fine-grained anomaly recognition using rule induction

Table 7.11 shows results of fine-grained anomalies recognized using rule induction method (RIPPER). This rule induction based version of FABER is called *InductiveFABER* and the technique has been discussed in Chapter 6. In order to validate InductiveFABER, we have conducted experiments with smart home lab dataset and used MLN technique for activity boundary detection. For experiments, we have considered 5 anomalies, a subset of all anomalies present in smart home lab dataset. In the subset, 3 anomalies are non-critical, and 2 anomalies are critical. We have selected a subset of anomalies to conduct experiments with InductiveFABER because the rule induction method requires sufficient number of positive and negative examples

Table 7.9: Real home dataset. Accuracy of abnormal behavior recognition with SmartFABER and *smart aggregation*

ANOMALY	CODE	TP	FP	FN	PREC.	REC.	F1
Prepared meal at unusual time	G1	70	59	35	0.543	0.667	0.598
Meal eaten at unusual time	G2	47	38	40	0.553	0.54	0.547
Meal not eaten	Y1	60	17	7	0.779	0.896	0.833
Meal not prepared	Y2	32	17	9	0.653	0.78	0.711
Took a medicine outside prescribed time	Y3	75	6	13	0.926	0.852	0.888
Repeated preparing meal	Y4	0	0	6	/0	0	/0
Repeated eating meal	Y5	0	0	0	/0	/0	/0
Took a wrong medicine	R1	39	0	4	1	0.907	0.951
Missed a prescribed medicine	R2	167	17	1	0.908	0.994	0.949
TOTAL		490	154	115	0.761	0.81	0.785

Table 7.10: Real home dataset. Results of fine-grained abnormal behavior recognition based on different boundary detection methods

TECHNIQUE	PRECISION	RECALL	F1 SCORE
FABER (MLN)	0.716	0.729	0.722
SmartFABER-SimpleAggregation	0.62	**0.871**	0.725
SmartFABER-SmartAggregation	**0.76**	0.81	**0.785**

of each anomaly class for an effective learning. The smart home lab dataset includes only 21 individuals (one individual per day) in which the domain knowledge of activities changes frequently such as prescription of medicines and mealtimes. Due to the lack of stability in the domain knowledge, we have dropped some anomalies which depends on domain knowledge for their recognition. In this way, we can accurately evaluate the performance of InductiveFABER.

For the sake of generalization, we have merged same types of anomalies into one class. For example, in an activity "preparing meal", the subject can forget to close three repositories: fridge, cooking pan cabinet, and food cabinet. In this case, we assume only one anomaly i.e, "Repository left open";

Table 7.11: Fine-grained anomaly recognition using rule induction

	InductiveFABER			FABER		
Anomaly	TP	FP	FN	TP	FP	FN
NC1: Repository door left open	17	1	3	18	0	2
NC2: Medicine not returned	2	0	2	4	0	0
NC3: Food item not cooked	2	0	0	2	0	0
C1: Had meal without silverware	7	0	0	7	0	0
C2: Stove burner turned on by mistake	7	0	1	8	0	0
Total	**35**	**1**	**6**	**39**	**0**	**2**

Table 7.12: Comparing the performance of inductiveFABER with FABER

Technique	Precision	Recall	F-measure
inductiveFABER	0.972	0.854	0.909
FABER	1	0.95	0.974

instead of considering three anomalies for three different repositories in the same activity. This strategy particularly affects the number of cases of the anomaly "Repository left open", which are reduced to 20 from 25 (Table 7.4).

Table 7.11 compares the performance of InductiveFABER with FABER. In FABER, anomaly recognition rules are manually formulated. Results show that we have correctly recognized most of anomalies using InductiveFABER. In case of first anomaly "Repository left open", InductiveFABER produces 3 false negatives. Note that, FABER also produces 2 false negatives for this anomaly. While investigating the reason of these false negatives, it is revealed that InductiveFABER fails to recognize same 2 anomalies which FABER fails to recognize, and its reason is same i.e., activity boundaries are not recognized by the system in these cases. Hence, practically, in this case InductiveFABER fails to recognize only 1 anomaly. The second anomaly "Medicine not returned" produces 2 false negatives in the case of InductiveFABER, whereas in the case of FABER all anomalies of this class are correctly recognized. This anomaly involves learning of a threshold time; duration for which the medicine is being retained by the subject. In fact, InductiveFABER produces 2 false negatives due to the lack of sufficient number of training examples for this anomaly. The sufficient number of training examples is necessary for learning such threshold values. For the rest of anomalies, InductiveFABER performs like FABER with the exception of 1 false negative for anomaly "Stove burner turned on by mistake".

Table 7.12 presents a summary of these results which are comparable; InductiveFABER f-measure value is 0.909 and FABER f-measure value is 0.975. Naturally, f-measure value of FABER is higher because it involves manual rule formulation. In conclusion, we have achieved almost the same accuracy of anomaly recognition from InductiveFABER as it is achieved from FABER with key advantages of the revised model such as flexibility, scalability, portability, and a time in expensive solution.

