SCALABLE PROBABILISTIC ONTOLOGY-BASED METHOD FOR HUMAN ACTIVITY RECOGNITION

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چکیده (برای ثبت ایران‌داک)

عنوان: متد مقیاس‌پذیر برپایه آنتولوژی احتمالی برای تشخیص حرکات انسان

این پژوهش مدلی برای تشخیص حرکات انسان (HAR) با استفاده از سنسور ارائه می‌دهد که بر پایه آنتولوژی است. آنتولوژی یکی از موثرترین مدل‌ها برای نمایش، استنتاج و استفاده دوباره از دانش است. آنتولوژی‌ها بسیار مورد استفاده قرار گرفته‌اند، ولی مادامی که به صورت فایل‌های متنی تخت ذخیره گردند، بر روی پایگاه‌های دانش بزرگ از کارایی بالا برای پردازش کوئری‌ها برخوردار نخواهند بود (در مقایسه با پایگاه‌های داده رابطه‌ای، کارایی بالایی ندارند). رسیدگی به عدم قطعیت نیز موضوع دیگری در پژوهش‌های حوزه آنتولوژی بوده که هم بحث روز و هم چالش برانگیز است. پژوهش‌های پیش از این به این دو موضوع بطور جداگانه پرداخته‌اند، و نه بطور همزمان. مدلی که در اینجا برای ذخیره آنتولوژی در پایگاه‌های داده رابطه‌ای ارائه گردیده به فرم جدول‌هایی است که محتوای اطلاعات معنایی آنتولوژی را به همراه مقادیر احتمال مربوطه ذخیره می‌نماید. در نتیجه تریگرها و توابع SQL برای الزام قیود پایگاهی که احتمالی است تعریف شده و سپس استنتاج احتمالی برای پاسخگویی به کوئری‌ها به کار گرفته می‌شود. برای ارزیابی این نظریات، یک دیتاست پژوهشی اتحادیه اروپا بنام OPPORTUNITY مورد استفاده قرار گرفته تا داده‌هایی که از سنسورهای متصل به بدن و عناصر محیطی را تامین گردیده با هدف پیدا کردن فعالیت‌های سطح بالا مورد استفاده قرار گیرد. در مرحله اول متدهای پردازش سیگنال طراحی و ارائه گردیده تا سیگنال‌های خام دریافتی از انواع مختلف سنسور را تبدیل به اطلاعات احتمالی درباره فعالیت‌های سطح پایین و موقعیت کاربر نماید؛ که چنین اطلاعاتی به شکل تریپل‌های معنایی تصادفی در پایگاه داده ذخیره می‌گردد. مرحله دوم، استلزام منطقی تصادفی بین محل کاربر و فعالیت‌های سطح پایین او با فعالیت‌های سطح بالا تعیین می‌گردد که این امر یا با استفاده از اطلاعات برچسب خورده و یا با استفاده از دانش زمینه‌ای فرد مطلع انجام می‌گیرد. فعالیت‌های دانه درشت از طریق فرآیند استنتاج بر روی فعالیت‌های دانه ریز و با استفاده از اصول موضوعه بدست می‌آیند که هر البته دو اینها دارای طبیعتی احتمالی و تصادفی هستند. نتایج به دست آمده از مرحله اول شامل محتمل‌ترین کاندیداها برای حرکات سطح پایین با نتایج شرکت‌کنندگان مسابقه‌ای که سازندگان دیتاست ترتیب داده بودند، مقایسه گردید. نتایج حاصله از این پژوهش از نظر دقت به نتایج آنها بسیار نزدیک اما از حیث تعداد فیچرها و زمان پردازش پژوهش حاضر نسبت به آنها برتری دارد. در مرحله دانش محور، علاوه بر مزایای سمانتیک مدل ارائه شده، نتایج در مقایسه با سایرین حاکی از بهبود از نظر دقت و افزایش قابل توجه کارایی زمانی پردازش بود. ارزیابی کیفی مدل ارائه شده نیز نشان دهنده جامعیت و برتری آن در مقابل مدل‌های موجود است. نتایج بدست آمده از فرضیه این پژوهش حمایت می‌کند که بکارگیری مدل آنتولوژی-احتمالی و نیز پایگاه‌های داده رابطه‌ای در سیستم‌های تشخیص حرکات انسان می‌تواند موجب افزایش کارایی و بهینگی سیستم پایگاه دانش شود. برخلاف اکثر سیستم‌های تشخیص حرکات انسان که برسیستم‌های بلادرنگ متمرکز شده‌اند، این پژوهش مشارکت‌های علمی دیگری را عرضه نموده است: مقیاس‌پذیری؛ بمعنای پردازش حجم عظیمی از دیتای سنسوری در یک زمان معقول که کاربردهای متنوعی دارد از جمله در نظارت بر کارکنان، نظارت بر مجرمان تحت آزادی مشروط و نیز مطالعات پزشکی و مطالعاتی که به اعمال روزمره انسان‌ها می‌پردازند.

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SCALABLE PROBABILISTIC ONTOLOGY-BASED METHOD FOR HUMAN ACTIVITY RECOGNITION

POUYA FOUDEH

A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy (Computer Science)

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DEDICATION

To *Afra*, *Paya* and *Zeytuna*

my beloved children who showed me the other side of life.

ACKNOWLEDGEMENT

Praise be to **the God**; everything I have is from him.

I wish to express my deepest gratitude to my father, **Dr. Hossein Foudeh** for supporting me in this long journey, my wife, **Dr. Aida Khorshidtalab**, not only for encouraging me and praying for me during my research, but also for actively assisting me all throughout the research process.

I am thankful to my wonderful friends in **SCRG research lab** and **Prof Naomie's research group**. Our daily discussions extended my knowledge and were inspiring to me. I also thank **School of Computing UTM academic and non-academic staff** who were very kind and helpful to me.

And…. There is no word to express my gratitude to a person who made a huge difference in my life. To the best of my knowledge she is the only person in the world who could make me do this research:
The painstaking supervisor **Professor Dr. Naomie**.

ABSTRACT

This research proposes an ontological model for sensor-based human activity recognition (HAR). Ontology is one of the most effective models for knowledge representation, reasoning and reuse. Even though they are widely used, ontologies as flat text files are not efficient enough for query processing over large knowledge bases as compared to relational databases. Handling uncertainty is another ongoing and challenging research topic in ontologies area. Previous researches address these problems independently, and not both simultaneously. A model for storing ontologies in relational databases is proposed in the form of tables that contain ontology's semantic material with accompanying probability values. Subsequently, SQL functions and triggers for keeping probabilistic database constraints are defined, in which it later performs probabilistic reasoning to answer queries. To assess these approaches, a European Union research dataset, "OPPORTUNITY" that provides data from the body and environment sensors with the aim of identifying high-level activities is utilized. Firstly, signal processing methods is proposed to convert raw signals from different types of sensors into probabilistic information about low-level subjects' activities and location, in which information was stored as probabilistic semantic triples in a relational database. Secondly, probabilistic implication between subjects' location, low-level activities and high-level activities are determined from labelled instances and can be developed or edited by the user according to his own background knowledge. Coarse-grained activities are obtained from a reasoning process that uses fine-grained instances and assertion axioms that are both probabilistic in nature. The results of the first stage consisting of the most probable candidates of low-level activities are compared with a real challenge participant, organized by developers of the dataset. The proposed method obtained very close results in terms of accuracy while it is more optimal in terms of the number of features and required time. In the knowledge driven stage, in addition to semantic advances of the proposed model, the results indicate improvement in terms of accuracy and significant performance in terms of time. The qualitative assessment of the proposed model reveals its advantages against existing models. The results provided support for the hypotheses that utilization of probabilistic ontological modelling and relational database management systems in a HAR system can improve the performance and efficiency of the knowledge-based system. Unlike most efforts on sensor-based HAR which focus on real-time systems, this research has yielded many contributions: scalability; processing over a considerable amount of sensor data in a reasonable time; beneficial in different applications including employee monitoring, under-parole criminal monitoring; and medical or praxeological studies on people behavior.

ABSTRAK

Kajian ini mencadangkan satu model ontologi untuk digunapakai dalam pengenalpastian aktiviti manusia (Human Activity Recognition-HAR) yang berasaskan sistem deria manusia. Ontologi adalah satu model yang paling efektif dalam perwakilan pengetahuan, taakulan dan penggunaan semula. Walaupun digunakan secara berleluasa, penggunaan ontologi sebagai fail teks rata (flat text file) adalah tidak efisien untuk pemprosesan pertanyaan ke atas pangkalan pengetahuan yang besar berbanding pangkalan data hubungan. Satu lagi cabaran dalam bidang kajian ontologi adalah menangani ketidakpastian, di mana kajian-kajian lepas menangani masalah-masalah ini secara berasingan dan bukan kedua-duanya secara serentak dalam masa yang sama. Satu model untuk menyimpan ontologi dalam pangkalan data hubungan dicadangkan dalam bentuk jadual yang mengandungi bahan-bahan ontologi semantik dengan nilai-nilai kebarangkalian dan seterusnya mendefinisi dan mencetuskan SQL untuk menyimpan kekangan pangkalan data probalistik, disusuli dengan menjalankan pemikiran kebarangkalian untuk menjawab pertanyaan. Untuk menilai kaedah-kaedah ini, dataset “OPPORTUNITY” dari Kesatuan Eropah telah digunakan yang mana ianya memberikan data daripada pengesan badan dan persekitaran yang bertujuan untuk mengenal pasti aktiviti-aktiviti tahap tinggi. Pertama sekali, kaedah pemprosesan isyarat telah dicadangkan untuk menukar isyarat mentah daripada pengesan-pengesan yang berbeza kepada maklumat kebarangkalian tentang aktiviti dan lokasi subjek-subjek pada tahap rendah. Maklumat telah disimpan sebagai triplet semantik kebarangkalian dalam pangkalan data hubungan. Keduanya, implikasi kebarangkalian di antara lokasi subjek, aktiviti-aktiviti bertahap tinggi dan rendah adalah ditentukan berdasarkan contoh data yang berlabel dan boleh dibangunkan dan diedit oleh pengguna berdasarkan latar belakang pengetahuannya. Aktiviti-aktiviti butiran kasar diperolehi daripada proses penalaran yang menggunakan tika yang dihalusi dan aksiom penerapan yang mana kedua-duanya berbentuk probabilistik. Hasil kajian pada tahap pertama adalah tentang calon-calon yang paling berkemungkinan untuk aktiviti-aktiviti tahap rendah, berbanding dengan cabaran peserta yang diberikan oleh pembangun set data. Kaedah yang dicadangkan boleh memberikan hasil yang hampir sama dari segi ketepatan dan optimum dari segi bilangan ciri-ciri dan masa yang diperlukan. Pada tahap berdasarkan pengetahuan, di samping kemajuan-kemajuan semantik pada model yang dicadangkan, hasil kajian menunjukkan penambahbaikan dari segi ketepatan dan prestasi yang signifikan dari segi masa. Penilaian kualitatif model yang dicadangkan menunjukkan kelebihannya berbanding model yang ada. Hasil kajian ini juga menyokong hipotesis bahawa penggunaan model ontologi probabilistik dan sistem pengurusan pangkalan data hubungan dalam sistem HAR dapat meningkatkan prestasi dan kecekapan sistem berasaskan pengetahuan. Tidak seperti kebanyakan usaha ke atas HAR berasaskan pengesan yang memfokus ke atas sistem-sistem masa nyata, kajian ini telah memberikan beberapa sumbangan: kebolehan berskala dan memproses data pengesan dalam jumlah yang besar di mana ianya sangat bermanfaat dalam pelbagai aplikasi seperti pemantauan pekerja, pemantauan banduan dalam tahanan dan juga dalam bidang kajian perubatan serta kajian praksiologi ke atas gelagat manusia.

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LIST OF ABBREVIATIONS

ACCEL	-	Accelerometer
BN	-	Bayesian Networks
BHO	-	Both-Hands interaction with Objects
DBMS	-	Database Management System
GYRO	-	Gyroscope
HAR	-	Human Activity Recognition
IMU	-	Inertial Measurement Unit
IPS	-	Indoor Positioning System
KNN	-	K Nearest Neighbour
LAP	-	Location, Angle, Posture
M5P	-	M5 model trees
MEBN	-	Multiple Entity Bayesian Networks
OWL		Ontology Web Language
PCA	-	Principal Component Analysis
PM	-	Probabilistic Mode
PRDBMS	-	Probabilistic-Relational Database Management System
RDBMS	-	Relational Database Management System
RDF	-	Resource Description Framework
RFID	-	Radio-Frequency IDentification
SQL	-	Structured Query Language
SVM	-	Support Vector Machine
W3C	-	The World Wide Web Consortium
XML	-	Extensible Mark-up Language

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Human activity recognition has various applications such as employee monitoring to improve productivity, senior and elderly monitoring for safety and improving the quality of life, smart homes, and gaming. A possible approach to HAR is sensor based: attaching wireless sensors to subjects' clothes (wearable sensors) and/or to the objects of interest that the subject interacts with (environmental sensors). Sensors' failure, wireless commutation errors and imperfection of data driven recognition methods are causes of incapacitation of data driven recognition systems to produce certain results (Riboni and Bettini, 2011a). There are two approaches; first is the data-driven approach, which is to process the signals and to classify them using machine learning techniques. Second, knowledge-driven approaches that develop a knowledge base on human activities (Lara and Labrador, 2013). There are some researches that show probabilistic approach is applicable for human activity recognition (Helaoui, Riboni, and Stuckenschmidt, 2013; Aloulou et al., 2015). Rather than HAR techniques and methods, this research involves other areas of research including ontology, as a structure for knowledge bases, reasoning about uncertainty, probabilistic ontology, storing ontologies in databases and probabilistic databases.

For the first time, ontology term was used in the computing area by Gruber (1993); according to his definition: An ontology is a description (like a formal specification of a program) of the concepts and relationships that can exist for an agent or a community of agents (Gruber, 1995).

The most usual way for representing ontologies is the deployment of knowledge representation languages; OWL (Ontology Web Language) is an RDF/XML (Resource Description Framework/ Extensible Markup Language) based language to represent regular ontologies in flat text files, endorsed by W3C and capable of interpretation by computers as well as human (Hitzler et al., 2009). They went under the spotlight after being one of the pillars of the semantic web.

While the accuracy is important in HAR systems, scalability, ability to do processing of big data in a reasonable time, is another important challenge in this research. While in some applications such as elderly monitoring and gaming, the process must be real time, in others such as employee monitoring, on parole criminals monitoring and medical or praxeological studies on people behaviour, batch processing is an option. In such cases, a big amount of data must be processed in a reasonable time. In other words, managing CPU time usage in an efficient way does matter, regardless of accuracy; the system fails if it is not ready for being scalable to perform on big data.

Relational (Codd, 1970) Database Management Systems (R-DBMS) with SQL language (Chamberlin and Boyce, 1974) for querying are available to use with lots of efforts and investments behind them that dominates them in terms of performance and security. Besides processing of OWL flat text files, another approach is transforming an ontology to a relational database which is the process aimed to store data, instances, and the structure of an ontology in a database managed by a DBMS. Cpmpairing ontologies that are in OWL text files, commercial database management systems are more efficient especially for big data, more secure, easy to share and easy to interact with applications (Astrova, Korda and Kalja, 2007).

Human knowledge is limited. Therefore, sometimes, information is incomplete or contradictory. This happens under certain circumstances, when the data are the result of unproven theories and it is impossible to do a perfect experiment or data is made by an unreliable source, for example a faulty sensor. When an ontology is developed using such information, the information would be obviously inconsistent; and inconsistency is unsustainable in any kind of knowledge. In short, rather than how people deal with deterministic data, a different approach to uncertain information is needed (Haase, and Völker, 2008).

This research aims to develop an ontological fully probabilistic knowledge model for sensor based HAR domain and utilizes the commercial high-performance Relational Database Management Systems (RDBMS) for storage and reasoning engine. Raw electrical signals received from sensors, available in the chosen dataset, are replaced with low-level probabilistic activity information, for example sitting or taking a cup with left hand. At the next step, obtained information are formed in a probabilistic ontology; the assertion axioms are extracted, and the reasoner of the ontology are able to discover the high-level activities, for example cleaning or resting. The model is implemented in a scalable way, which means it can be applied for batch processing of big data.

1.2 Problem Background

Human activity recognition, with various applications such as employee monitoring to improve productivity, senior and elderly monitoring for safety and improving quality of life, smart homes, and gaming, is a hot and challenging topic in artificial intelligence. One of the widely used approaches for human activity recognition is to deploy a video camera and then process the captured images to recognize what activity the target person is performing. However, using this method is not the best solution in all cases. Due to privacy issues, video filming is not possible in some places and another problem is pervasiveness, which is the difficulty of extracting activity at the desired level of detail with recorded video. Finally, storage and processing of the acquired data is costly. This problem is more significant when the data are massive due to long recording time or a large number of subjects.

Another solution is sensor based human activity recognition: to attach some sensors to body of the person or environmental objects to recognize what the person is performing in a specific time. It is a useful area of research and there are several researches on it. There are two approaches to human activity recognition through sensors. Data-driven approach, which is to process the signals and to classify them using machine learning techniques. Although this approach is adequate for recognition of primary movements, it is not applicable for recognizing complex, high-level activities, which requires some background knowledge and reasoning. In this case, knowledge-driven approaches that develop knowledge bases on human activities are more effective. This research lays on both of two approaches:

First, data-driven methods for converting sensor signals to low-level activities and locations. In HAR area, there are several proposed methods for sensor arrangement, signal processing for feature computation, feature selection and classifier selection. Almost all of them are focused on the higher recognition rate only because they supposed the method to be used in real-time recognition, therefore, it is fast enough if the feature computation time plus testing time is less than the activity time. On the other hand, for batch processing of big data the processing time, including training time, should be as short as possible and the volume of stored data should be minimal. In addition, as the input data of the second part of the research, the first part must predict low-level activities and IPS (Indoor Positioning System) locations in form of probabilistic data, that none of the former researches did that.

Second, knowledge driven methods to develop an ontological model which is able to convert low-level activities and indoor locations to high-level activities; such an ontology discovers logical relationships between activities and does reasoning about instances. Chen and Nugent (2009) and Riboni and Bettini (2011c) were the first researchers who proposed an integrated framework for activity recognition based on a conceptual essence. In those researches and several researches after them, only the reasoning rules, assertion axioms, are probabilistic but the whole method, including input data, is not fully probabilistic. In contrast, the proposed method in this research input instances, low-level activities and locations, are also probabilistic. Using uncertain input data, the system is more likely to have higher accuracy particularly when sensors are faulty, or data is noisy.

To represent knowledge bases, in general, and ontologies, knowledge representation languages are developed: Resource Description Framework (RDF), Web Ontology Language (OWL) and finally OWL2 (McGuinness and Van Harmelen, 2004). All of these languages are in flat text files; in one hand, they are capable of interpretation by computers as well as human; in another hand, storing flat text files are not the best option for storage of big data in terms of time performance. There are Knowledge Management Systems (KMS) that store OWL ontologies, one well-known product is Protégé (Knublauch et al., 2004). Although they are very popular in the academic community, they are far from commercial products in terms of performance.

Commercial relational database management systems are high-performance well-established system software. The problem is they are designed for storage of data, in the form of tabular data, and not knowledge, in the form of ontology (Vysniauskas, Nemuraite and Sukys, 2010); and supposed to manage deterministic data without any kind of uncertainty. Managing the probabilistic knowledge is a useful topic in artificial intelligence and data engineering domain because it enables them to accept uncertain information. Nowadays, while it is a real need in many domains of research, there are several challenges that slow down the advancement of the probabilistic knowledge management systems.

Ontologies and relational databases can be used to represent the same thing: propositions. Indeed, highly efficient relational database management systems can be utilized for storing and managing ontologies which are in a different structure. There are some researches on storing OWL ontologies in relational databases (Vysniauskas and Nemuraite, 2006; Xu, Zhang and Dong, 2006; Astrova et al., 2007), however, no effort to integrate these two, ontologies and relational databases, and answer the questions of the developers whose practical approaches are focused exclusively on relational databases or ontologies (Martinez-Cruz, Blanco and Vila, 2012). Unlike deterministic ontologies that there are few researches in storing them in RDBMSes, there is no literature about storing probabilistic ontologies in relational databases.

Probabilistic databases were first introduced by Cavallo and Pittarelli (1987) but because of privation of efficient query processing algorithms, only after 2005 they become an attractive research area; when other research areas, such as semantic web, needed probabilistic databases. Query processing time is still the main challenge of this area. To answer a query, the system needs to calculate all possible worlds related to that query which for some queries it is in #P complexity class. In other words, before starting the query processing, the system must determine if it is able to answer the query or not (Suciu et al., 2011). There are some implementations of Probabilistic-Relational Database Management Systems (PR-DBMS), however, they are in the research stage and, unlike R-DBMSes, none of them is released for commercial use with high performance for big data. Although this research is not going to use current PR-DBMSes, ideas behind them are beneficial in storing probabilistic ontologies in relational databases.

There are some efforts to adopt the probabilistic information in OWL ontologies including designing a framework and structure for them and developing a logical and reasoning tool for these ontologies. PR-OWL (Da Costa, Laskey and Laskey, 2008) is an effort to develop a probabilistic version of OWL which is based on MEBN (Multiple Entity Bayesian Networks) (Laskey, 2008). “UnBBayes” is a framework for documenting, maintaining and evolving the probabilistic ontologies (Carvalho et al., 2014). PR-OWL was an effort to fill the gap between probabilistic information and OWL ontology, but in that stage, it was not successful to be fully compatible with OWL and therefore it is not an endorsed standard. The current research is also interested on probabilistic ontologies; this ontology is set of probabilistic triples representing instances and assertion axioms stored in a database and a description language, like OWL, is not a necessary part of the model.

To the best of our knowledge, this research is the first ontological sensor-based activity recognition work with probabilistic observations. Current approach leads to more accurate results in high-level activity prediction. Plus, the proposed system is more capable to handle uncertainty including noisy data and incomplete ambiguous information.

1.3 Problem Statement

Managing the probabilistic knowledge is an interesting topic in artificial intelligence and data engineering area. This study is conducted to answer the following question:

How can probabilistic knowledge bases with ontology structure, kept in a relational database management system, used for human activity recognition be better than regular data-driven and knowledge-driven activity recognition methods in terms of time performance for batch processing of big data?

To answer this question using the Opportunity dataset, the answer to these sub-questions, need to be found:

1- How the electronic signals received from the body, environmental and IPS sensors can be converted to probabilistic triples?

2- How to represent a model for Human Activity Recognition in form of a fully probabilistic ontology for detecting high level activities, which can extract axioms and do reasoning?

3- How to develop a method for transforming the probabilistic ontology into a relational database that improves the time performance, that would perform on big data?

1.4 Research Goal and Objectives

This research goal is to propose an effective a probabilistic ontological structure in sensor-based human activity recognition domain, stored in a relational data base management system, suitable for big data.

To support this goal the following objectives are aimed:

1- To represent data-driven sensor based human activity recognition methods to find low-level activities and subject’s location in the room in form of probabilistic data. Time and storage efficiency are important, and the accuracy of predictions must be high.

2- To develop a fully probabilistic ontology model to store the low-level activity information and then extract and/or use manually entered axioms and do reasoning about them to predict high level daily activities during the activity time.

3- To represent a method to transform the developed ontology into an SQL based Relational database that utilizes its commercial grade high performance for storage and reasoning engine, which could make the system capable of dealing with big data.

1.5 Research Scope

The following aspects are the scope of the research for slight objectives.

- The intended ontology is set of probabilistic triples representing instances and assertion axioms. Nevertheless, they are easily convertible to OWL code and vice versa.

- This research will use relational model from high level perspective; it will not enter low level storage topics. The design will be according to relational algebra and standard SQL for regular, deterministic, database management systems.

- This research is focused on converting sensor signals to probabilistic information and design a model for HAR from them. Concepts such as producing human activity data sets and details about it, such as sensor choosing, wireless communication, and proper method of labeling the activities are not in the scope of this research.

1.6 Significance of Research

This study will introduce an ontological probabilistic approach for a human activity recognition knowledge base stored in a relational database management system. There are some efforts on flat text OWL probabilistic ontologies, and some researches on storing non-probabilistic ontologies on relational databases, plus some studies on probabilistic database management systems. Nevertheless, combining all together and developing a model for probabilistic ontologies stored in high performance relational database management systems is an innovative approach.

Besides, this research proposes new signal processing and feature extraction methods for human activity recognition via body and environment sensors. This part, in harmony with the whole research, puts scalability, saving time and storage, in priority to be suitable for batch processing of big data.

1.7 Expected Contributions of Study

The expected contributions of this research are:

- A set of time and storage-efficient data-driven methods for converting sensor signals to probabilistic information, suitable for batch processing of big data.

- A structural model for an ontological probabilistic knowledge base in human activity recognition (HAR) domain equipped with a reasoner.

- A method for transforming probabilistic ontologies in relational databases and including the implementation of the reasoning engine with database management system facilities for above mentioned purposes.

1.8 Thesis Organization

There are five chapters in the thesis, which are as follows:

Chapter 1, Introduction: The current chapter is a comprehensive introduction to the proposed research and the formal declarations about it including the problem background, problem statement, objectives of the study, research scope, significance of the study and the expected contributions.

Chapter 2, Literature Review: This chapter represents an overview of (1). Uncertain data, reasoning about uncertainties, and probabilistic ontologies. (2). Relational databases, Probabilistic relational databases and storing ontologies in databases. (3). Sensor-based data-driven human activity recognition including signal processing and feature extraction and classification methods. (4). Knowledge-driven human activity recognition including ontology modelling of human activities.

Chapter 3, Research Methodology: In this chapter the methodology applied in this research aiming to solve the research problem, including the research framework and the research components and phases. The material applied to the current research, applied dataset, data pre-processing, and evaluation methods for results will be discussed in this chapter

Chapter 4, Probabilistic ontology based HAR. This chapter contains proposed several methods for feature computation to make probabilistic predictions of low-level activities and locations from sensors readings. Third sub-chapter presents a probabilistic ontology model for HAR and then discuss how to transform the probabilistic ontology in a relational database.

Chapter 5 presents the obtained Results, and Chapter 6 has a Discussion on them; presenting the Conclusions of the research, outlines the contributions of the work and recommends for possible future works.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Human activity recognition system is an automatic system that can monitor a human subject and tells what he/she is doing. In other words, HAR is a group of methods that recognizes subjects' actions at a particular time. The activities that fall to two categories: Fine-grained activities including primary movements and locations, usually are performed in short period of time, few seconds of less. Cutting butter with knife is an example of this category. In contrast, coarse-grained activities are activities formed from a number of fine-grained activities, for example the time of eating breakfast. Their performance time is usually long.

Sensor-based human activity recognition (HAR), with various applications, is a hot and challenging topic in artificial intelligence and there are several published researches on this topic. There are two approaches to sensor based human activity recognition. First is the data-driven approach, which is to process the signals and to classify them using machine learning techniques and is adequate for recognition of fine-grained activities. Second is the knowledge-driven approach, which is applicable for recognizing complex, high-level activities; it requires some background knowledge and does reasoning to discover the coarse-grained activities. For both of these approaches the correctness and accuracy of the predictions is usually the first and objective of the HAR systems; however, the processing time is also important. For batch-processing, not real-time processing, the amount of data may be increases, therefore, the system should be scalable.

Gruber (1993) used the ontology term in the computing area for the first time, as a hierarchical and conceptual model for the representation of knowledge bases. Thereafter, ontologies have been accepted and used in different applications by computer science and knowledge engineering community. Various tools are presented including ontology languages, ontology editor and ontology reasoner software.

Human knowledge is limited. Therefore, sometimes, information is incomplete or in opposition. It usually happens when the data are the result of unproven theories or it is impossible to do experiment, or they are collected from untrusted sources (Halpern, 2017). When an ontology is developed using such information, the ontology would be obviously inconsistent. In such a situation, there are two strategies: First, identifying inconsistencies and letting the system to eliminate some part of ontology aiming to make it consistent, usually means take only the most probable data. Clearly, this strategy omits some useful information from an ontology. Second, another strategy is keeping adapting uncertain data, usually can be called probabilistic, data in the ontology. For realizing this strategy, there are some efforts for developing a probabilistic ontology, but they are still far from an ideal model for knowledge. Besides uncertainty, the storage and query processing are problems for scalable ontologies that are going to be too time and storage consuming for big data. Relational database management systems (R-DBMS) or probabilistic-relational DBMSes are highly efficient for big data but they have their own problems in working as storage for knowledge-bases because they are not designed for this purpose.

2.2 Data-Driven Methods for HAR

While some types of sensor's data, such as location from RFID (Radio-Frequency IDentification), can be directly used in knowledge bases, analog sensors' signals must be processed by data-driven methods. There are different approaches for adding analog sensors to the ambiance. One approach is installing sensors on subjects' body and environmental objects, current research applies this approach. Another approach is the deployment of smart phones for activity recognition. Smart phones are programmable computers that already have various kind of sensors. They are cheap; indeed, everybody has one. On the other hand, relying on one sensor system installed on one part of body is less accrue. When the phone is in loose positionsfor example in user's hand or loosely at pocket, unlike sensors that attached to body or cloths tightly, it becomes worse especially for GYRO (Gyroscope) sensors. Users personal habits in keeping their phones prevent generalization and training data is needed for each user. Nonetheless, they are limited to few sensors, all of them integrated into one point only (Chen and Shen, 2017). For this research, the first one, installing sensors not smart phone, is more favorable; even though it is more expensive, having sensors in different parts while they are attached tightly, produces more information which is needed for processing and obtaining more accurate results.

2.2.1 Feature Extraction

Some HAR systems apply simple statistical measures on sensor reading values in a particular interval; such as mean value, standard deviation, variance, maximum and minimum value (Chavarriaga et al., 2013).

Some other researches applied more complicated methods for feature computation: Fourier transform (Bao and Intille, 2004; Altun, Barshan and Tunçel, 2010), discrete cosine transform (He and Jin, 2009) and autoregressive modelling (Khan et al., 2010) of acceleration signals are already used as features, pattern recognition (Aminian and Najafi, 2004) and feature computation algorithms (Varkey, Pompili and Walls, 2012) have been used in this context. However, while simple statistical measure has low accuracy, these methods are too slow to be used for batch processing of big data. For example, Fourier Transform is in O(n2) and Fast Fourier Transform is in O(n.log(n)). In proposed methods of this research, computation speed is one of the main concerns.

In some cases, the higher accuracy is the only goal of researchers. For example, Yang et al. (2015) used deep learning techniques that spent about 1 hour for training and 8 minutes for testing of a dataset that contains 90 minutes of training and 35 minutes of testing data. These kinds of techniques are not applicable for batch-processing of big data, when hundreds of hours of recording must be processed, because the processing time will too long.

This research applied two outstanding and highly cited methods on the same dataset that has been used in the current research, “Opportunity” dataset. Ghayvat et al. (2015) proposed a method for ACCEL (accelerometer) sensors. They calculated 24 features for each sensor. Altun et al. (2010) applied IMUs (Inertial Measurement Unit) which include an accelerometer, GYRO and magnetic sensors. They calculated 234 features per sensor and then used PCA (Principal component analysis) and reduced 1428 total features to 30 but at the cost of losing some F-measure. The details of these methods are elaborated in Section 5.2.1. A subset of the Opportunity dataset has been used for a challenge competition. Competitors are judged based on the labels they obtained and there was no obligation to disclose the method they applied to obtain the labels which mean that some stages even might have been done manually. There were 3 categories and each competitor was allowed to enter each one separately: Task A, recognition of postures; Task B, recognition of gestures; and Task C, recognition of gestures for subject person 4, whose dataset has altered and missing data and rotated sensors in the middle of the activities. Eight groups participated in this task, their results were published as well as the result obtained by the providers of the dataset, and tested with different classifiers, to establish the baseline. The method presented in this research also applied to the same sub dataset. These methods are compared with the results of current research in Section 5.

2.2.2 Classification method

Selection of the appropriate classifier is another part of the data-driven phase of the research. There are some researches on the performance of different classifiers for human activity recognition (Attal et al., 2015; Janidarmian et al., 2017). Nonetheless, in HAR domain it seems that the performance of classifiers depends on the feature extraction method and results of other researches cannot be generalized. For instance, decision tree-based methods, that produces the best results in the current research, leads to the worst results in all 293 tested classifiers in Janidarmian et al. (2017). In the baseline testing, which has done by developers of the Opportunity dataset, KNN-3 had the best performance between five classifiers (Chavarriaga et al., 2013) while in Altun et al. (2010) SVM (Support Vector Machine) was the best.

Some classifiers are tested in current research, regarding both classification accuracy and time, and the selected classifier is a regression based classifier with M5P (M5 model trees), a model tree in the form of a decision tree with regression at its leaf nodes, which is applied from Weka package (Hall et al., 2009). The decision tree is called the M5P model tree (Quinlan, 1992; Wang and Witten, 1997). M5 is an adaptation of a regression tree algorithm; it uses a more computationally efficient strategy to construct piecewise linear models, compared to other regression trees (Loh, 2011), because it forms a piecewise constant tree first and then fits a linear regression model to the data in each leaf node.

2.2.3 Subject Tracking

Finding the subjects' location is a helpful task for HAR. Global Positioning System (GPS) is not accurate enough to track a human subject in a small area and cannot be used under a roof. Indoor positioning systems are practical for most HAR systems.

Some HAR methods applied the subject tracking; but almost all of them used RFID tags to detect the presence of the subject near some environmental objects. RFID can be used in knowledge modeling without any processing. On the other hand, IPS (indoor tracking system) is able to track the subject in indoor places. There are some researches on processing signals from IPS systems (Ye, Redfield and Liu, 2010), but not for HAR. The current research converts continuous IPS signals to discrete data and then applies it for HAR purpose.

2.3 Knowledge-Driven Methods for HAR

In knowledge-driven methods, knowledge-based structures and reasoning are applied for HAR (Chen et al., 2009). They are usually used for deducting coarse-grained activities from fine-grained activities.

2.3.1 Ontology-based Frameworks

Nowadays, ontologies are one of the best tools for activity recognition purpose (Rodríguez et al., 2014a). Chen et al. (2009), proposed an ontology-based approach which was one of the first integrated frameworks for activity recognition based on a conceptual essence. On that preliminary research, they did not use any dataset and presented the framework with a sample ontology. However, in an extension of their work (Chen, Nugent and Okeyo, 2014), later they presented an activity recognition system based on the previously presented ontological model. The method was designed to confront a cold start, a common problem in data-driven activity recognition, when at the beginning point there is no, or there are few labeled data for learning the system. At the starting point, there is an ontology that is developed according to human knowledge. Thereafter, Using, the ontology reasoner does the labeling of some activities, and then new activities are discovered using labeled information and data-driven techniques. The labeled information is used to discover more activities via data-driven learning; discovered activities are used to populate the ontology. By running all steps more than one time, more information is labeled; consequently, ontology becomes more completed. In short, in proposed frameworks by Chen and Nugent, the information stored in the ontology is non-probabilistic; although the axioms and the machine learning process are probabilistic.

Another pioneer research in HAR is an OWL 2, ontology web language, based model proposed by Riboni and Bettini (2011c); they also developed another hybrid, statistical and ontological, activity recognition method (Riboni and Bettini, 2011a). It was published at the same time with Chen and Nugent method and both believed to be founder of ontology-based HAR. This method obtains low-level, simple and short time, activities using data-driven techniques from the body and environmental sensors and gathers the subject’s location from GPS for outdoor and RFID for indoor. They used a novel technique, named “historical variant”, performs temporal optimization for obtained low-level activities. This research utilized ontological reasoning, only about locations, to predict high-level, complicated and long time, activities. Input and output data and reasoning process were not probabilistic; always the most probable state was chosen as the deterministic answer.

Helaoui et al. (2013) is slightly similar to the current research; not only for using ontology and a probabilistic model but also for utilizing the earlier version of the same dataset, Opportunity. This dataset is about daily morning activities; subjects' bodies and environmental objects are covered with different kind of sensors, and RFID tags installed in his gloves to track the subjects' location. In a newer version of the dataset, which is used in the current research, the state-of-the-art IPS system is utilized for indoor tracking. Beside sensor data, the dataset contains labels for postures, low (right and left hands Interaction with objects and hand movements) and high-level activities. Annotations are made via video checking. Additionally, this particular research annotated two medium-level activities: simple activities and manipulative gestures. The probabilistic ontological reasoning process is done in different levels.

Information about location and posture are ignored; hands' interaction with objects and hands' movements are combined and named atomic gestures (Level 4). A set of related and sequential atomic gestures characterize a manipulative gesture (Level 3), for example, "opening a drawer" and "fetching a knife" is "taking the knife". In the same way, a set of manipulative gestures characterize a simple activity (Level 2), and a set of simple activities characterize a high-level, complex, activity (Level 1). Level 4 labels are available in the dataset, meaning that regardless of errors they are somehow obtained from sensor data. For levels 3 to 1, the state of each level is deducted from lower level using ontological reasoning. The axioms, Tbox, of ontology are manually developed and weighed as confidence property, the probability of working of the assertion axiom. The manually annotated labels for levels 1 to 3 are used to evaluate the method. There are two points to note. First, the inputs and outputs of each level are not in form of probabilistic. In other words, the reasoner with probabilistic rules receive deterministic values from the lower level and pass the only most probable value to the higher level (similar to the aforementioned works). Second, model reusability is not achievable in this method. For each individual person with his own lifestyle, the HAR system needs a special set of simple activities and ontology assertion axioms.

2.3.2 Location-based models

Probabilistic Markov model is frequently used in location-based approaches. Boger et al. (2005) used this model for predicting users' situation while low-level activities are provided to the system and Liao, Fox and Kautz (2007) proposed a location-based activity recognition using Markov model. In some recent research works including Liu et al. (2017) and Gayathri, Easwarakumar and Elias (2017), Markov model and knowledge bases are applied together and has been called hybrid approach. Logical reasoning has been used for recognition and prediction of human activities from several years ago (Henry and Allen, 1986); it took a big step forward after modern knowledge representation models and tools arose.

There are a few research studies about adopting ontologies and location-based probabilistic model and reasoning in activity recognition. Yamada et al. (2007) is a preliminary research on this area. The environmental objects are equipped with RFID tag and RFID reader sensors installed in the activity area. They are supposed to track the location of objects; however, because of the overlap between activity spaces and unreliability of the RFID system; the data and process is probabilistic.

2.3.3 Temporal Reasoning

Ontologies, in the original style and with OWL language, do not support temporal reasoning. Without temporal reasoning, the knowledge-driven system will recognize activity instances as independent parts of information; in this approach the efficiency decreases (Riboni et al., 2011b). There are some proposals to add time information in RDF language (Gutierrez, Hurtado and Vaisman, 2007). For filling this gap, Meditskos et al. (2013) proposed a framework for a combining OWL and SPARQL to be used for activity recognition. SPARQL is a query language suitable for querying knowledge bases and able of handling temporal relations. In Meditskos, Dasiopoulou and Kompatsiaris (2015), they extend the framework and combined it with a semantic activity model and finally in Meditskos and Kompatsiaris (2017) they presented a similar framework with SPARQL and implemented a HAR system it in the field of healthcare to monitor people with Dementia. SQL is another query language that is used in the current research; similar to SPARQL, it can deal with temporal information. However querying systems of relational databases, including SQL language, do not support semantic knowledge querying directly.

2.3.4 HAR with Uncertain Observations

One of very few works on activity recognition with uncertain observations, similar to what the current research is going to do, is Roy, Abidi, and Abidi (2017). Similar to the previous research, they designed a multilevel reasoning model. However, in contrast it is not ontology-based, and their approach is possibilistic, not probabilistic; meaning that each attribute's value is characterized by a degree of certainty. Activities, and events are modelled based on possibilistic networks, not ontologies. In other words, each level (including the lowest level: sensors' reading) pass one or more values to the higher level or no value at all for total ignorance. The model is designed for recognizing only one specific activity: "Did the patient take his medication?". Therefore, unlike general HAR systems, the design of activities for different levels and the reasoning system is feasible.

2.3.5 Benchmarking for Recognition Rate

There are some researches that applied to the same dataset that have been used in the current research, which can be used to compare the recognition rate of the current research with results of others. All of them used manual labels of low-level activities and because there was no label for the location, they did not use it. In current research, all the used probabilistic information, activities and location, is computed from sensors information. Manzoor et al. (2010) tried different classifier on the dataset to find out which classifiers have the best performance. Mittal, Gopal and Maskara (2015) applied two modern methods for activity recognition: neutrosophic (Smarandache, 1998) lattice and fuzzy lattice.

2.4 Uncertainty and Ontologies

Ontology as a model for knowledge bases and uncertainty as a property of knowledge are two important topics in knowledge engineering.