Chapter 8

Conclusion

In this chapter, we will present the summary of the main contributions of this thesis, lessons learned from our experiences, and future work directions.

8.1 Technical contributions

The recognition of abnormal behavior is a challenging problem. Due to the large scope of the project, it was divided into various sub-tasks which were completed by a team of researchers and industry partners within SECURE[1] project. In SECURE project, contributions of this thesis work includes proposing a sensing solution, evaluating the performance of various supervised machine learning techniques for activity boundary detection, fine-grained anomaly recognition, and using rule induction methods to automate the process of rule generation for fine-grained anomaly recognition. Various types of anomalies have been identified by domain experts within SECURE project, which are categorized as omissions, commissions, and additions. Domain experts provided us natural language descriptions of these anomalies which are used to construct the knowledge-base.

Unlike existing researches in the domain, we focused on fine-grained anomaly recognition which is the major novelty of this work. In order to infer fine-grained anomalies, knowledge is represented as a set of first order logic rules. In particular, rules are formulated by translating natural language descriptions of anomalies into first-order logic rules. The rule-based

[1] The project details along with the list of industrial partners are available at: `http://secure.ewlab.di.unimi.it/`

system involves time-based reasoning and infers anomalies periodically, for example at the end of each day. Various types of facts are represented in the knowledge-base which include contextual information, domain knowledge, and recognized activities.

We evaluated the proposed framework using two different smart environments: the smart home lab environment, and real home environment. Both smart spaces were developed within SECURE project, in collaboration with industrial partners. The lab environment enables us to discern potential shortcomings of the proposed framework, before experimenting with it in a real home environment. We experimented with several supervised machine learning techniques to improve the accuracy of activity recognition which ultimately results in an improved anomaly recognition.

Results show that we have successfully recognized most of fine-grained anomalies with a high accuracy in both environments. According to the directions of clinicians, the system infers anomalies at the end of each day. Inferred anomalies provide necessary information to clinicians such as the name of the activity in which anomaly occurred, time at which anomaly occurred, objects involved in the anomaly, and its level of seriousness using three color codes: Green, Yellow, and Red. A Green anomaly has a least level of seriousness, whereas a Red anomaly has a highest level of seriousness.

In FABER, anomaly recognition rules are manually formulated. Manual rules are formulated for a specific environment, hence these are not seamlessly portable to other environments. We realized that due to manual rule formulation, the overall process of rule-formulation becomes time expensive and arduous. To address these problems, we proposed *InductiveFABER*, which aims to provide a flexible, scalable, portable, and time inexpensive solution. In InductiveFABER, we automated the process of rule formulation by using a rule induction method (RIPPER), which learns rules from an annotated dataset. InductiveFABER with its potential benefits shows a comparable performance with FABER for the same set of anomalies.

8.2 Lessons learned

We experienced some difficulties during implementation and evaluation phases. In this section, we will briefly discuss those difficulties and lesson learned from our experience.

8.2.1 Sensing infrastructure

The performance of FABER highly depends on the quality of data acquired from the sensing infrastructure. We list down some factors which influence the quality of sensed data in FABER.

- Calibration: a precise calibration of sensors is very important to acquire a good quality data. For example, we used PIR sensors to detect movements and the presence of a person in various regions of the home. An imprecise calibration of PIR sensor results in a false detection of a human presence in a particular region which may change semantics of a sensed event, and ultimately may result in false anomaly detection.

- Environmental conditions: stable environmental conditions are highly demanded in a smart home to accurately detect various events. The instability in environmental conditions can directly influence measurements of some sensors such as temperature sensor. We used temperature sensor to detect the stove usage. It is deployed above a stove burner, however, ambient temperature variations can influence its measurements and we may not be able to accurately detect lightning up and blowing out events of the stove burner.

- Improper deployment: an improperly deployed sensor may not detect an event. For example, we used a pressure sensor to detect a "sitting" action on a chair. The pressure sensor measures the load when the force is exerted on it. The pressure sensor may give false measurements if it is deployed on a soft material on chair.

- Sensing range: the sensing range is very important in case of RFID based monitoring. For example, we attached RFID tags with various food items and medicines. we used passive RFID tags with limited range (upto 5cm). The subject has to bring the tagged item in the specific reading range of the RFID reading module, otherwise, the reader is unable to detect the retrieved item. A failed RFID tag reading leads to an ambiguity; the subject has really retrieved the required item (food or medicine) or RFID tag on the item is not properly swiped. This in turn results in a false anomaly detection

8.2.2 Annotations

We need an annotated dataset to train the supervised machine learning algorithm and to evaluate the validity of recognized activities and anomalies. In case of real home experimentation, due to privacy reasons, it was difficult to observe the subject to get annotations. In fact, we got few opportunities to observe the subject while performing activities. Thus we considered commonsense knowledge based technique to annotate the dataset. Therefore, a privacy friendly and reliable annotation method is very important to improve the performance of FABER.