2.4.1 Dealing with uncertainty

The probability theory is not the only approach to deal with uncertainty. Other approaches including belief functions, possibility theory (based on fuzzy logic), plausibility theory is also used to model problems with an uncertainty of different nature (Halpern, 2017). The uncertain essence of human activity recognition calls for probabilistic logic and reasoning (Philipose et al., 2014). Nevertheless, early attempts preferred to avoid probabilistic logic because of its difficulties (Allen et al., 1991) and most recent research attempts to avoid probabilistic ontologies because there is no established model and standard for that. There are some research works on activity recognition that used non-probabilistic models to confront challenges made by an uncertain essence of activity recognition task. For example, (Rodríguez et al., 2014b) utilized fuzzy ontologies, Roy et al. (2017) proposed a possibilistic reasoning method and Noor et al. (2016) developed an ontological reasoning process with belief functions (Dempster–Shafer) theory, these researches are all about knowledge-driven human activity recognition. Nevertheless, the oldest method to deal with uncertainty and incomplete data, probability, is still the most popular method. Table 2.1 compares well-known knowledge-driven human activity recognition methods between 2007 and 2017.

Table 2.1 Comparison of well-known knowledge-driven human activity recognition methods (2007-2017)

Approach	Proposed by	Model Basis			Activity Model				Uncertainty Handling		Sensor Data				
		Ontology	Low-Activity	Location	Scalability	Flexibility	Reusability	Temporal Reason	Probability	Other	Noise	Ambiguity	Inaccuracy	Uncertainty	Uncertainty Multiple Candidates
Ontology-based (OWL)	Riboni et al. (2011c)	✓	✓	½	½	✗	✗	✗	✓	✗	✗	✗	✓	✗	✗
Ontology-based	Chen et al. (2014)	✓	✓	½	½	½	✓	✗	✓	✗	✗	✗	✗	✗	✗
Hybrid reasoning	Riboni et al. (2011a)	✓	✓	½	✗	½	✗	✗	✓	✗	✗	✗	✗	½	✗
Multi-level reasoning	Helaoui et al. (2013)	✓	✓	✗	✗	½	½	✗	✓	✗	✗	✗	✗	½	✗
Probabilistic tracking	Yamada et al. (2007)	✓	✗	✓	✗	✓	✗	✗	✓	✗	✗	✗	✗	✓	✗
Fuzzy ontology	Rodríguez et al. (2014b)	✓	✓	✓	✗	✓	✗	½	✗	✓	✗	✓	✓	✓	✗
Logic-based ontology	Meditskos et al. (2013)	✓	✓	✓	✗	½	✗	✓	✗	✗	✗	½	✗	✗	✗
Temporal ontology	Meditskos et al. (2017)	✓	✓	✓	½	✗	½	✓	✓	✗	✗	✗	✗	✓	✗
Possibilistic/uncertain observations	Roy et al. (2017)	✗	✓	✓	✗	✓	✗	✗	✗	✓	✗	✗	✗	✓	✓
Fully probabilistic ontology	**Current Research**	✓	✓	✓	✓	✓	✓	½	✓	✗	✓	✓	✓	✓	✓

½ = Seminal method is applied. / The problem is partially solved.

2.4.2 Probabilistic Ontologies

Ontologies have been used as a tool for knowledge organization. As a conceptual model, (non-probabilistic) ontologies are visually modelled in the form of graph regardless of how they are actually implemented and stored. Indeed, the knowledge graph, a knowledge base that uses a graph-structure, is another name of ontology. Ontology Web Language (OWL) is a language for representing ontologies.

There are a few frameworks proposed for probabilistic ontologies. The most cited of them is PR-OWL (Da Costa et al., 2008); extended to (Carvalho, Laskey, and Costa, 2017) is a Bayesian framework probabilistic ontology which is based on Multi-Entity Bayesian Networks (MEBN) by Laskey (2008). Unlike OWL, PR-OWL has not endorsed by W3C as a standard language. It suffers from some problems; most specifically: it is not fully compatible with OWL. Besides, regular ontologies and OWL (not PR-OWL) are supported by well-established software, Protégé is the most famous one. Nevertheless, there are applications of PR-OWL based ontologies, for example in the automation of procurement fraud detection in Brazil. Office of the comptroller general is responsible for detecting government frauds in Brazil and one of the major concerns in this domain is procurements. According to laws, all procurements must be assigned in fair and competitive conditions. There are some rules to recognize front companies. For example, it is unusual when a large company is managed by a person who has little education or very low income. As well, when the managers of two different companies live in the same address, it looks like they have a family relationship. None of such or similar cases are criminal, but they are suspected and eligible to be investigated by comptroller general audits. The research develops a probabilistic ontology according to the database. This ontology is designed using UnBBayes. After reasoning according to particular rules, the system can provide the list of most probable cases of fraud in government procurements to be investigated by comptroller audits (Carvalho, 2013). The current research is not based on OWL or PR-OWL but because it is going to applicate probabilistic ontologies idea, it is necessary to elaborate the previous woks in this area.

There are a few research studies about adopting ontologies and probabilistic model and reasoning in activity recognition. Yamada et al. (2007) is a preliminary research on using ontology in activity recognition which applies the probabilistic modelling for tracking people.

2.5 Relational Databases and Ontologies

Relational databases are prevalent software for storing and querying data and ontology is a modern modelling method for storing and reasoning about knowledge.

2.5.1 Probabilistic Databases Vs Graphical Models

There are several situations that needed to be dealt with probabilistic data. For example, information retrieval systems from textual corpus produce probabilistic data; because of uncertainty on knowing the fact in the text or imperfectness of information retrieval methods, there are some discovered relationships without one hundred percent confidence. Such data needs to be stored and queried efficiently. Therefore, database community aimed to propose probabilistic databases to answer this demand.

Depending on the model of the probabilistic relational database, the probability might appear in some properties or the tuple level or a group of tuples known as block level. Whatever model is used; the amount of probability is stored as an extra property in the database. Query processing is not as easy as storage. Unlike conventional databases that work with “one world”, probabilistic databases deal with a numerous number of “possible worlds”. In this condition, computing of some queries is impossible since they are hard for #P, sharp P is a complexity class which is at least as hard as NP; especially in a system that is supposed to be scalable, meaning that the amount of data cannot be limited. Probabilistic Relational Database Management System (PR-DBMS) must determine whether or not the query can be evaluated before attempting to execute it. Beside probabilistic databases, probabilistic data can be stored and reasoned via a graph in the form of BN (Bayesian Networks) or Markov Networks.

In this case, the complexity is the tree-width which means there is no incomputable query. On the other hand, the data model becomes more complicated, and therefore, data modification in a static graph is not as easy and fast as adding some tuples in the database because many nodes and edges must be updated (Suciu et al., 2011).

To reach a high accuracy, in current research the system is modelled in a form of a fully probabilistic ontology, both data and axioms are probabilistic, while for scalability, it makes use of a highly efficient commercial RDBMS for data storage and processing. PR-OWL tools or the research-based PR-DBMSes could help this research to implement the model easier, but they are not very reliable and efficient to manage such a big data; for batch processing, millions of instances from hundreds of hours of activity recording need to be processed in a reasonable time. Even though the data model of current research is implemented without adopting PR-OWL and PR-Databases, the work is partly inspired by both of them. Table 2.2 compares data and knowledge bases management systems.

Table 2.2 Comparison of management systems, probabilistic and non-probabilistic, data and knowledge bases.

Storage	**Structure**	**Language**	**Systems**	**Advantage / Disadvantage**	**References**
Relational Database	Tabular Data	SQL	ORACLE SQL Server MySQL	Commercial implementations are high performance. Not designed for knowledge structures and uncertain data.	Codd (1970)
OWL Ontology	Structured Knowledge	OWL query: SPARQL	Protégé	Designed for knowledge structures. Not for probabilistic knowledge. Not scalable for big data.	Gruber (1993) McGuinness et al. (2004)
Probabilistic Relational Database	Tabular Data	PR-SQL	Trio MayBMS MystiQ Prob-View	Designed for handling the probabilistic data. The performance is not at commercial level. Not designed for knowledge structures	Cavallo et al. (1987) Suciu et al. (2011)
Probabilistic OWL Ontology	Structured Knowledge (Bayesian Networks)	PR-OWL query: MEBN	UnBBayes	Designed for handling the probabilistic data. Still not advanced, the standard is not endorsed. Not scalable for big data.	Da Costa et al. (2008) Carvalho et al. (2014)

2.5.2 Ontology Storage in Relational Databases

There are similarities and dissimilarities between ontologies and databases which can be categorized as a conceptualization of the information, data representation (tuples vs. instances), data modelling and, in practice, efficiency. In this regard, a new concept appeared: ontologies based on databases; which means using the relational data model to store the data represented in an ontology (Martinez-Cruz, Blanco and Vila, 2012). Initial works in this research field were focused on proposing algorithms for transforming information and modelling from an ontology to a relational schema (Gali et al. 2004; Vysniauskas et al., 2006; Vysniauskas et al., 2010) and satisfying rules of relational databases such as primary and foreign key and data types (Al-Jadir, Parent, and Spaccapietra, 2010). Further researches confront other problems in this area including query processing and optimization (Hazber et al., 2015; Abburu and Golla, 2015) and few works on inference (Astrova et al., 2007).

The regular method of storing ontologies is to save them as the OWL flat text files on disk, which is slow for large scale ontologies. The approach of this research in this concept is storing probabilistic ontologies in regular relational databases. Except one early work which is mostly on query processing (Udrea, et al. 2005), there is no literature on it to this date; but in one hand, it is fast and high performance and in other hand, it is able to store probabilistic ontologies which is preferred data model for HAR in this research.

Using SQL query processing engine for probabilistic reasoning and classification purpose in another aspect. There are few works of literature on this topic; the only published research could be found is Chaudhuri, Fayyad and Bernhardt (1999), a preliminary work that introduces a scalable naive Bayes classification method over SQL databases. The current research is going to store the ontology and its belongings in a relational database; therefore, the classifier and reasoning engine must be in the SQL based database.

2.6 Research Gaps

2.6.1 Issues in Data-Driven HAR

In last decade, several researches are published on data-driven human activity recognition. Almost all of them are focused on the higher recognition rate only and ignore the computation time, while if system is not fast enough, it is not suitable for processing of big data. They generate deterministic, not probabilistic, predictions; by using probabilistic data in the knowledgebase, this research can reach high accuracy in limited processing time. Most of them address finding low-level activities from sensors data but not the location and the direction of the subject. Some researches that included tracking the subject, have done this using old fashioned RFID technology and not IPS, indoor tracking system. Unlike RFID that can detect the person near some points, The IPS system tracks the person in whole indoor area and improves the activity recognition rate.

2.6.2 Issues in Knowledge-Driven HAR

Well-known knowledge-driven HAR methods are listed in Table 2.1 accompanying some key features (some elements and factors of ontology model for HAR are mentioned in Zolfaghari, Keyvanpour and Zall, (2017)). In case of the knowledge model, almost all of them are ontology-based. They have different performance against challenges like imperfect sensor data, reusability and scalability. Nevertheless, none of aforementioned approaches succeed in all the aspects of HAR area.

This phase of research aims to develop a practical high performance knowledge driven HAR system. It should be *scalable*, means it is able to do batch processing for big data in reasonable time for knowledge driven phase; *reusable*, works for different purposes in different environments; *flexible*, means the data model must be easily editable to work with complex data models; *failure resistance*, sensor failure and misplaces should have minimum negative effects on the system performance; and it must work with state of art physical and tracking sensors.

2.6.3 Issues in Storage in Relational Database

According to the research goal, a scalable knowledge structure in sensor based human activity recognition domain is aimed in this research and it is going to be in the probabilistic ontology form. Table 2.2 is a comparison of different available management systems for data and knowledge; but their advantages and disadvantages show none of these approaches is exclusively suitable for this goal; therefore, a knowledge structure must be designed and implemented to reach the abovementioned target. This structure employs the high performance commercial RDBMSes, suitable for big data, and stores the complicated probabilistic ontological knowledge model in it.

2.7 Chapter Summary

In this chapter, a review of the fundamental concepts and methods related to current research have been presented. The chapter begins with data-driven methods investigation that convert sensor signals to low-level activities and locations. The next section was on knowledge-driven HAR methods that applies knowledge structure and reasoning to convert fine-grained independent instances to an ontology of coarse-grained activities. In both cases, the main research concern is to have methods that are accurate, and fast enough to process big data in a reasonable time. Uncertainty and ontologies with uncertainty, including probability in the knowledge they represent and the reasoning axioms is discussed in this chapter. Storing ontologies in relational databases is reviewed in this chapter too.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents the methodology of the current research. The design and the operational framework of the research are discussed and explained in detail. At the core of this research is a design of a set of innovative methods to convert analogue sensor signals to probabilistic low-level activities, posture and locations, and then design an ontological probabilistic model for HAR to store this information and obtain the high level activities from them. To address the application of the proposed system for big data and batch processing, all designs and developments should consider the scalability objective. The applied dataset and the evaluation measures are discussed in this chapter.

3.2 Research Operational Framework

The research framework is the structured plan to assist researchers for tracking the research goals. For the current research, it is designed in five phases that aims to find an effective probabilistic knowledge structure in sensor-based human activity recognition domain. The research framework is illustrated in Figure 3.1.

Phase 1: Preliminary Study. First of all, the literature review, investigation of the related studies in data driven HAR including highly cited methods for feature extraction and classification of HAR sensor's signals, and knowledge driven HAR including ontology based and probabilistic efforts on HAR. This research also requires a vast study on various fields of computer science including uncertain reasoning, probabilistic ontologies, probabilistic data storage, relational theory, probabilistic relational databases and storing ontologies in relational databases. Choosing a dataset is an important task in this phase that will be discussed in section 3.3.

Phase 2: Design methods for data driven HAR. The goal of this phase is to find high accuracy and high performance (fast and storage efficient) HAR methods to convert sensors' data which are presented by analogue signals in the dataset to probabilistic data, representing postures, low-level activities and locations. There are three tasks that are needed to be done in this phase. First, innovative methods for converting electric signals into proper features must be designed. These features are calculated using semantic methods. To reach the scalability objective, these features must be few, in case of number, and the method should be fast, in case of time needed for computation. Second, select the efficient classification methods that are able to convert the calculated features to probabilistic postures and low-level activities; again, the processing time is important in this stage as well. Third, designing methods for processing signals from the indoor position system, aiming probabilistic allocating the subjects in a discrete area. Indoor areas are very prone to noise because there are many reflections and obstacles, and the proposed methods must be able to tackle this problem. Innovative signal processing techniques and noise reduction methods will be applied to achieve this goal.

Phase 3: Design an ontological model and develop methods for knowledge driven HAR. In this phase a probabilistic ontology model to be designed to organize the obtained information in phase 2 and then populated to predict high level activities. The knowledge model must be fully probabilistic, which means the Abox, primary data, and Tbox, the reasoning rules (assertion axioms), are all in probabilistic form.

In the first step, ontology Abox is made from triples from phase 2 and then it is smoothed using innovative smoothing algorithms for probabilistic data. For determining the assertion axioms (Ontology TBox), methods for automatic learning of axioms and software, an app, for editing and manually determining are to be designed. Inference methods use low level activities, locations and the axioms, combine their probabilities and do probabilistic reasoning for recognition of high-level activities and then populate the ontology including the high-level activities in the final step of this phase.

A model is to be designed for the probabilistic ontology to be transformed and stored in a SQL relational DBMS and therefore, all steps of this phase including determining axioms and reasoning and ontology population are to be done in the relational database and using the SQL queries.

Phase 4: Evaluation of the model and results. The evaluation measures are elaborated in section 3.4. The data model is evaluated using qualitative measures and the numeric performance measures including accuracy and time should be recorded for both data driven and knowledge driven phases and compared with well-known and highly cited methods. First, evaluating of the data-driven methods in case of accuracy and processing time; and compare with the results of the highly cited methods. Then turn to the proposed knowledge driven methods, evaluation of the data model evaluated using qualitative measures of ontological HAR systems and evaluating of the knowledge-driven methods in case of accuracy and time and comparing the results with others.

Phase 5: Writing the thesis. Finally, the report of the research including observations and obtained results are written in form of a thesis. Concluding important findings and drawing the future work plan are also in this phase.

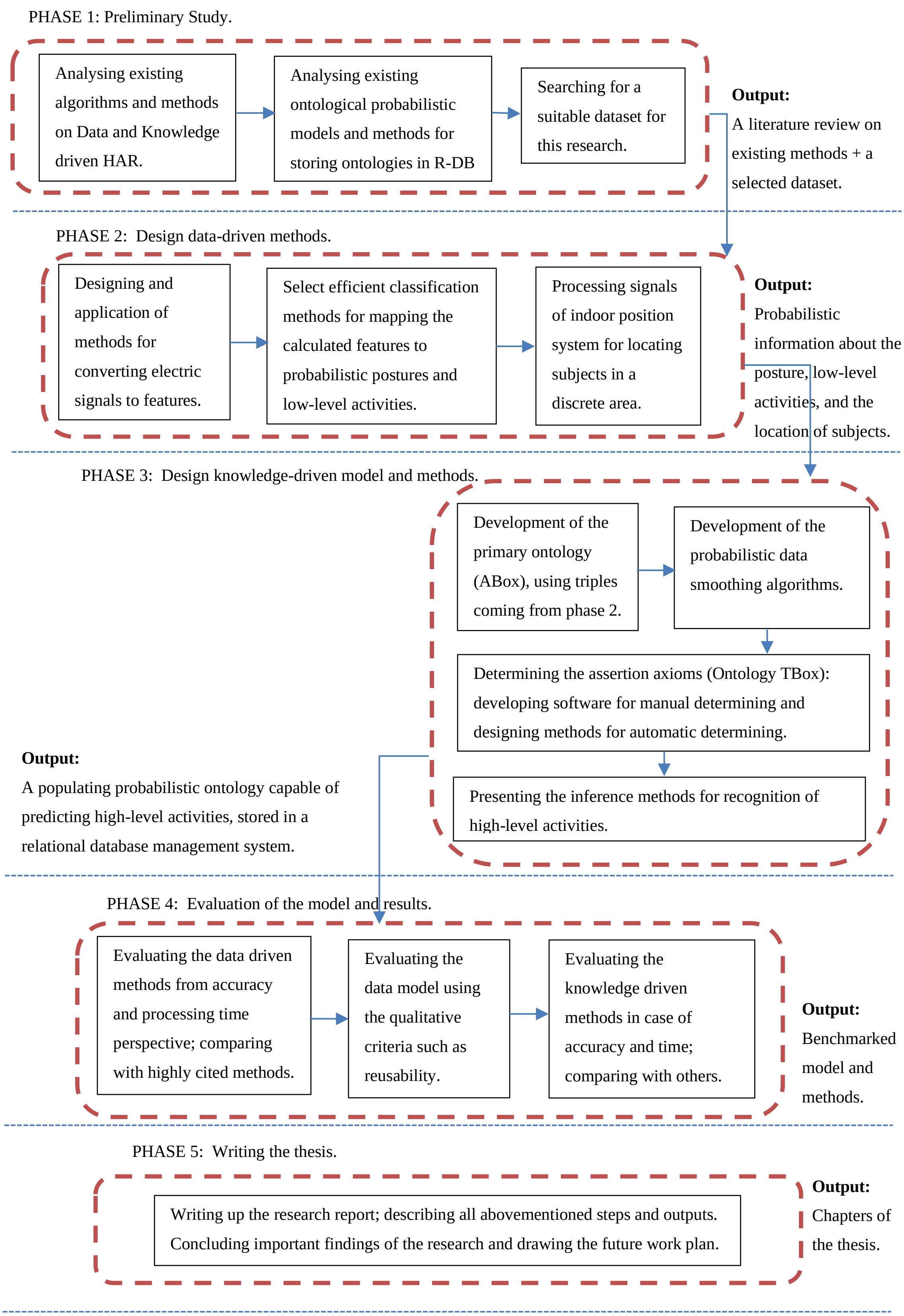

Figure 3.1 Proposed operational framework of the research

3.3 Applied Dataset

"Activity and Context Recognition with Opportunistic Sensor Configuration", or Opportunity in short (Chavarriaga et al., 2013), is an EU project. This dataset is suitable for the current research because it has been used for benchmarking methods in different activity recognition researches, including data driven methods in Yang et al. (2015) and knowledge driven methods in Mittal, Gopal and Maskara (2015), Helaoui et al. (2013) and Manzoor et al. (2010). The Opportunity dataset contains real-life data, collected from 4 person, subjects, while performing daily morning activities. For each subject, there are 5 regular morning sessions and one drill. The morning sessions consist of natural loosely defined activities, while the drill sessions contain repetitions of pre-defined acts. This dataset is a collection of data from wireless and wired networked sensor systems installed on the environment objects and attached to the subjects' bodies.

There are 3 positive features in Opportunity that make it the chosen dataset for this research. 1) In this dataset the sensor configuration on subjects' body and environment is intense, there are many sensors, and therefore the predistortions can be made with high probability. 2) Having uncertain data, for example incomplete and noisy signals, make it more challenging for a probabilistic HAR system. 3) It has been used in other ontology based HAR systems, so the results are comparable especially in knowledge-driven phase.

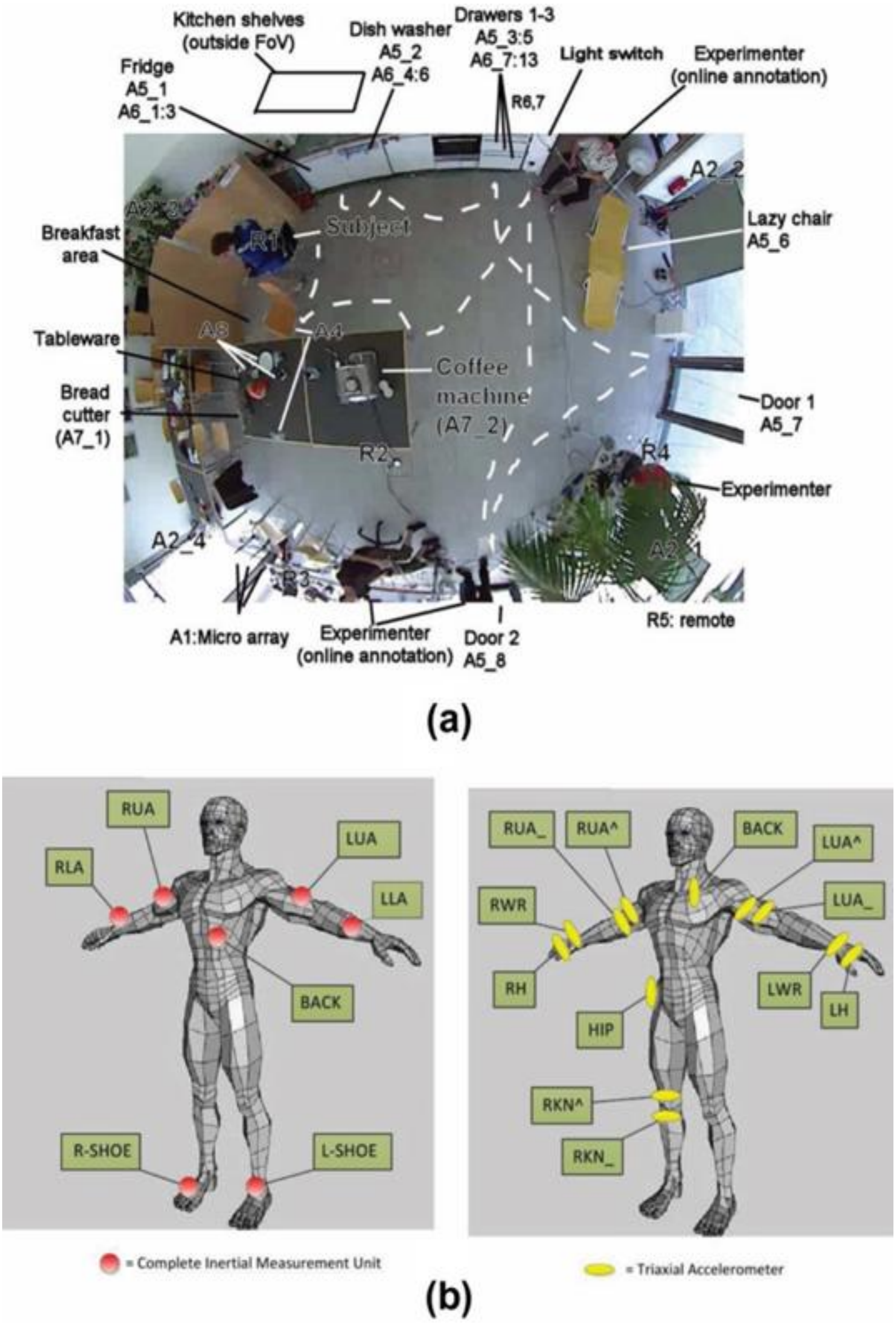

Figure 3.2 Opportunity dataset setup. (a)View of the recording room. The dashed line is a typical user route. (b) On-body sensors, red: IMU; yellow: Accelerometer. [1]

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[1] Reproduced from Chavarriaga et al., (2013), by permission of Elsevier.

The body sensors in the experiment consist of 7 IMU (Inertial Measurement Units), 2 on the shoes and 5 in the jacket, and 12 triaxial ACCEL (Accelerometer), as shown in Figure 3.2. Each complete IMU provides simultaneously nine measured physical properties, including GYRO (Gyroscope) angular rates, linear accelerations, and magnetic field components, all along 3 axes. IMUs on shoes provide electric compass instead of 3D magnetic sensors.

To record interactions with objects, a sensor is attached to each of the following 12 objects: *cup*, *salami*, *water*, *cheese*, *bread*, *spoon*, two different *knives*, *milk*, *sugar*, *plate*, and *glass*. Each sensor provides triaxial ACCEL and biaxial GYRO data simultaneously. To detect opening and closing doors of the two *entrances*, *refrigerator*, *dishwasher* and three *drawers*, 7 ACCEL is attached to them. There are 13 magnetic reed switches and magnet pairs, 3 on each of 4 doors, entrance doors are excluded, and 1 for the lower drawer, which has 3 magnets but only 1 reed switch.

Activities are video captured and using these videos, data are manually labelled with posture (modes of locomotion), gestures, hand-movements, and hands-object interactions with right and left hands daily activities. (Lukowicz et al., 2010). For example, in a particular moment, the subject is in the room in a square with coordination (3,5) he is in sitting position (posture), his right hand is cutting (hand-movement), working with cheese knife (hands-object interactions). His left hand is idle. Low level activities such as this usually take just few seconds or less.

The aim of the knowledge-driven part of this research is to predict the high level activities. High level activities are long time, several minutes, activities during morning. They are: 1) *Relaxing* 2) *Coffee time* 3) *Early morning* 4) *Cleanup* 5) *Sandwich time*. High level activities are also manually labelled in the dataset using video records. Regarding the high level activities, the person in the abovementioned example is in Sandwich time.

In the original Opportunity dataset, sampling rate is 30 instances per seconds. For pre-processing, in all the applied methods in this research, sample reduction of 10 to 1 is carried out and finally each 30 “Instances” per second are converted to 3 “Segments” per second. Labels of each new segment is replaced with the mode value of respective ten instances. The summary of labels is presented in Table 3.1. All dataset labels are listed and described in Appendix C.

Table 3.1 The description of labels of the Opportunity dataset.

No	Name	Description	Example
1	Postures	The position of body	sitting
2,3	Hand movements	For left and right hand	unlock
4,5	Hand-object interactions	For left and right hand	dishwasher
6	Gesture	Both hands movement + objects	open dishwasher
7	High-level activity	Long time activities during morning	sandwich time

Data loss is common in sensor networks due to disconnections, sensor failures, and transmission errors. There is a considerable amount of missing data in this dataset mainly due to disconnection of wireless sensors. In addition, up to 60° rotational error was added at random times to the test sessions of subject 4, affecting all ACCEL, GYRO, and magnetic sensor data. Both data loss and rotational noise are expected in real-life experiments with body sensors. In this case, a probabilistic HAR can perform better and reach higher accuracy because it considers many probable estates.

Ubisense Indoor Positioning System (IPS) is used during activities, four sensors located in the corners of the room send ultra-wide band pulses to tags, which are then used to determine exact location of the person in 3D in the room, based on Time Difference and Angle of Arrival. A tag is a small trackable device carried by a person. To reduce the effects of noise, four independent tags are connected to the front and back of right and left shoulders of one subject.

3.4 Evaluation Measures

The result of human activity recognition, for both data and knowledge driven methods, is usually reported in the form of accuracy, F-measure, and AUC (Chavarriaga et al., 2013; Fawcett, 2006). F-measure, the harmonic mean of precision and recall, is the most common measure for HAR and it is the preferred measure for reporting performance in current research because the amount of data for different classes varies, and the results of other researches that are benchmarked against the obtained results, are also reported in F-measure. The performance time is also recorded and compared with others researches in cases that they also had reported the running time.

Besides the accuracy, the ontological HAR model can be qualitatively evaluated and compared with other models using criterions measures (Zolfaghari et al., 2017). Qualitive measures can highlight some aspects of model and illustrate the capabilities of the model.

3.5 Chapter Summary

In this chapter, the methodology of the current research is presented: an overview of design and framework of the whole research, the applied dataset and evaluation measures are elaborated.

CHAPTER 4

PROBABILISTIC ONTOLOGY-BASED HAR

4.1 Introduction

This chapter presents innovative methods for ontology-based human activity recognition that are fully probabilistic, fast in case of processing time and have high accuracy in predicting high level activities. The presented methods are arranged in two phases. In the data-driven phase, data-driven methods, the signals from sensors are converted to fine-grained activities in form of probabilistic information. In the knowledge-driven phase, modelling the obtained information in the form of probabilistic ontology and methods for storing it in a relational database, are presented.

4.2 Data-Driven Methods

The goal of this phase of study is to develop a data-driven sensor based human activity recognition methods to find low-level activities and subject location in the room in form of probabilistic data. To be suitable for big data, features must be minimal in terms of number and fast in terms of calculation and the accuracy of predictions must be high. While in some applications the process must be real time, in others batch processing is what system must do. In such cases, a big amount of data must be processed in a reasonable time. In other words, besides accuracy, how fast the method is, CPU time usage, does matter. Therefore, the main objective of this phase of research is to propose a set of data-driven time efficient methods that uses sensor data as input and produces posture, movements and location in the form of probabilistic data, that feeds required data, instances, of a probabilistic ontology. Using this data, the ontology is capable of reasoning, recovering errors and extracting high-level activities.

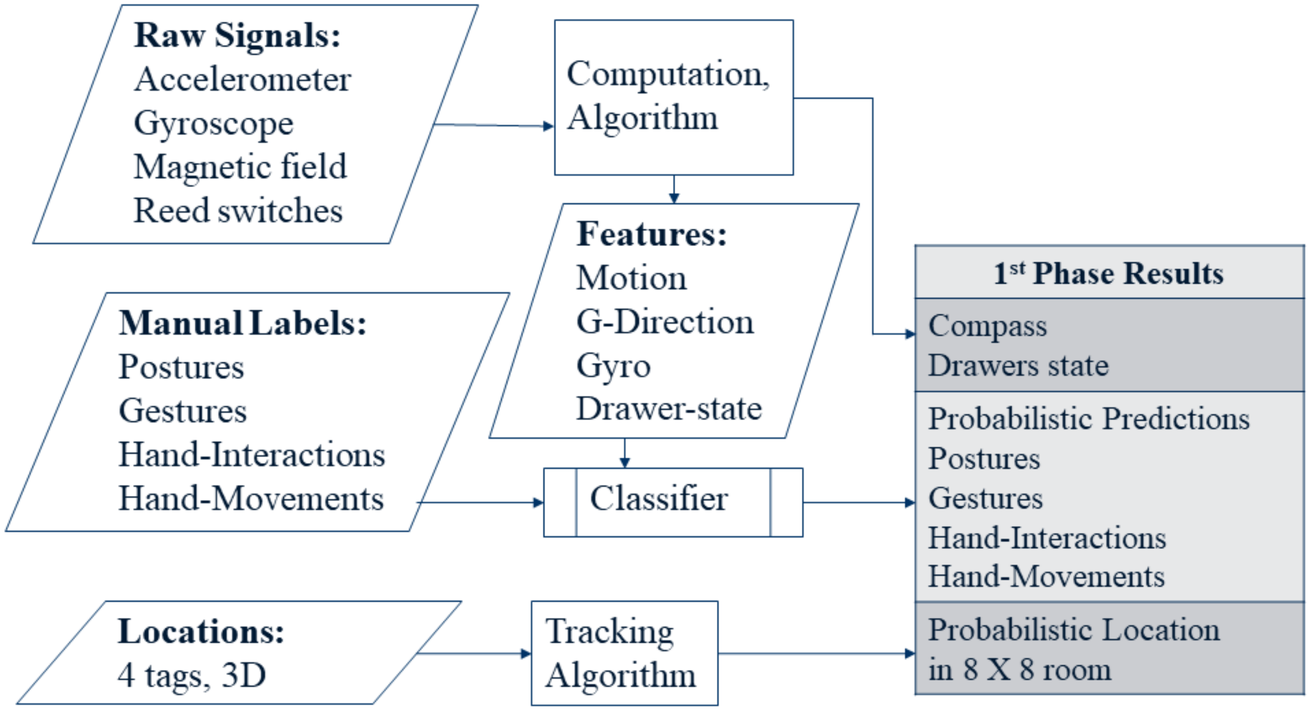


Figure 4.1 Data flow diagram for data-driven phase of the research.

Figure 4.1 shows the flow of data in the data-driven phase of the research. Input data of this phase of system is signals from sensors. Using proposed methods features are calculated from these signals and then with a classifier postures and low-level gestures are obtained. Other information including the location of the person in room are also calculated. All of this probabilistic produced information is output of this phase and will be used in the knowledge-driven phase.

4.2.1 Smoothing Accelerometer Signals and Baseline correction

First, if recorded velocity and gravity force are separated, extracted features from them are more meaningful. Savitzky-Golay digital smoothing filters are commonly applied to increase the signal-to-noise ratio. These filters are optimal in minimizing the least-squares error in fitting a polynomial to frames of noisy data. The obtained signal from the filter is deducted from the original signal and the result is the levelled signal with zero. Subsequently, G-force is eliminated by this method. The filter needs two parameters: the order of polynomial and the frame size. The order of polynomial must be less than the frame size and the frame size must be odd. It should be noted that if even one of the values of the selected frame is null, the output of the signal is null. This filter has been applied in many feature extraction procedures (Luo et al., 2005)

The acceleration data along x, y, z-axes are divided into segments of 10 instances. The sample reduction of 10 to 1 is carried out by replacing each segment with its mean value. If all 10 instances of a segment are missing, then the replaced value is null. Savitzky-Golay algorithm is unable to deal with null, therefore, each null value is replaced by the mean value of the five previous non-null instances. The smoothed signal is calculated by Savitzky-Golay algorithm of order 5 with a sample window size of 49. The baseline corrected signal is obtained from deducting the smoothed signal from the original signal as depicted in Figure 4.2. After baseline correction, all the null values that had been changed are replaced by null again.

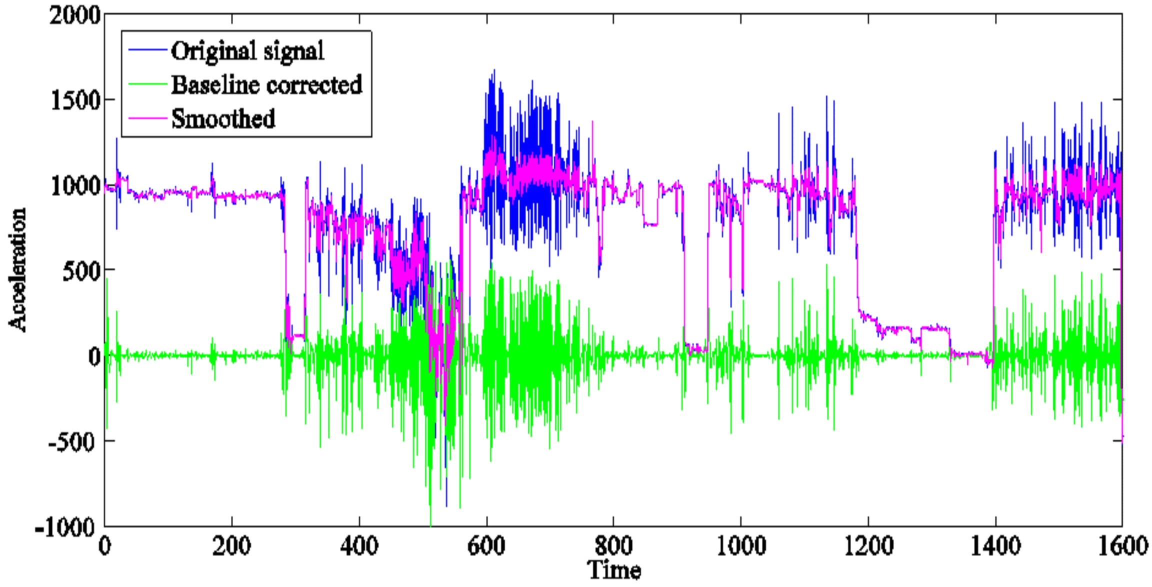


Figure 4.2 Upper Knee y acceleration signal, Subject 1, Activity 1.

4.2.2 Motion Extraction

In this dataset, routine activities of regular people, motion and changing in velocity usually happens at the same time; in other words, high total acceleration means the sensor is in motion. The result of the baseline correction procedure is named *xc*. The same procedure is carried out for the acceleration signal along y and z axes, to get *yc* and *zc*, respectively. Thereafter, the magnitude ac_i of the vector (xc_i , yc_i , zc_i) is calculated as follows, where *i* is the current segment.

$$|ac_i| = \sqrt{xc_i^2 + yc_i^2 + zc_i^2} \tag{4.1}$$

The value of total acceleration, ac_i, is one of the extracted features from the acceleration sensor.

4.2.3 Gravity Direction Extraction

Another feature extracted from the acceleration sensor is the direction of gravity, which indicates which face of the sensor is facing toward the earth. It is calculated and digitally coded as follows: For each instance, if the value of xci from the previous part is between -500 and +500, then dx_i is set to zero, under the influence of at least ½ G-force, which is 1000. If xci is greater than 500, dx_i is set to +1, and if it is less than -500, dx_i is set to -1. In the same manner, dy_i and dz_i are calculated. It should be noted that the possible values for dx_i, dy_i and dz_i are 0, 1, -1 and Null. Therefore, the vector $D_i = (dx_i, dy_i, dz_i)$ is defined by the code assigned to it according to Figure 4.3.

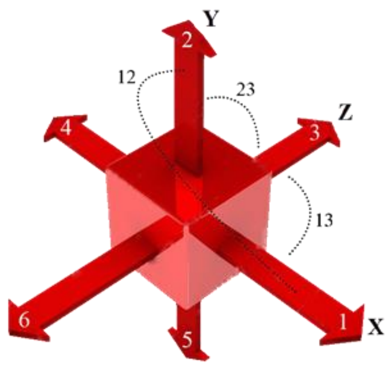


Figure 4.3 Coding the gravity direction

For instance, "4" code is assigned to (-1,0,0) and "5" is assigned to (0,-1,0); consequently, between two faces (-1,-1,0) is coded as "45". The same rule applies to other coordinates. (0,0,0) is set to 0 and 9 is assigned to (1,1,1). To be identified as a non-numeric field by classifier, an "a" character is added in the beginning of code number. If any one of dx_i, dy_i or dz_i is null then Null is assigned to D_i.

4.2.4 GYRO Signals

Another feature, which is related to subjects and environmental objects, is extracted from the gyroscope sensors. In some of the previous studies angular velocity signals from the body, not environmental, sensors were used; to calculate features they did in the same way as acceleration signals (Altun et al., 2010; Khan et al., 2010).

In the employed dataset, the sensors provide triaxial angular velocity through the IMUs attached to jackets and shoes, and biaxial angular velocity through object sensors. Raw angular velocity is not used as a feature; instead, the deviation angle from the straight line is calculated from it. The following procedure is carried out to remove the noise effect and offset and then the angular deviation is calculated.

```
FOR all Instances DO
        gy = gy - offset
        //offset between 400 and 420, depends on sensor)
        IF gy < noise rate THEN
                gy = 0
                //(noise rate between -1, 1 ACC, -100,120 IMU)
FOR all Segments DO
        compute AD from the folowing formula
        //(t is time of the first instance of the Segment)
```

$$A = \int_0^t gy$$

The obtained result, the blue line in Figure 4.4, is the angular deviation from rest position with the assumption that the applied gyroscope sensors are ideally accurate. As this assumption is too optimistic, the result gets out of calibration as time passes. To solve this problem, baseline correction is performed using the same method used for acceleration signals, with order 1 and a window size of 49 samples. It works well, especially for the environmental objects, the pink line in Figure 4.4, because the objects are usually in a steady position when they were not in use. Thus, two features extracted from 2D sensors, for each object and three features for each IMU on the jacket are extracted from the angular velocity signals. In this dataset, there are about 10,000 segments per activity, which is not very long. Otherwise, for being time efficient, activities should be broken into smaller blocks.