8.2.3 Anomaly recognition

Currently, the anomaly recognition method is based on non-probabilistic rules that impose strict criteria on a set of observation for inferring anomalies. The strict criteria influence the performance of anomaly recognition, which may result in an increased number of false detection. The rules cover some temporal aspects with fixed temporal threshold values which are derived from domain knowledge. A hard rule fires even if there is a slight difference between the temporal observations and fixed temporal threshold values. For example, consider the case of taking a prescribed medicine, a missed medicine rule fires if the person takes a prescribed a few seconds before or after the prescribed time interval. Furthermore, the noise in the sensed data also reduces the accuracy of predicted anomalies. In conclusion, a confidence factor is required with each anomaly which defines the accuracy and reliability of detected anomaly.

8.2.4 Concurrent and interleaved activities

For the sake of simplicity, we did not consider concurrent and interleaved activities, which definitely affected the anomaly recognition results in case of real home experimentation. In routine life activities, the subject can start an activity and then switch to another activity and afterwards switch back to the original activity. We observed several such cases in the real home dataset; particularly taking medicine in between preparing meal or eating meal. Thus, the inability of handling concurrent and interleaved activity results in an increased number of false predictions.

8.3 Research directions

We have achieved certain objectives which we set for this research, however, this work can be refined or extended with the following research directions.

8.3.1 Alternative sensing solution

We have already listed some factors which influence the performance of FABER by affecting the quality of sensed data. Considering these factors, we propose to use more reliable sensing infrastructure. Due to intricacies involved in human activities, it is necessary to understand that how can we detect human actions with more contextual information. In fact, adding more sensors generate more contextual information which in turn increases the quality and reliability of sensed data. For example, in the current implementation we used PIR sensor to detect the subject's presence near dinning table and use this contextual information to recognize the activity: eating meal. However, we have not used any body worn sensor such as an accelerometer to detect the hand and wrist movements. The body worn sensors adds more contextual information in the system, but at the cost of increased obtrusiveness. Therefore, a detailed research is required to understand the acceptance level of body worn sensors for an elderly person. Off course, the acceptance level varies from person to person, however, such research will help us in the selection of more accurate sensing solution.

The object based fine-grained anomaly recognition needs a very reliable sensing for object detection. Considering our experience with passive RFID tags, we do not propose to use them in such researches. In fact, by using passive RFID tags, we cannot differentiate between two cases: 1) the subject really forgets to retrieve a required item (food or medicine) ; 2) the subject retrieves the required item, but do not properly swipe it. Therefore, we propose to use more sophisticated sensing technologies such as active RFID tags or Bluetooth low energy (BLE) beacons. In particular, we are experimenting with the BLC due to their properties such as miniaturization and low power consumption.

8.3.2 Predictive anomaly recognition

The inherent inaccuracy of sensor readings, especially in real-world deployments, needs for reasoning methods taking into account uncertainty. Currently, sensor data provided as facts to our activity recognition algorithm are not associated with confidence values. To solve this limitation, context facts should be provided as probabilistic axioms to the activity recognition module.Also, the current anomaly recognition method is non-probabilistic which cannot handle the small variations occurs in the human daily routine. For example, it's not necessary that every day the subject takes the prescribed medicine during prescribed time. Due to personal reasons, sometimes the subject can delay (or advance) the activity with minor time difference. However, the non-probabilistic reasoning detects this situation as an anomaly. Although, we added time margins in our rules, but still the time margins do not reflect the exact seriousness level of the anomaly.

8.3.3 Monitoring additional behaviors

Besides cognitive impairments, the abnormal behaviors are also observed in other clinical conditions such as stress, schizophrenia, and parkinson's disease. In fact, we can use the proposed model (with certain modifications) to detect the disorder and help the person to live a quality life. Some data, such as sleep quality, could be acquired by simply integrating off-the-shelf devices into our system. Other behavioral data are more challenging to acquire. Measures of psychomotor agitation and aberrant motor behavior could be acquired monitoring the mean number of exits per day, the average time spent outside per day, the mean number of crossing domestic doors, the time spent idle and the walking speed. Measures of motor activity in the home could be estimated based on the number of sensor firings. A relevant reduction over time of the amount of motor activity compared to the usual activity patterns of the patient may be associated with non-cognitive symptoms, including depressive symptoms, apathy, early fatigue, psychomotor slowness, reduced attentional resources. Conversely, a significant enhancement in the amount of activities may be associated with psychomotor agitation, aggression, disinhibition, irritability, aberrant motor behavior. Of course, those measures are strongly influenced by the personal habits and the social life of the senior. Since many MCI patients are still socially active, those measures should be considered in correlation with the seniors activities and situation, and should be monitored over time

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