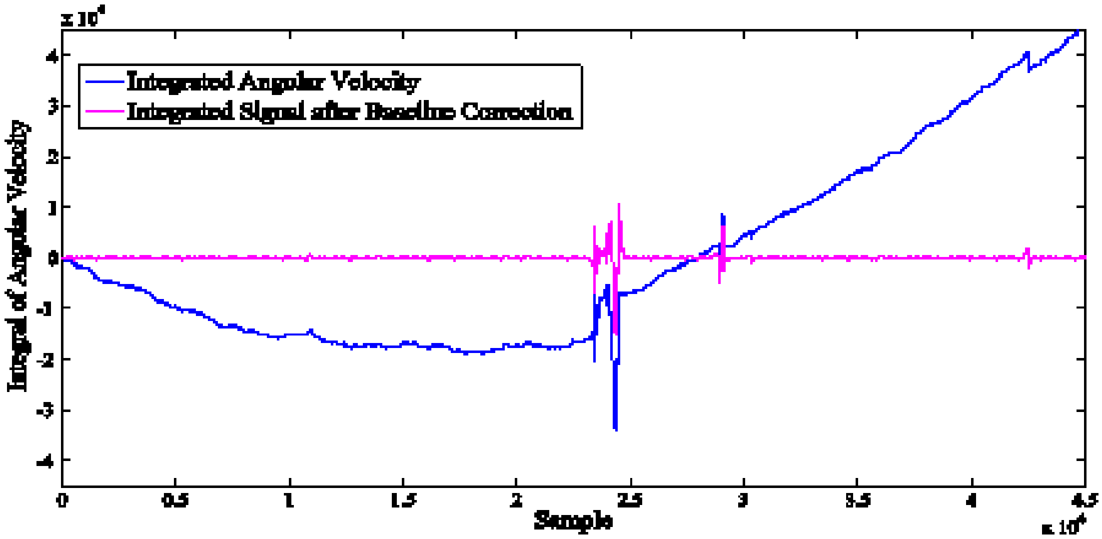


Figure 4.4 Integrated Angular Velocity of x, milk senor.

4.2.5 Electronic Compass

The direction in which the subject's body is facing is a useful feature for some types of activity recognitions. It determines the compass measure, which shows the deviation angle of the person with respect to the north magnetic pole. Electronic compass has been used in some studies in this area (Aminian and Najafi, 2004). Compass sensors and magnetic field sensors lose their accuracy when they are near massive iron mass or ferrite magnets. Two sensors attached to the subject's shoes and one IMU attached to the back of the jacket can be used to extract the features.

The two sensors attached to each of the shoes provide compass data, which shows the angle of the direction of shoes' tip with the magnetic north pole of the earth. Almost all (99.5%) of the corresponding data are between -180 and +180 degrees, except for a few instances which are affected by noise. Therefore, all the values greater than 180 are replaced with 180 and all the values less than -180 are replaced with -180. The data received from the compass sensors on the left and right shoes are divided into segments of 10 instances. From each segment of the left shoe and its corresponding segment from the right shoe, the direction that the subject's body is facing is determined by calculating the circular mean of all 20 values, as shown in Equation 4.2.

$$C = atan2(\sum_{i=1}^{10} (\sin(Lshoe_i) + \sin(Rshoe_i)), \sum_{i=1}^{10} (\cos(Lshoe_i) + \cos(Rshoe_i))) \quad (4.2)$$

IMUs are equipped with triaxial magnetic sensors, which are sensitive to magnetic fields and can be indirectly used as compass sensors as well. The IMU attached to the back of subject is least affected by body movements. If it is assumed that the sensor is attached to the jacket vertically and is not rotated, from its magnets x and y, the deviation angle of the subject can be calculated from the magnetic north pole. First, the data of the x and y axes are segmented, and the mean value of each segment is calculated. Then, angle M is calculated as follows, shown in Figure 4.5.

$$M = atan2(\,Ymagnet\,, Xmagnet\,) - 90 \quad (4.3)$$

The obtained value has a 90° offset. If this offset is deducted from M, the obtained value is the closest to what the compass sensors show. Notably, if M is less than -180, it is rearranged by adding its value to 360.

Like 3D angles of the gravity direction, 2D angles of the compass are coded to facilitate reasoning. 360 degrees is divided into 6 equal sections and each section is assigned a number from 0 to 5. For example, 0 is assigned to [0, 59.99] and 5 is assigned to [300, 359.99].

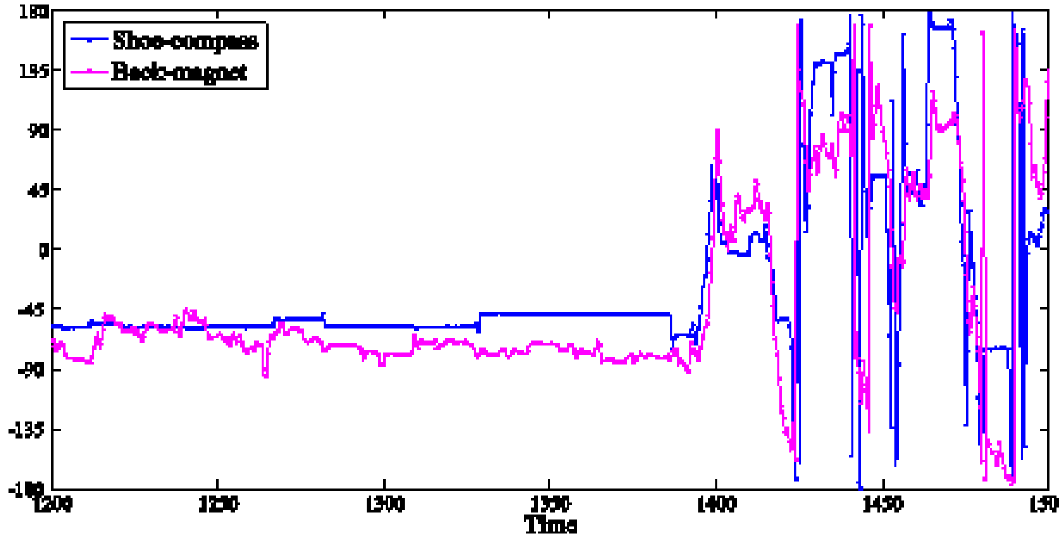


Figure 4.5 Compass and magnet signals after processing.

4.2.6 Reed Switches

Reed switches are binary sensors. If the reed switch is in a strong magnetic field (in this experiment, near a small ferrite magnet), then the reed switch sensor will have a value of 1. Reed switches are attached to the drawers', the refrigerator's and the dishwasher's doors. Three pairs of magnets and switches take action one after another during the opening or closing process. Basically, there are four states with three magnets: state 1 is closed, state 2 is partly open, state 3 is open and state 4 is extremely open.

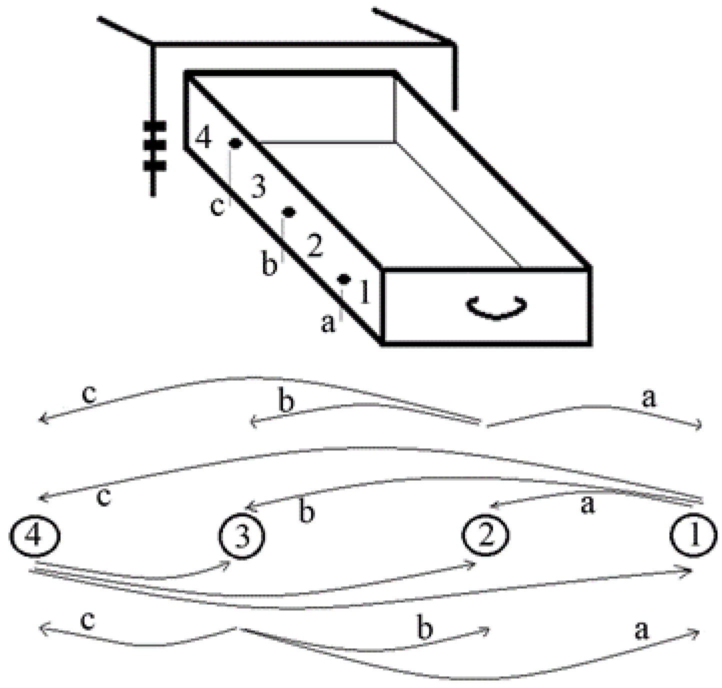


Figure 4.6 Three reed switch sensor configurations, according to the state diagram and with current state and triggered switch, new state is determined.

States are determined according to the diagram in Figure 4.6 and the following algorithm. We assume at the beginning of each activity the doors are closed; the algorithm can make the correction after some interactions in case this assumption is wrong.

```
FOR each set of reed switches on one door DO
    take each 10 Instances as one Segment
    FOR each switch DO
        FOR each Segment DO
            IF ins1 V ins2 V ins3 ..... V ins10 = 1 THEN
                Segment value = a (or b or c depends on
                activeated switch)
        IF two/more consecutive Segments same value THEN
            exept the first Segment, set all the rest = Null
    State = 1 (door is closed)
    FOR all Segments first to end of acticity DO
        IF Segment valure is not Null THEN
            State = new state (according to state diagram)
```

The reed switches attached to upper drawer have a different configuration. There are still three magnets attached, but they are at the same level and there is only one reed switch for all of them. Therefore, the only switch of drawer_1 can be “set/unset” with each of the 3 magnets. For this case only two states are obtained: open, 3, for being in the process of opening or closing and 1 otherwise. It is assumed that the maximum length of each interaction with this drawer is 100 segments, for a total of 30 seconds. The state of the drawer is computed using this algorithm.

```
FOR each segment DO
    IF ins1=1 V ins2=1 .... V ins10 = 1 THEN
            State = 3
    ELSE
            State = 1
IF length of each block of "1" less then 100 Segments THEN
    set all of it's Segments = 3
```

4.2.7 Indoor Positioning

Global Positioning System (GPS) is not accurate enough to track a subject in a small area and cannot be used under a roof. Indoor positioning systems are developed for this purpose; with different topologies. The system that employed for localization of subjects in this dataset, “Ubisense”, uses remote positioning system topology. In this topology, signal transmitter is carried by subject and several fixed receivers are installed in the area. It tracks subjects with Time Difference of Arrival (TDOA) and Angle of Arrival (AOA) techniques. This system determines the location of the subject in 3D with 15 cm accuracy. Despite high accuracy, the robustness of Ubisense system is poor (Batty, 2011; Liu et al., 2007; Deak, Curran and Condell, 2012). This system is prone to noise; because of reflection and blockage of the signals by objects or walls, which is called AOA and TDOA estimation error (Ye, Redfield and Liu, 2010). To minimize the effect of noise, four independent tags are attached to the left and right shoulders of the subject, in the front and back, each one producing an independent location signal.

As recognition of posture, *sitting*, *standing*, *walking* or *lying down*, is achievable with high accuracy, the z-axis information are ignored of the location system; only x- and y-axis information are used to find the 2D locations of the subject. There are various types of noises in this system; sometimes the location data are not available and sometimes the subject is indeed stationary but the system reports that the subject is moving in a direction with steady and slow speed and continues the same report until the subject actually moves; then, the system reports that the subject suddenly goes back to the location where it was. To overcome this noise, the displacement between two successive segments is calculated, to obtain the total velocity. The following algorithm is developed to remove the noisy data for each tag.

```
Separate each 10 Instances as a Segment,
Loc = Mode (all ten locations on instanses)
FOR all Segments DO
    IF velocity < 1 or > 4.5 m/s THEN
        Mark Instance as suspicious
IF a suspicious block is longer than 3 seconds THEN
    Mark all Instances of block as invalid
IF any valid block is shorter than 3 seconds THEN
    Mark all Instances of block as invalid
Replace values of all invalid blocks with mode value
of 5 Instances before and after the invalid block
```

The result is four coordinates for each segment from four independent tags that some of them may be highly inaccurate. To predict the subject's location, the room is divided into 64 rectangle regions, like a chessboard, 8 × 8. Each square is known by its coordinate; the square in the top left is 11 and the square in bottom left is 18. After this, from 4 available reported locations, only for 48.6% of the instances at least two tags are in agreement on the location of a subject.

For example, for instance_id number 6 (subject 1 performing activity 1 at 1.66 seconds), the locations of the subject reported by the tags are 54, 65, 65, and 64. To decide which square is the location of the subject, the proposed algorithm finds the most probable locations by scoring each square.

```
Set the score of all 64 squares = 0
FOR all 4 or less reported squares DO
        add 10 scores to the reported square
        add 6 scores to all neighbours of the..
        reported square respectively
a, b, c, d are the four most scored squares
IF score(a)=score(b)=score(c)=score(d) THEN
        report Nothing
IF score(a)<> score(b)=score(c)=score(d) THEN
        report a
IF score(b)<> score(c)=score(d) THEN
        report a, b
IF score(c)<> score(d) THEN
        report a, b, c
FOR x= a, b, c (if available) DO
        probability (x) = score (x) / (score (a)+
        score (b)+score (c)) * (score (a) / 40)
```

All the reported scores are normalized first and then adjusted with highest current score and the maximum possible score, 40, to calculate the probability. The same example is carried on; when the system reports 54, 65, 65, and 64; first, 0.36 is assigned to square 65, with a score of 32, and 0.32 is assigned to 54 and 64, then all multiplied with 32/40. The calculated probability for square 65 is 0.292 and for square 54 and 64 is 0.254. In the applied dataset, this method is able to make a decision for 95.1% of instances.

The number of instances which are in a high-level activity, for example *sandwich time*, varies for each of 64 squares, shown in Figure 4.7. Therefore, combining with the results obtained for posture, gesture and hand activities as part of the probabilistic knowledge base, it helps in the recognition of high-level activities.

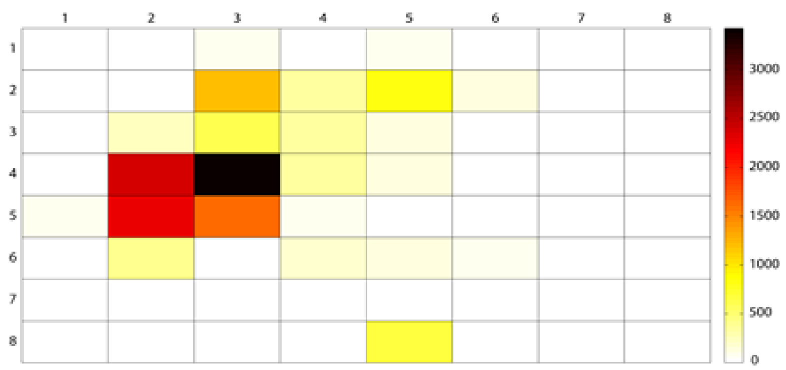


Figure 4.7 Number of subject's instances in a location in *sandwich time*.

4.2.8 Classifier, Feature Selection, Probability Calculation

In this research, four different categories of recognition are applied on the dataset: posture, gesture, hand movements and hand-object interactions both for right and left hands. For each subject, first three recorded sets of daily activities and the drill were used as training set and then the model is tested with the two remaining daily activities.

M5P – via regression classifier calculates the probability of each target in the following manner. With the assumptions that all attributes contribute equally to decision making and are independent of each other; for categorical attribute likelihood is calculated with Naïve Bayes method and for numeric attributes contribution to likelihood is calculated as follows.

$$f(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{(x-\mu)^2}{2\sigma^2}} \qquad (4.4)$$

μ is mean value, σ is standard deviation, x is the instance under consideration, and f(x) is the contribution to likelihood. Then the obtained likelihoods are normalized and are sum to 1 to obtain probability. For instance, for data $(P_1, P_2, P_3, \ldots, P_n)$, $P_1 + P_2 + P_3 + \ldots\ldots + P_n = 1$. All the possible attributes are considered as an option and are branched according to different possible values. For each attribute, Information and Information gain are calculated as follows.

$$Info\ (P_1, \ldots, P_n) = -P_1 \log P_1 - P_2 \log P_2 - \cdots - P_n \log P_n \qquad (4.5)$$

$$Gain = Info\ before\ division - Info\ after\ division \qquad (4.6)$$

The attribute which gives Maximum Information Gain is selected for division. This procedure continues until each branch terminates at the attribute which gives *Info*

= 0. As all the possible attributes are considered, all the probabilities are calculated. The leaf with the highest probability is selected and reported as the target class.

A few classifiers are tested and the selected classifier of current research is a regression based classifier with M5P tree, a model tree in the form of a decision tree with regression at its leaf nodes, which is applied from Weka package (Hall et al., 2009). The decision tree is called the M5P model tree (Quinlan, 1992; Wang and Witten, 1997). M5 is an adaptation of a regression tree algorithm; it uses a more computationally efficient strategy to construct piecewise linear models, compared to other regression trees (Loh, 2011), because it forms a piecewise constant tree first and then fits a linear regression model to the data in each leaf node. Weka also produces the report of classification which includes the probability of each target class.

Support Vector Machine (SVM) with an extension of sequential minimal optimization algorithm for training was another option for performing classification on this dataset, the performance of the selected classifier is very close to SVM as it is reported in Figure 4.8 and Table 4.1. Although, training time, the time spent to build the model, is much longer. K-Nearest Neighbours is also tested, KNN K=3 (3NN). The regression approach along with the decision tree model proved to be a better fit because for big data, training for numerous subjects with SVM is not time efficient, the same goes to very long testing time in KNN which has lower performance too.

Table 4.1 F-measure, training and testing time, for subject 2.

Posture			
Classifier	**F-measure**	**Time-train (s)**	**Time-test (s)**
M5P	0.83	30.39	0.26
SVM	0.83	218.46	0.22
3NN	0.80	0.01	22.86
Gesture			
M5P	0.85	91.52	0.91
SVM	0.86	374.04	1.38
3NN	0.83	0.01	27.83

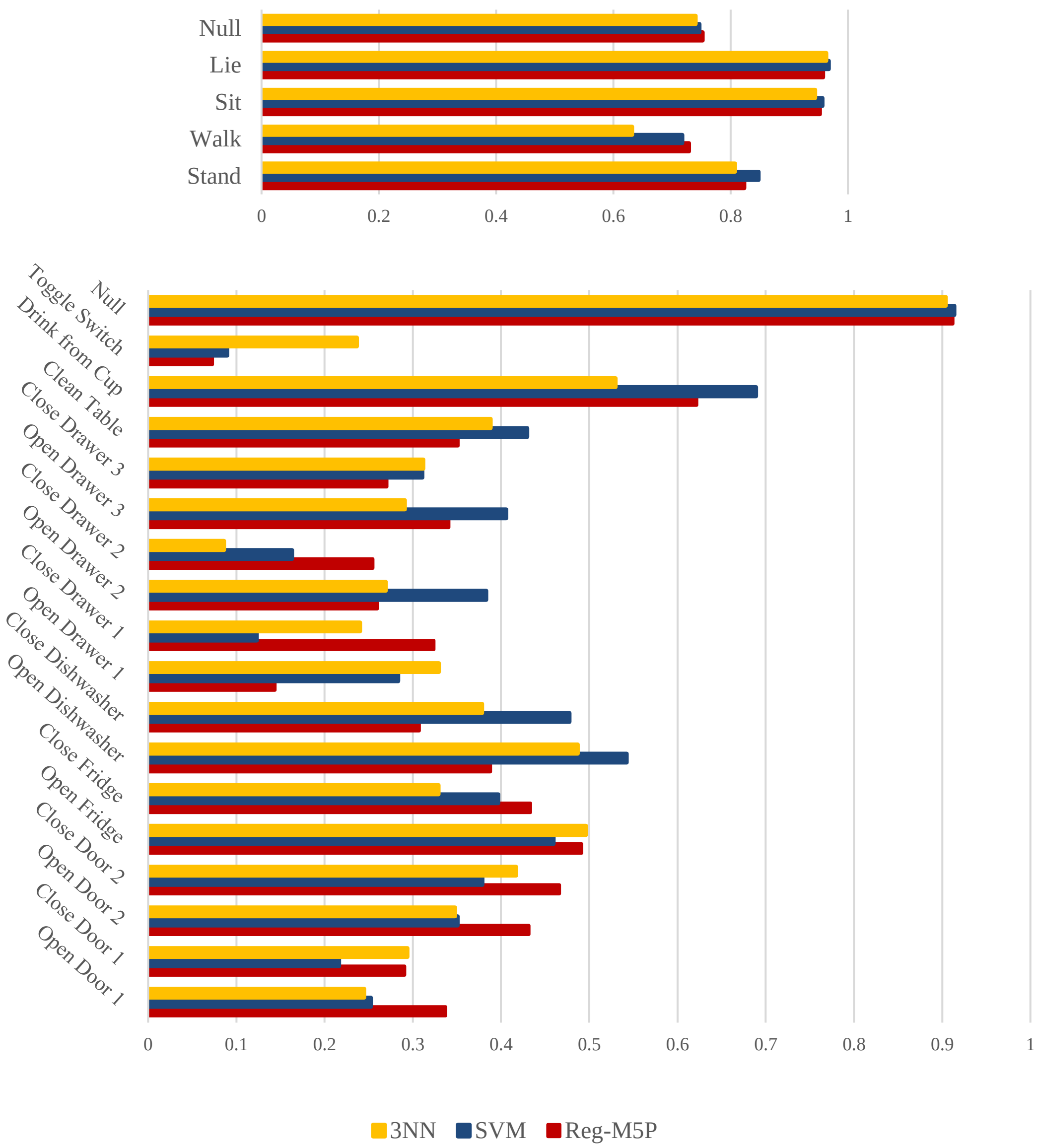


Figure 4.8 Average F-measure for each target class of all subjects for (above) posture and (below) gesture, M5P (via regression), SVM and 3NN.

After some try and errors for choosing sensor sets, it is decided to use IMUs on the jacket and shoes and ignore accelerometers. For objects, the direction of gravity also provides similar information as gyroscope sensors and has no benefit. Therefore, for all activity recognitions, they are not part of the training data for the applied classifiers. The performance of assemblies of sensors is elaborated in section 5.2.2. In the case of posture, environment sensors are not used for classification. For gestures, the gravitational direction of objects does not help the classifier to achieve better recognition. For hand-movements, features from both environmental and body sensors are used except for those mentioned above. For hand-object interactions, the gyroscope of the jacket sensors was also not used. The doors states were used but the extracted features from compass sensors were not beneficial for classification. Coded data for compass and doors status is reported for the knowledge base dataset.

There are researches on the performance of different classifiers for HAR (Altun et al., 2010; Janidarmian et al., 2017). Nonetheless, because each research uses different feature extraction methods, their results are cannot be generalized and be applicable to the current research. For example, in Janidarmian et al., (2017) decision tree based methods leading the worst results in all hundreds of tested classifiers but M5P is one of the best in current research.

4.3 Probabilistic Knowledge-Driven Methods

Knowledge-driven approach in HAR is developing a set of models and methods for a particular knowledge-based systems and logical reasoning on it. One of the challenges in HAR systems is uncertainty. The input information is essentially uncertain: sensors used in activity recognition are usually powered by unreliable batteries, data transmission is in a noisy wireless medium and sensors might be displaced from their original position. Moreover, the classification methods that are used for predicting low-level activities are not perfect. In short, there is no guarantee that whatever obtained from sensors' data is correct; however, the degree of belief, the probability of having correct information, is calculable.

In this phase the probabilistic data, obtained in data-driven phase, will be used to recognize the high-level activities. When information, such as low-level activities and indoor locations, is available, one popular approach is storing them in a knowledge base like an ontology. After that, the knowledge base system does reasoning and infers high-level activities. In model that proposed by this research, not only the system is dealing with probabilistic observations from sensors, which is known as ABox, the activity recognition knowledge base is uncertain because the definition set, TBox, is also uncertain. For example: if Alice is certainly standing in place x in the kitchen taking a cup with her right hand and moving the chair with the left hand, she is probably in “tea time” (80%), or she is in “cleaning time” (20%). In this research, uncertainty is modelled with probabilistic representation and make use of a probabilistic ontology to develop the proposed human activity recognition knowledge base.

Another aspect of HAR systems is their computing mode which can be real-time or batch processing. Real-time systems are for applications such as elderly monitoring and gaming, while batch processing is suitable for applications like employee monitoring, on parole criminals monitoring and medical or praxeological studies on people behaviour. While real-time HAR systems the processing time should be only less than or equal the performing time, and also the window size should be small, the batch processing recognition systems must be able to deal with a significant amount of data came from several subjects each performed in a long time span. Therefore, scalability is one of the key challenges in these systems. In current research, a method for sensor-based is proposed, batch processing human activity recognition to overcome these obstacles. Considering the amount of data, storing and reasoning about the knowledge base are two critical challenges in batch processing HAR. There are some knowledge management systems (KMS) for storing and reasoning about conceptual knowledge bases. They are fantastic for a limited amount of data in research labs. On the other hand, relational database management systems (RDBMS), even though they are not designed to deal with complex knowledge structures, are incredibly efficient. Decades of experience, billions of investments, millions of active users have enabled them to store and manage huge databases reliably and securely. In order to achieve scalability in this research, a procedure is designed to store activity recognition knowledge and do reasoning about them in a relational database. There are some research works on storing ontologies in databases, but we did not find any research on storing probabilistic ontologies on databases.

4.3.1 Primary Information

For each subject, person, performs five sets of activity recordings. The first three activities and drill, repeated activities, are used as training set, and the system gives some probabilistic recognitions for labels 1 to 6. (1-Postures 2,3-Right and Left hand movements 4,5-Right and Left hand-object interactions 6-Gesture). High-level activities are more complicated to be efficiently predicted by a data-driven method. Adopting probabilistic predictions enhances the accuracy; while the relying on the first choice is not very efficient, Figure 5.3 shoes the probability of detection in different number of candidate recognitions. The probability of having the right answer in the first three choices, in 18 choices of gestures, is about 0.9. Beside predicting those 6 labels for the test set, the research proposes methods for calculating two more properties that are not labelled in the dataset. The remaining labels are: 7-Compass: the direction of the subjects' body (non-probabilistic). 8-Location: The performance room is divided into 64 rectangle regions, 8 × 8; and the system must detect which rectangle is the current location of the person. Because of the noisy nature of indoor tracking systems, the system makes a probabilistic guess, even though the subject carries four independent tags. The chosen labels to be stored in the ontology are shown in the blue box in Figure 4.9.

All calculated probabilistic results that are obtained in the data-driven phase will not be used in this phase research, nevertheless, all calculated data is stored in a new probabilistic dataset that is published for public use, more details in section 6.3. Because posture recognition accuracy was very high, used as non-probabilistic property, only the most probable choice is used. In practice, it is observed that hand movements, not hand-object interactions, do not have a significant effect on the recognition rate of high-level activities. It makes sense in a way that when the subject is interaction with a cup, he is in breakfast or cleaning activity, no matter he reaches the cup or releases it. Therefore hand-object interactions are used in this research and hand movements are not. Figure 4.9 shows the flow of data in the knowledge-driven phase of the research; starts from probabilistic information from data-driven phase and finally reaches to the high-level activities.

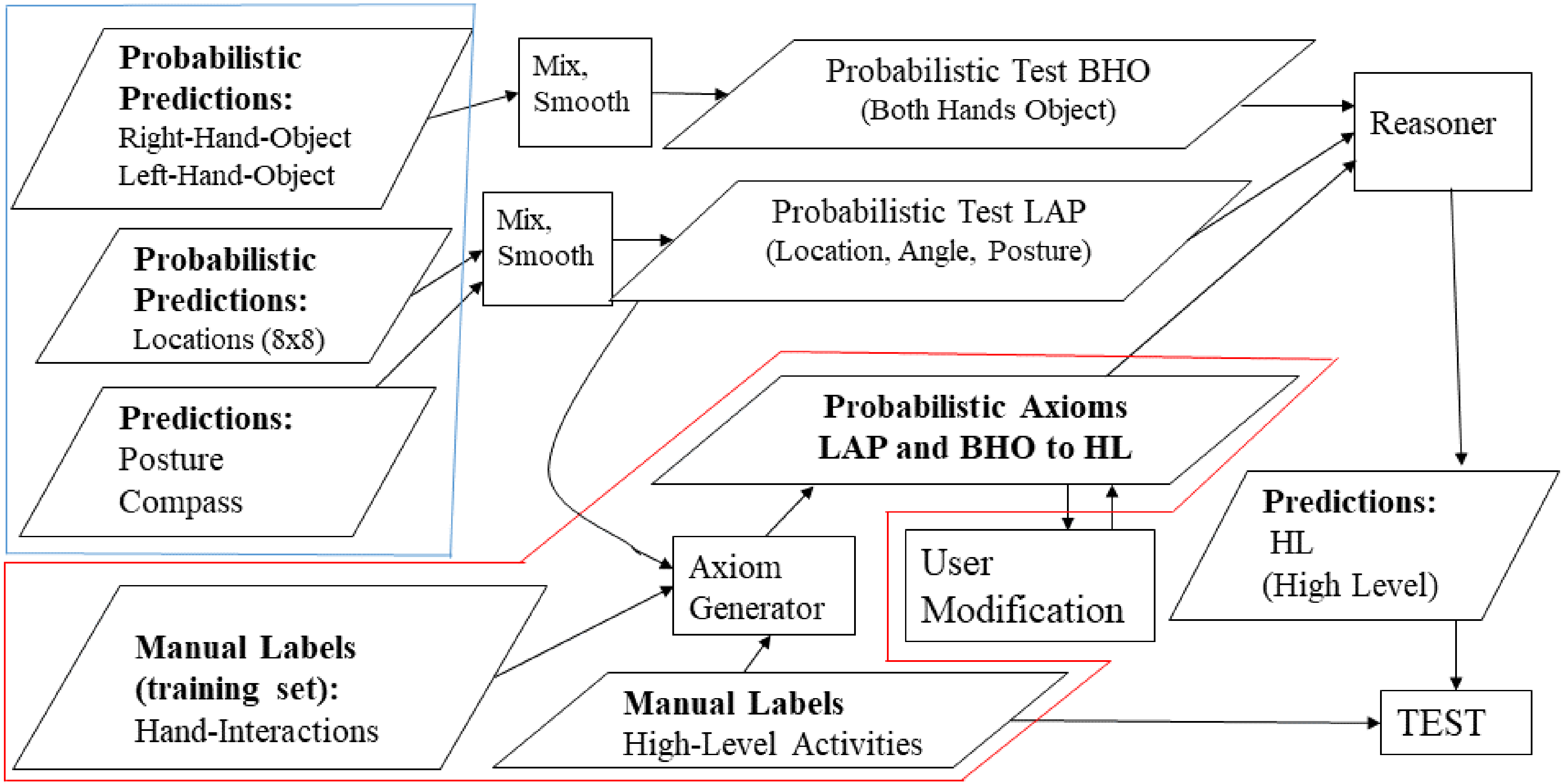


Figure 4.9 Data flow diagram for knowledge-driven phase of the research. In blue line: Primary information, probabilistic observations from sensors, (Ontology ABox); in red line: Knowledge base is definition set, assertion axioms (Ontology TBox).

4.3.2 Ontology Model, Population and Constraints

In the proposed model of this research, the RDF triples, instances stored in three linked data pieces, constitute the foundation of the primary ontology. The ontology is drawn using Eddy, a drawing tool (Lembo et al., 2018); because the ontology will be implemented in a relational database and we are not going to code it in OWL, Eddy is a suitable graphical tool for this purpose. It also guarantees the syntactic correctness of the design. As shown in Figure 4.10, each instance has a unique ID and two other attributes: serial and time plus LAP (location, angle, posture) and BHO (both hands-objects interactions) made from combining LHO, left hand, and RHO, right hand which are information on subjects' situation during the instance. HL (high-level activities) are empty at the starting point for under investigation instances and must be assigned during the reasoning process. For available training instances, BHO is deterministic and HL are known; both are manually labelled. In the primary ontology, each instance (triple) represent 0.33 seconds of activity; and are independent from other instances. After starting the process, ontology is extended: some triples are replaced with more exact ones, assertion axioms are added to the ontology, the high-level activities are formed gradually and finally, the secondary ontology, which contains high-level daily activities, is developed. In other words, the semi-automatic ontology population process (Petasis et al., 2011), adding new instances of concepts to the ontology is done in a step by step data fusion; integrates data starting from fine-grained independent instances and finally gets to an ontology of coarse-grained activities. The stages of ontology population and the manual of ontology drawing are included in Appendix A.

Ontologies are modelling tools for the semantic web. AAA Slogan (Anyone can say Anything about Any topic) and Open World Assumption (some statements have not been said yet) are regular conditions in web data environment. For example, having both statements are acceptable: "Taj Mahal is in China" and "Taj Mahal is in Afghanistan", while in fact "Taj Mahal is in India". In other words, inconsistency is acceptable and there is no constraint for the restriction of such data. In the proposed probabilistic ontology, inconsistency is acceptable too, but it is limited by probability rules. Inconsistent statements are accepted only when the summation of probabilities of them is less than or equal one. The open word is limited to one minus the summation of known probabilities. For example: “Taj Mahal is in China” with a probability of 0.3 and “Taj Mahal is in Afghanistan” with a probability of 0.2 are acceptable because (0.3+0.2) is ≤ 1 and the probability of being in anywhere, the open world space, is 1 – (0.2+0.3). The implemented ontology must enforce this constraint. For current ontology, for each unique instance, the summation of probabilities of LAP or BHO must be less than or equal 1.

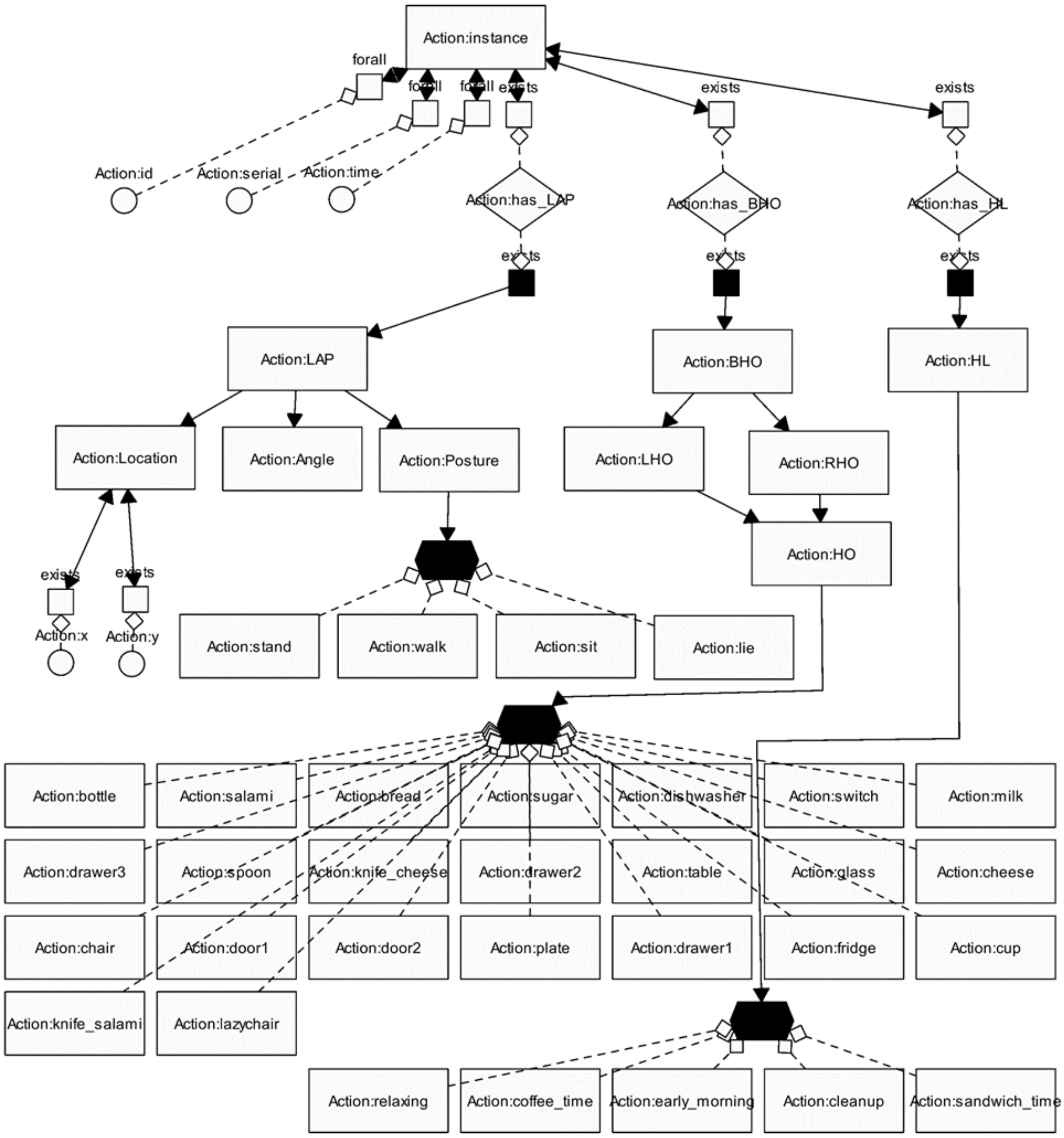


Figure 4.10 The primary ontology, from triples coming from signal processing.

4.3.3 Probabilistic Data Smoothing

All instances are computed only from sensors' reading during the time of that particular instance. In other words, each instance is independent of others. This is not very realistic because the instance time is much shorter than the duration of an activity and it is more likely that consecutive instances have the same value. For example, <*walk, walk, lie, walk, walk*> are five consecutive instances. It seems the fourth instance is not correct, and it must be replaced. In this process, which is named data smoothing, data that are not in a normal pattern (outlier) are alternated. Moving average is one of the most common data smoothing algorithms; the value of each point is replaced with mean of values of an interval that the point is in its centre, or in real time systems at the end of it. For non-numeric data, mode of data at the interval can be used instead of the mean value. However, this algorithm is for deterministic data, while the proposed system deals with probabilistic data.

There is limited literature on probabilistic data smoothing. Indeed, the only work could be found is Merigó, Casanovas and Yang (2003) which is based on expertons theory and fuzzy logic. This method cannot be used for the purpose of this research; besides the fundamental incompatibilities, it is for two states (win and lose) systems while current activity recognition system must deal with the multiple states in both LAP and BHO. As the system is developed for batch processing, access to future instances is feasible. The probabilistic version of statistical mode is introduced to be used in the interval.

A new operator is defined for aggregating information (Xu and Da, 2003); Probabilistic Mode (PM). Let $\{A_1, A_2, ,...,, A_n\}$ be a collection of probabilistic arguments and $D = \{v_1, v_2, ,...,, v_m\}$ a countable domain. Each A_i is a set of pairs; the first part is the value, from domain D and the second part is its probability. For example, D = {*sitting, standing, walking, lying*} and A_3 = {<*sitting*,0.6>, <standing,0.3>}. The probability of what not mentioned in this set, in this example *walking* and *lying*, is 0, in known probabilities area. When the summation of probabilities is less than 1, there is an open world, unknown, space, in this example

0.1, that belongs to all the members of the domain. PR_{ai_j} is the probability of v_j in A_i. In this example: PR_{a3_1} = 0.6, PR_{a3_2} = 0.3, PR_{a3_3} = 0 and PR_{a3_4} =0.

In the following formula, n is the size of the interval, m is the cardinality of the domain B is a temporary variable, contains set of pairs same as each A_i and f is the Probabilistic Mode (PM) operator.

if B = f ({A_1, A_2, ,...,, A_n}) then

for j = 1 to m { $PR_{B\_j} = (\sum_{i=1}^{n} PR_{Ai\_j})/n$ }

Regular mode function, non-probabilistic, can be defined according to the probability theory: mode is the value in the set that is most probable to be sampled. The probabilistic mode function that is defined is compatible with regular mode; with deterministic inputs, each sample has one element with probability of 1 and others are 0, and it will work same as regular mode function if the most probable element of the result is taken. However, the probabilistic mode returns a probabilistic set, in the same format with arguments of the function input. Loosely speaking, PM calculates the average of probability of each domain value. Probabilistic mode function deals with known probabilities and does not consider the open world space, if any.

PM function (Probabilistic mode) will be used for data smoothing of both probabilistic properties of an activity instance. For BHO, the interval size is 5 and the current instance is replaced with the PM of 11 instances: 5 instances before, 5 instances after and the current instances. For LAP the interval size is 3. For instances that are located in the start or end of an activity serial, the interval length is less. After the data smoothing process, still there is a probabilistic set of values for instances, but the probabilities are updated, and outlier data are inconspicuous.

4.3.4 Obtaining and Defining the Assertion Axioms

In order to attain the reasoning process, a set of assertion axioms is needed. The premises, left side, is what is already known from the applied dataset and the conclusion, right side, is what we are going to discover that it is true or false. The following simple example is an assertion that leads to the activity from the location: (Bob is in the bed) → (Bob is in a resting time)

In real world situation, the axioms of HAR systems are probabilistic; If Bob is in bed, he is in a resting time with a probability of 0.80 and he is in a reading time with a probability of 0.2. Axioms like this can be developed in two different ways. An expert user, in this example a person who knows the habits of Bob, may define them. They also can be obtained from a training dataset. In this simple example, Bob's bedroom area can be video recorded for some time, e.g. 3 days, and then his activities in the bed are statistically investigated.

In the current research, for each instance, there are two types of premise data: BHO (both hands-objects interactions) and LAP (location, angle, posture). A set of assertion axioms that lead from and possible instances of BHO or LAP to HL (high-level activity) is needed. Both methods, defining by the user and obtaining from the training data, are provided in the proposed system.

In the case of user defining, there are two visual interfaces, shown in Figures 4.11 and 4.12. For BHO, Figure 4.11, the user is able to define the probability of being in a particular high-level activity while the right hand is in interaction with object X and the left hand is interaction with Y. There are 23 objects and there are $23^2=529$ different states for both hands, but since many of them are unlikely to happen, there is no need to define all of them. For each "hands state" the user sets the probability for all five high-level activities. The application enforces the constraint that th e summation of these five probabilities must be less or equal 1. If it is less than 1, the remaining probability is assigned to nothing, which works same as Null.

For LAP, Figure 4.12, the interface is more complicated; the subject person is in a Location in the room, his body direction has an Angle with the direction of north and his posture is *sitting*, *standing*, *lying*, or *walking*. According to all of these parameters, the user determines the probability of being in a particular high-level activity.

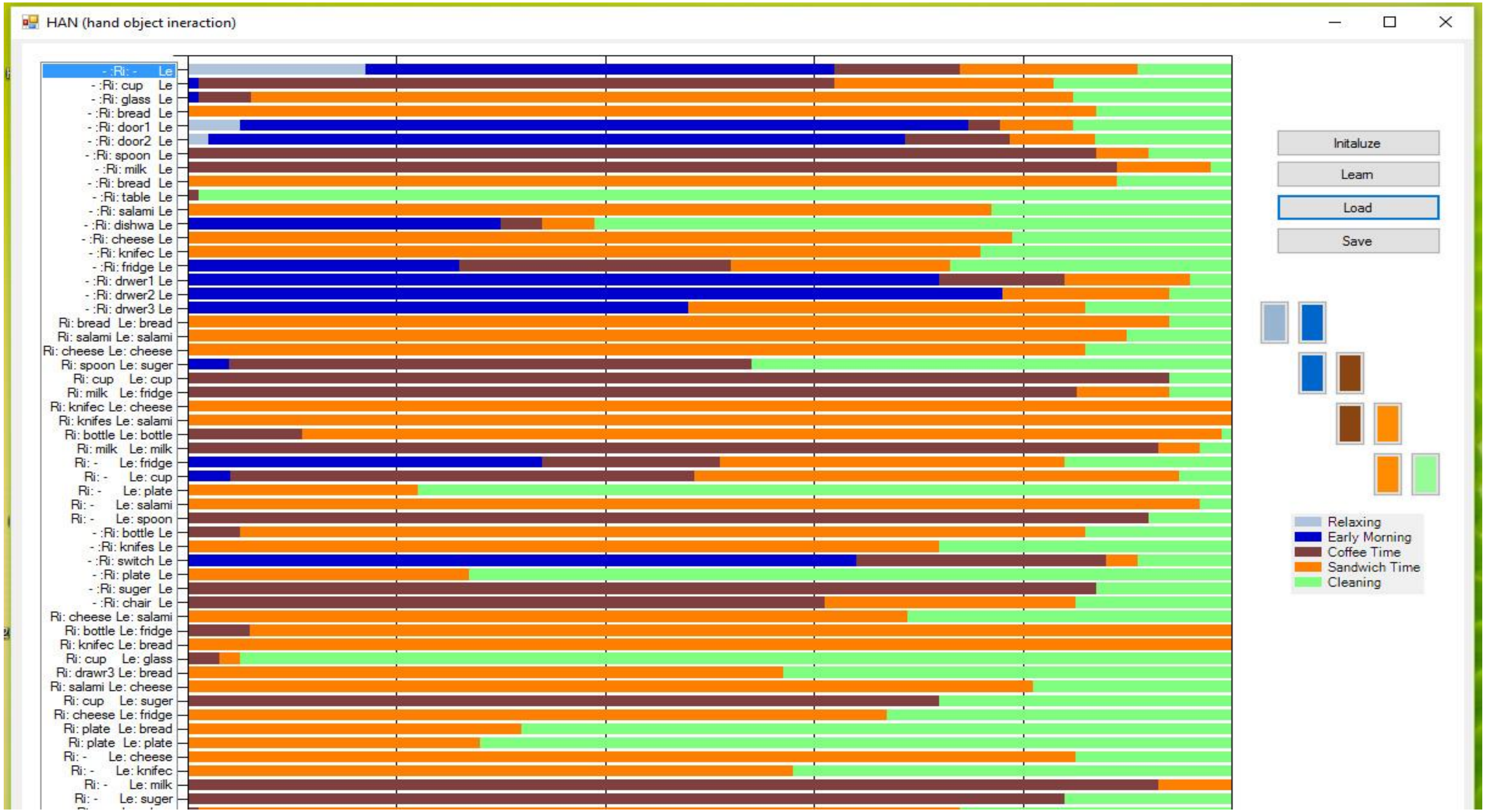


Figure 4.11 The interface of the developed application for defining the assertion axioms for BHO (Both-Hands interaction with Objects).

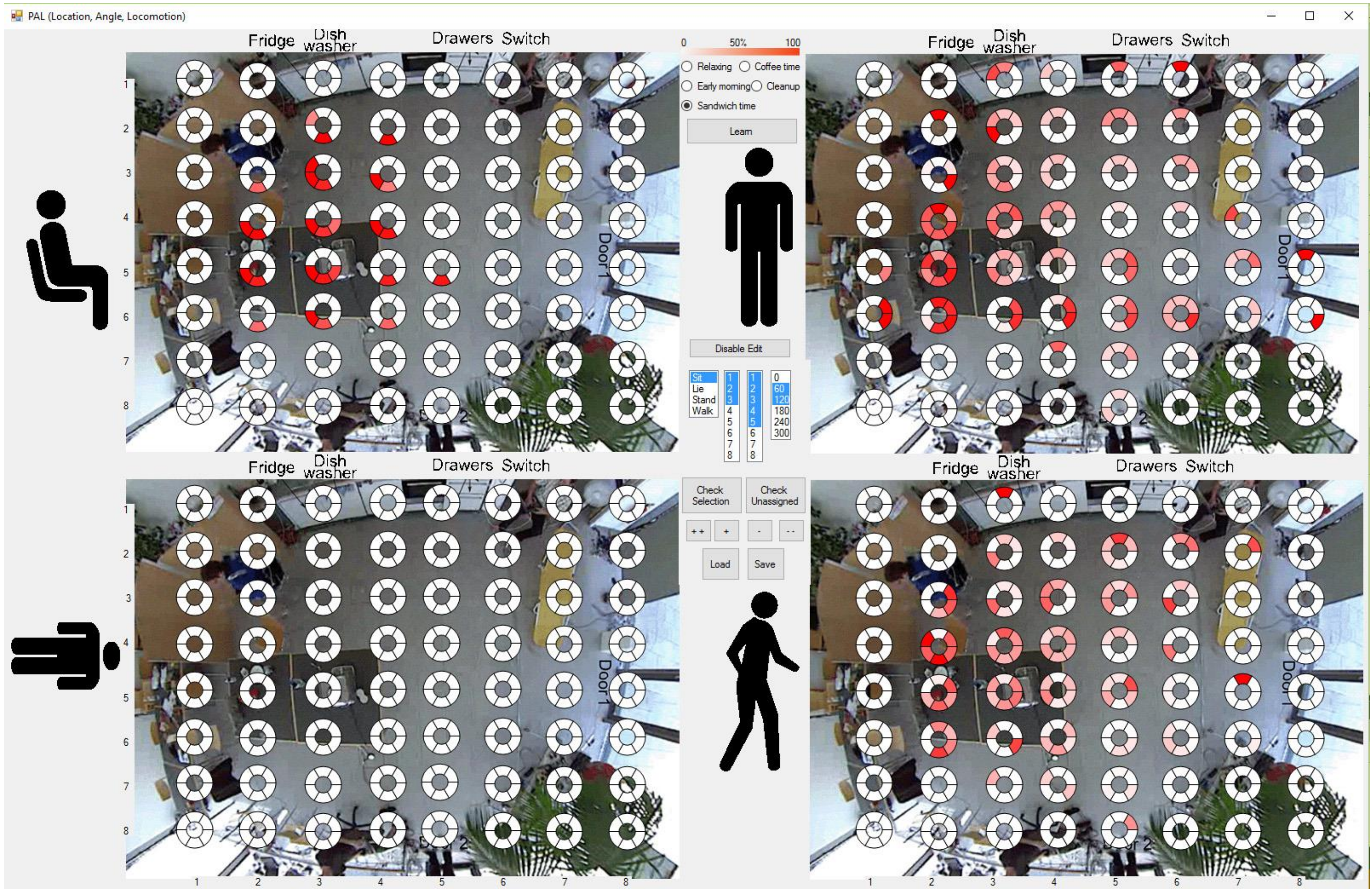


Figure 4.12 The application interface for defining the assertion axioms for LAP (Location, Angle, Posture). Each circle shoes location, in the room and angle and four parts are for postures: (clockwise) sitting, standing, lying and walking

For this purpose, he should choose the activity first and then select a particular wedge from a particular circle. A group of circles and angles can be selected as well. He can increase or decrease the probability and its colour changes accordingly, from white for zero to vivid red for one. The app enforces the probability constraint; the summation of probabilities of each wedge for all high-level activities cannot be more than one. For example, if the probability of a wedge is set to one, vivid red, for *coffee time*, the probability of four other activities cannot be increased from zero and they remain white if the user tries to do that.

Assertion axioms can also be automatically obtained, also known as ontology learning. In this case, some manually labelled data are needed. For BHO, we have everything we need; manually labelled properties for high-level activities and low-level activities, including interaction with objects with right and left hand, are available in Opportunity dataset. For LAP, there are labels for high-level activities but there is no label for location and angle. What is predicted for angle is supposed to be correct and the most probable location and posture is assumed to be the genuine. The naïve Bayes classification algorithm is applied. Axioms are calculated according to the Kolmogorov definition:

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \tag{4.7}$$

For example, let’s take a training dataset with 1000 instances. The method is going to calculate the probability of being in *sandwich time* if “right hand is in interaction with bread”.

$$P(sandwich_{time}|RH_{bread}) \tag{4.8}$$

$$= \frac{\frac{Number\ of\ instances\ in\ "sandwich\ time\ and\ right\ hand\ interacts\ with\ bread"}{\cancel{1000}}}{\frac{Number\ of\ instances\ in\ "right\ hand\ interacts\ with\ bread"}{\cancel{1000}}}$$

For all the available, not all the possible, BHO and LAP codes the probability of being in each high-level activity can be calculated. To determine the probabilities, there are two options: manual defining which needs a user, known as the expert person, who knows all details of activity environment. The other one is automatic defining that requires a large amount of training data, to collect a fairly accurate set of assertion axioms. Both methods have their own drawbacks; in practice, the combination of both methods has the best performance: Initially, axioms are obtained using the automatic learning process; then, a user can visually check them and do some modifications. For example, there is a seat in the room that the subjects may use it while eating, but in the applied training dataset, accidentally no one has used it. In this case, the expert user can edit the learned axioms to add this particular space to the eating area.

4.3.5 Inference Process

Up to the current stage, there are some assertion axioms and some instances. Each instance has three or fewer BHO and three or fewer LAP states accompanying their probability values. For each BHO or LAP state, there is an assertion axiom, connecting it to the five probable high-level activities (target): *Relaxing*, *Coffee time*, *Early morning*, *Cleanup* and *Sandwich time*. After multiplexing probabilities of axiom and state and then Cartesian product of BHO (3) and LAP (3) states (given), for each instance there are nine or fewer items:

$$<PR_{\mathrm{BHO\_relax}}, PR_{\mathrm{BHO\_coffee}}, PR_{\mathrm{BHO\_morning}}, PR_{\mathrm{BHO\_clean}}, PR_{\mathrm{BHO\_sandwich}}>,<PR_{\mathrm{LAP\_relax}}, PR_{\mathrm{LAP\_coffee}}, PR_{\mathrm{LAP\_morning}}, PR_{\mathrm{LAP\_clean}}, PR_{\mathrm{LAP\_sandwich}}> \quad (4.9)$$

For each item, there are two sets of probabilities of all high-level states, one obtained from BHO and another obtained from LAP. Since BHO and LAP are from different and independent processes, the combination of probabilities, e.g. for relaxing, can be calculated according to:

$$PR_{\mathrm{relax}} = 1 - ((1 - PR_{\mathrm{BHO\_relax}}) * (1 - PR_{\mathrm{LAP\_relax}})) \quad (4.10)$$

Even though the above formula is theoretically intact, in practice, some modifications improve the accuracy of prediction of high-level activities. In fact, BHO and LAP do not have equal affection on a high-level activity and it should be manually adjusted. For each high-level activity, the weighting coefficients is defined, m and n, between 0 and 1 and rewrite the formula as follows (where $PR_{\text{BHO\_relax}}$ refers to the probability of bening in relax activity according to information from BHO, both hands-objects and $PR_{\text{LAP\_relax}}$ rfrom LAP, location, angle and position):

$$PR_{\text{relax}} = 1 - ((1 - m*PR_{\text{BHO\_relax}}) * (1 - n*PR_{\text{LAP\_relax}})) \qquad (4.11)$$

According to the experiment of this research, the reported coefficients in Table 4.2 leads to the relatively better results.

Table 4.2 Coefficients for high level activities.

	Relax	Coffee	Morning	Clean	Sandwich
m	0.7	0.5	0.5	0.7	0.5
n	0.7	0.7	0.4	0.9	0.6

At this point, for each instance there are 3*3=9 or fewer items, each has a probability for each high-level activity. Despite the whole process which was fully probabilistic, the final step should determine a deterministic suggestion for the high-level activity that the subject is performing during the instance. For each high-level activity, the highest probability value from all items are chosen and then the most probable high-level activity is the final candidate for the instance. Table 4.4 presents an example of calculation of probabilities: the actual calculation of probability of one particular instance (instance no: 14940) using LAP, BHO (according to formula 4.11) and total combination of both of them (6_1_predict in appendix B).

Table 4.3 Calculated probability of being in a high level activity, for one instance, L from LAP, B from BHO and T from both.
(the predicted and actual target class is 103, *early morning*)

id	L101	L102	L103	L104	L105	B101	B102	B103	B104	B105	T101	T102	T103	T104	T105
14940	0	0	0	0	0	0	0	0	0.11...	0.04...	0	0	0	0.07...	0.02...
14940	0	0	0.33...	0	0	0	0	0	0.11...	0.04...	0	0	0.13...	0.07...	0.02...
14940	0	0	0.33...	0	0	0	0	0	0.11...	0.04...	0	0	0.13...	0.07...	0.02...
14940	0	0	0	0	0	0.13...	0.09...	0.35...	0.07...	0.13...	0.09...	0.04...	0.17...	0.04...	0.06...
14940	0	0	0.33...	0	0	0.13...	0.09...	0.35...	0.07...	0.13...	0.09...	0.04...	0.28...	0.04...	0.06...
14940	0	0	0.33...	0	0	0.13...	0.09...	0.35...	0.07...	0.13...	0.09...	0.04...	0.28...	0.04...	0.06...

After obtaining a high-level activity for each instance, the system can work on a group of instances to develop the final ontology. The final ontology has the same elemental information, ID, serial and starting time as well as high-level activity label; there is no need for fine-grained labels: BHO and PAL. In this ontology the duration of instances varies; therefore, a need extra property is needed, length, that indicates the duration of the instance in seconds. It is very likely that the high-level activity of a particular instant is same as instances before and after it. This situation is similar to BHO and PAL properties of instances; however, in this case, data smoothing methods cannot be used. A low-level hand activity or physical position of the subject usually takes a few seconds, while there are three instances in one second; although, a high-level activity usually takes several minutes, means hundreds of instances.

```
new_ontology = old_ontology
rearrenge (new_ontology)
delete instances with length <15
rearrenge (new_ontology)
delete instances with length <35
rearrenge (new_ontology)
delete instances with length <55
rearrenge (new_ontology)

define rearrenge(an ontology)
* FOR current_instant From last_instant TO one_after_first_instant DO
      IF HL_activity (current_instant) = HL_activity (previous_current_instant) THEN
            Delete (current_instant)
* FOR current_instant From first_instant TO last_instant DO
      length (current_instant) = id(current_instant)- id(next_current_instant)
```

The above algorithm is designed for developing the final ontology and then improving its accuracy of prediction of high-level activities by eliminating some potential prediction errors (three-step elimination). First, the ontology is copied to a new ontology that the structure is slightly different: each instance has a timestamp (zero at start on a recording) and a duration. Then the ontology is rearranged which merge the consecutive instances that have same value for high-level activity and make instances with long duration and filling gaps. At first step of removing, the instances with less than 15 seconds are eliminated and rearranging will fill each gap by extending the duration of the activity that was before it. For example, an activity of *coffee time* with duration of 3 seconds is removed and the recognized activity before that which was relaxing with duration of 483 seconds is updated to 486 seconds. The same process is done for step two and three for removing instances with less than 35 and 55 seconds.

After rearranging the ontology, all consecutive instances which have the same high-level activity are replaced with only one instance. In other words, a large ontology with plenty of instances is converted to an ontology with a few instances. It will be even smaller and also more accurate after each step of elimination of short length instances. The ontology is rearranged after each step because possibly there are consecutive instances with the same high-level activity value, after removing some instances.

4.3.6 Ontology Storage in a Relational Database

In this section, there is an overview of methods for storing the ontology on a relational database. Unlike other ontology-based HAR researches which store the ontology in OWL flat text files, relational databases are applied in this research. The storing model is slightly different from the methods for storing regular ontologies in regular databases. The main difference is having a probability for all tuples in Tbox and Abox; plus, different database constraints rules including rules of the primary key. Although, the inference process for probabilistic ontologies is entirely different from the reasoning process about non-probabilistic ontologies. Considering this fact, the proposed model is for activity recognition purpose only and query language and running queries on general probabilistic ontologies in databases is out of the scope of this research.

The information that came from the processed dataset is stored in the base relations. Each step of the population of the ontology is performed by running a view on the former version of the ontology. For example, a view receives unsmoothed data from another view and sends the smoothed information to the next view. It should be noted that in modelling, there is no difference between base relations and views; both of them are known as relations or SQL tables (Date 2005). Thus, in any phase, there is a relation that presents the current version of the ontology. In some cases, views are materialized and stored in the form of base relation. There are automated serial numbers for all tuples in the base SQL tables that are set as the primary key but never used in the proposed model. Instead, the probabilistic primary key constraint, as defined in Section 4.5.2, is enforced by defining SQL server triggers. It guarantees that improper data will not appear in the base relations and, therefore, in the views.

It is unnecessary to include all views and tables here; just key functions and view are presented. They are formulated in the relational algebra. It is shorter than SQL code and easier to understand. The syntax of SQL code in different DBMSes also varies; for example, a MS SQL Server code usually cannot run My SQL, for complicated queries, and writing code from relational algebra formula is easier than converting different SQL codes. For data smoothing the following SQL table valued function is defined (it gets an id number and finds the replacement set of probabilistic values for location of that instant with interval = 5):

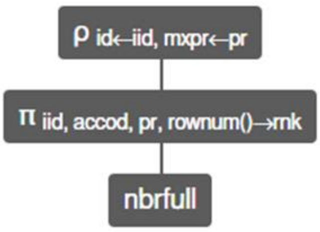
```
datasmooth (@id)  returns @trackingItems (location, pr)
declare @temp (acv,prr) table
declare @sm float
@temp = π arc, pr σ id between (@id - 5) and (@id + 5) triples_loc
@trackingItems = τ E1 asc π acv, E1 γ acv; SUM(prr)/11→E1 @temp
@sm = π sm γ ; SUM(pr)→sm @trackingItems
@trackingItems ← π pr trackingItems
Retuen @trackingItems
```

There is a preliminary work on using SQL for classification (Chaudhuri et al., 1999). For obtaining naïve Bayes axioms, as explained in 4.5.4, these set of consecutive views:

1. **ranked_obj =** ρ id←iid, mxpr←pr π iid, hand, pr, rownum()→rnk
2. **mixed_arc =** ρ arc←location, mxpr←pr π iid, location, pr, rownum()→rnmx
3. **finalfr_arc =** π id, arcc, pr γ id;max(mxpr)→pr,max(arc)→arcc (σrnmx=1 or rnmx=null mixed_loc ⋉ iid = id triples_main)
4. **tr_ar =** π triples_main.id, finalfr_arc.arcc σ (triples_main.subject = 1) or (triples_main.subject = 2) or (triples_main.subject = 3) (finalfr_arc ⋉ finalfr_arc.id = triples_main.id triples_main)
5. **c101 =** π c101 , codt γ codt;count(tr_ar.id)→c101 (σ Lhlev <> '101' (tr_ar ⋈ tr_ar.id = tr_lab_train.id tr_lab_train))
6. **hrul =** π tot.codt, c101 / ct→p101, c102 / ct→p102, c103 / ct→p103, c104 / ct→p104, c105 / ct→p105 (tot ⟗ tot.codt = a101.codt a101 ⟗ tot.codt = a102.codt a102 ⟗ tot.codt = a103.codt h103 ⟗ tot.codt = a104.codt a104 ⟗ tot.codt = a105.codt a105)
7. **predict** = (ts_ar ⋉ arcc = arct arul) ⋉ ts_ar.id = tr_lab_test.id ((hrul ⋉ codt = accod ts_ho) ⋉ ts_ho.id = tr_lab_test.id tr_lab_test)
8. **mixhoar** = π id, Lhlev, 1 - (1 - 0.7 * p101) * (1 - 0.7 * h101)→v101, 1 - (1 - 0.7 * p102) * (1 - 0.5 *h102)→v102, 1 - (1 - 0.4 *p103) * (1 - 0.5 *h103)→v103, 1 - (1 - 0.9 * p104) * (1 - 0.7 * h104)→v104, 1-(1 - 0.6 * p105) * (1 - 0.5 * h105)→v105 predict

The implementation, a short description, the visual illustrations of implementation in relational algebra, and sample results of above formulas, Tables, are included for clarification. The SQL codes of above-mentioned formulas are included in Appendix B,

Query (14_ranked_obj in appendix B) uses nbrfull function, giving smoothed probability, and its ranking, of hand-object activity for each instance (Query illustration in Figure 4.13 and sample results in Table 4.4).



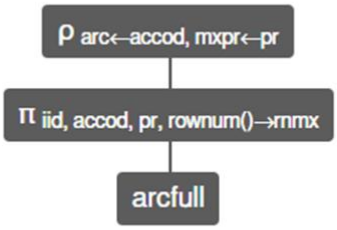
ρ id←iid, mxpr←pr **π** iid, accod, pr, rownum()→rnk **nbrfull**

Figure 4.13 Using smoothing function for BHO in relational algebra.

Table 4.4 Sample results for ranked_obj.

id	accod	mxpr
11067	h0000	0.832425901972224
11067	h1600	0.14735426586919
11067	h1300	0.0202198321585859
11068	h0000	0.837381870835796
11068	h1600	0.142996294308209
11068	h1300	0.0196218348559957

This query (23_mixed_arc in appendix B) uses arcfull function to give smoothed probability of angle, posture, location for each instance (Query illustration in Figure 4.14 and sample results in Table 4.5).



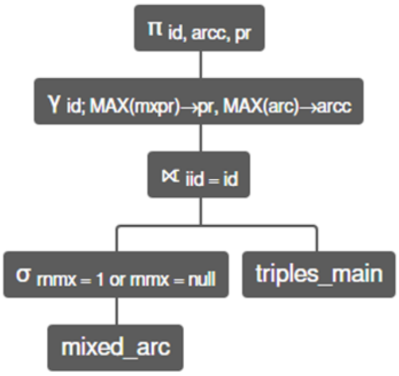
$\rho_{arc \leftarrow accod,\ mxpr \leftarrow pr}\ \pi_{iid,\ accod,\ pr,\ rownum() \rightarrow rnmx}$ **arcfull**

Figure 4.14 Using smoothing function for LAP in relational algebra.

Table 4.5 Sample results for ranked_obj.

iid	arc	mxpr	rnmx
1	a6400	0.370502792435049	1
1	a6500	0.323834853949423	2
1	a6550	0.305662353615528	3
2	a6400	0.369460975496527	1
2	a6500	0.322417589155967	2
2	a6550	0.308121435347506	3

This query (24_finalfr_arc in appendix B) chooses the most probable arc for each instance. It will be used for training purpose (Query illustration in Figure 4.15 and sample results in Table 4.6).



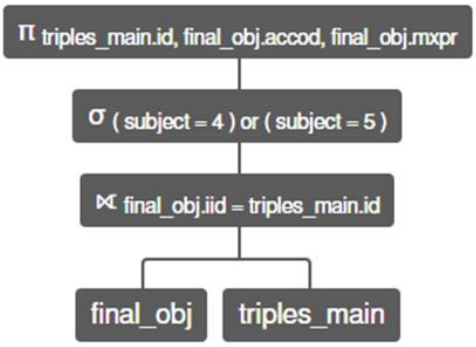
$$\pi_{\text{id, arcc, pr}}\ \gamma_{\text{id; MAX(mxpr)}\rightarrow\text{pr, MAX(arc)}\rightarrow\text{arcc}}\ (\sigma_{\text{rnmx = 1 or rnmx = null}}\ \textbf{mixed\_arc} \ltimes_{\text{iid = id}} \textbf{triples\_main})$$

Figure 4.15 Choosing the most probable instance in relational algebra.

Table 4.6 Sample results for finalfr_arc.

id	arcc	pr
1	a6400	0.370502792435049
2	a6400	0.369460975496527
3	a6400	0.340643987378273
4	a6550	0.342694974522508
5	a6550	0.347951086670369

This query (3_tr_ar in appendix B) prepares the training data for angle, posture, location. Dataset is not annotated for location and angle, therefor the most probable choice supposed to be true for training part (Query illustration in Figure 4.16 and sample results in Table 4.7).



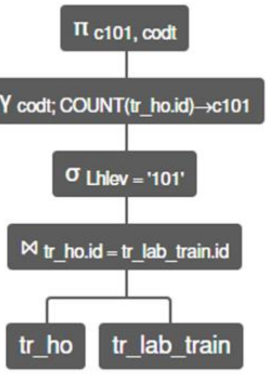
$$\pi_{\text{triples\_main.id, final\_obj.accod, final\_obj.mxpr}}\ \sigma_{(\text{ subject} = 4\text{) or (subject} = 5 \text{)}}\ (\textbf{final\_obj} \bowtie_{\text{final\_obj.iid = triples\_main.id}} \textbf{triples\_main})$$

Figure 4.16 Preparing the training data in relational algebra.

Table 4.7 Sample results for tr_ar.

id	arcc
1	a6400
2	a6400
3	a6400
4	a6550
5	a6550

This query (4_101 in appendix B) gives number of instances for each BHO class. It will be used to discover axioms (Query illustration in Figure 4.17 and sample results in Table 4.8). Similar query is needed for 102 to 105 classes for LAP.



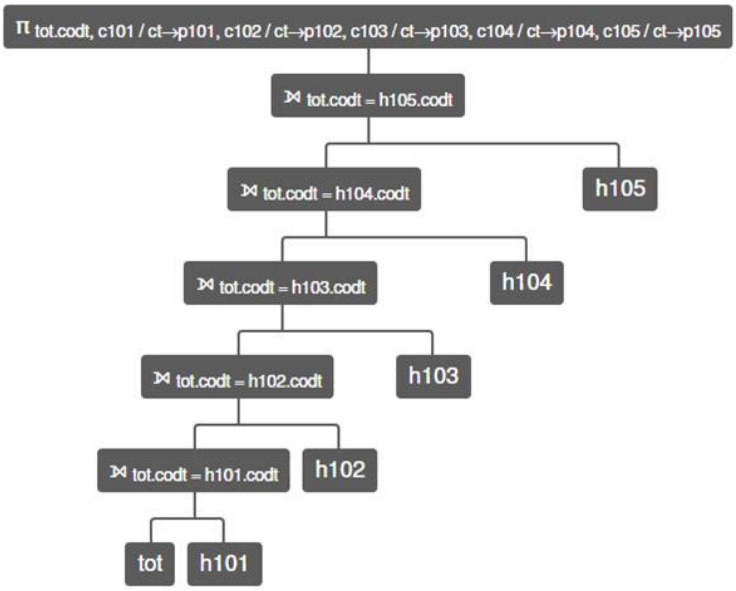
$$\pi_{\text{c101, codt}}\ \gamma_{\text{codt; COUNT(tr\_ho.id)}\rightarrow\text{c101}}\ (\ \sigma_{\text{Lhlev = '101'}}\ (\textbf{tr\_ho} \bowtie_{\text{tr\_ho.id = tr\_lab\_train.id}} \textbf{tr\_lab\_train}))$$

Figure 4.17 Calculating number of instances in relational algebra.

Table 4.8 Full results for 4_101.

c101	codt
4	h2300
13	h1700
27	h1600
28	h2323
37	h0023
2647	h0000

This query (4_hrul in appendix B) gives learned axioms for both hands objects activities (Query illustration in Figure 4.18 and sample results in Table 4.9).



$$\pi_{\text{tot.codt, c101 / ct}\rightarrow\text{p101, c102 / ct}\rightarrow\text{p102, c103 / ct}\rightarrow\text{p103, c104 / ct}\rightarrow\text{p104, c105 / ct}\rightarrow\text{p105}}\ \mathbf{tot} \bowtie_{\text{tot.codt = h101.codt}} \mathbf{h101} \bowtie_{\text{tot.codt =h102.codt}} \mathbf{h102} \bowtie_{\text{tot.codt = h103.codt}} \mathbf{h103} \bowtie_{\text{tot.codt = h104.codt}} \mathbf{h104} \bowtie_{\text{tot.codt = h105.codt}} \mathbf{h105}$$

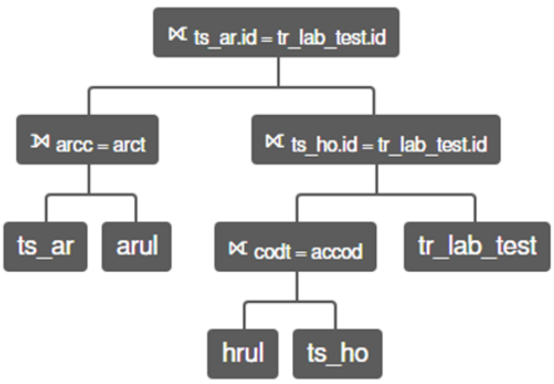
Figure 4.18 Learned axioms for BHO in relational algebra.

Table 4.9 Sample results for hrul.

codt	p101	p102	p103	p104	p105
h0000	0.170...	0.117...	0.454...	0.088...	0.168...
h0001	0	0.116...	0	0.05	0.833...
h0002	0	0	0	0.028...	0.971...
h0003	0	0	0	0.106...	0.893...
h0004	0	0.841...	0	0.158...	0
h0005	0	0.157...	0.142...	0.7	0
h0006	0	0.321...	0.464...	0.214...	0
h0007	0	0.928...	0	0	0.071...

At this stage, the assertion axioms, learned or defined by user, are available. For reasoning process, the system applies these axioms on instances that should be recognized. For example, if the subject is in h0001 state, the second row in table 4.10, which means he does nothing with left hand and right hand is in interaction with the bottle, then he is not likely to be in relaxing or *early morning* time, he is in *sandwich time* with probability of 83%, 12% in *coffee time* and 5% in *cleanup*.

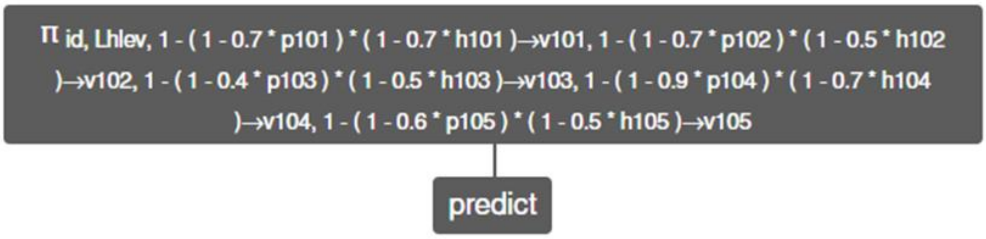
This query (6_1_predict in appendix B) gives predictions for each instance, separate calculation by hand and location. Sample results has already shown in 11 left columns of (Query illustration in Figure 4.19 and sample results in Table 4.3).



$$(\textbf{ts\_ar} \ltimes_{\text{arcc = arct}} \textbf{arul}) \ltimes_{\text{ts\_ar.id = tr\_lab\_test.id}} ((\textbf{hrul} \ltimes_{\text{codt = accod}} \textbf{ts\_ho}) \ltimes_{\text{ts\_ho.id = tr\_lab\_test.id}} \textbf{tr\_lab\_test})$$

Figure 4.19 Predictions for instances by BHO and LAP in relational algebra.

This query (6_2_ mixhoar in appendix B) presents the probabilities being in a high-level activity for each instance (Query illustration in Figure 4.20 and sample results in Table 4.10).



π id, Lhlev, 1 - (1 - 0.7 * p101) * (1 - 0.7 * h101)→v101, 1 - (1 - 0.7 * p102) * (1 - 0.5 *h102)→v102, 1 - (1 - 0.4 *p103) * (1 - 0.5 *h103)→v103 , 1 - (1 - 0.9 * p104) * (1 - 0.7 * h104)→v104, 1 - (1 - 0.6 * p105) * (1 - 0.5 * h105)→v105 **predict**

Figure 4.20 The probability of high level activities in relational algebra.

Table 4.10 Sample results for mixhoar.

id	v101	v102	v103	v104	v105
11067	0.174...	0.049...	0.256...	0.052...	0.070...
11067	0.139...	0.049...	0.219...	0.052...	0.167...
11067	0.145...	0.049...	0.257...	0.089...	0.070...
11067	0.088...	0.002...	0.131...	0.015...	0.005...
11067	0.049...	0.002...	0.088...	0.015...	0.108...
11067	0.056...	0.002...	0.133...	0.053...	0.005...
11068	0.175...	0.050...	0.257...	0.052...	0.071...
11068	0.139...	0.050...	0.220...	0.052...	0.167...

Figure 4.21 illustrates the relational data model of the whole system. In this figure, base relations (tables), deducted relations (views), materialized views and functions with their properties as well as the data flow of the system are shown.

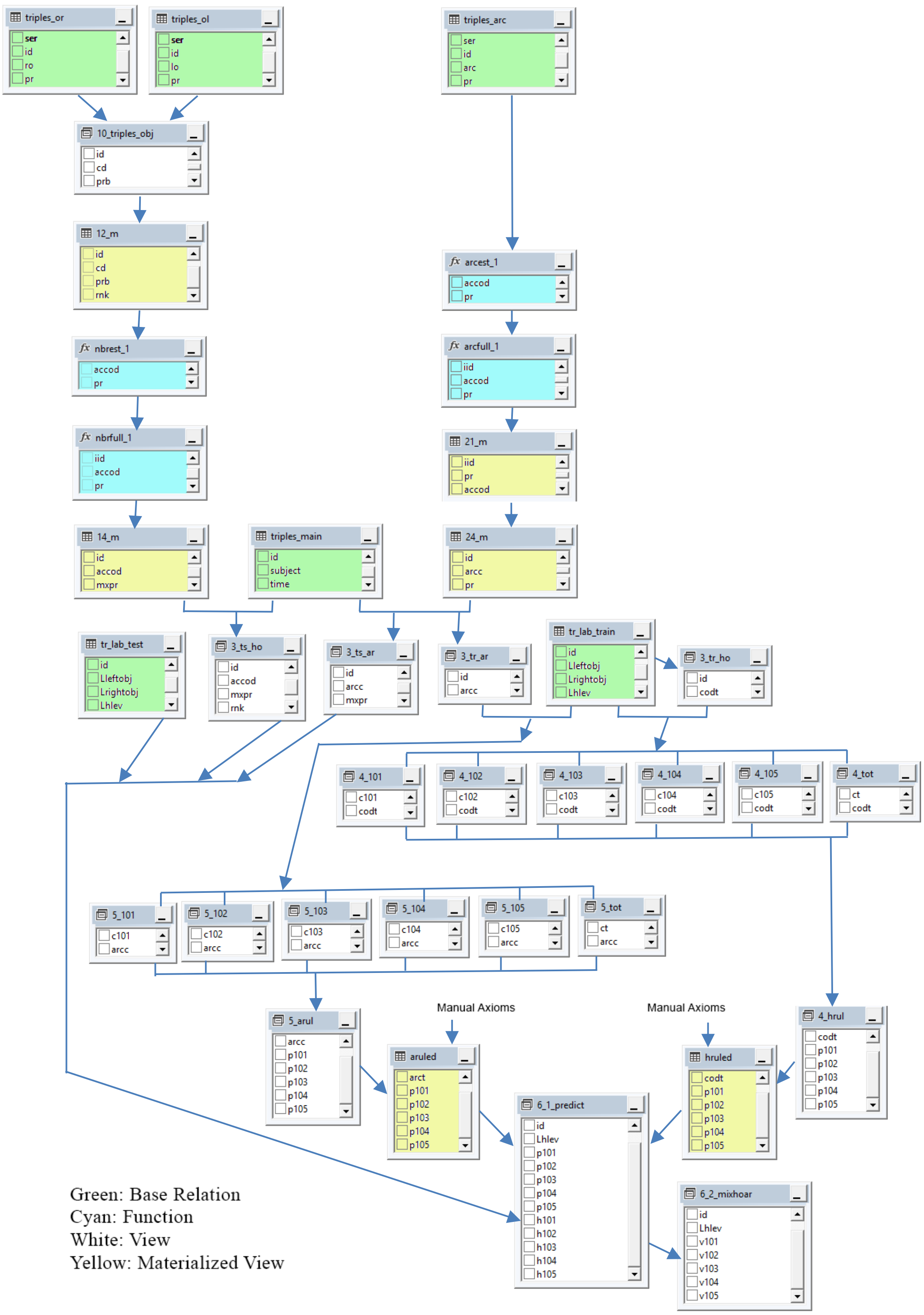


Figure 4.21 The relational data model, designed for this research

4.4 Chapter Summary

In this chapter, developing an ontology from information of sensors for human activity recognition and storing it into a relational database are presented. The applied methods of the research are presented in two phases. In the data-driven phase, data-driven methods, the signal processing, feature computation, and classification techniques are presented. They convert ACCEL, GYRO, Magnetic and IPS sensors signals to fine-grained activities in form of probabilistic information. The knowledge-driven phase was about modelling the obtained information from data-driven phase in the form of probabilistic ontology; that is able to find out the axiom rules and use them in the reasoning process that obtain high-level, coarse-grained, human activities. The probabilistic is designed to be stored in a high performance SQL-based relational DBMS. The data and knowledge driven methods are designed to perform fast and the storage is suitable for a large volume of data. In other words, the proposed system is scalable, it is able to process big data in a reasonable time.

CHAPTER 5

RESULTS AND DISCUSSION

5.1 Introduction

In this chapter, the results of two phases of this research, data-driven and knowledge driven, are reported and compared with well-known and highly cited researches in this field of study. The data-driven phase develops sets of sensor-based HAR methods to process signals from analogue sensors and convert them to probabilistic information about low level activities and the location of the subject. Data-driven phase is evaluated by comparing its results, the most probable candidate, with the results of some well-known HAR signal processing methods. The knowledge-driven phase represents an ontological model to store the probabilistic information obtained from the data-driven phase and do reasoning about them to obtain high level activities. This phase is evaluated in two stages. In the first stage the model is evaluated using criteria for HAR ontological models and in the second stage, the performance of recognition of high-level activities is compared with some state of art methods which are applied on the same dataset. The performance, the processing time, of the reasoning process in a SQL based relational database is also presented in this chapter. In short, the evaluation shoes how using probabilistic ontologies improves the accuracy and a considerable saving of the processing time make the system highly scalable.

5.2 Evaluation of the Data-Driven Methods

In this part of the research, the applied methods for converting sensors' signals to probabilistic information are evaluated. The primary objective of this phase of research is to demonstrate how to develop the necessary data for a probabilistic knowledge-base for daily activities in the form of three or four of the most probable targets for each property with probabilities values. Almost all former proposed data-driven methods aimed to reach the final and deterministic recognitions only, therefore, there is not enough literature on data driven HAR methods with probabilistic output and for benchmarking of proposed methods only the most probable targets are considered.

The classification was performed for each of the four subjects, persons, for all of the following categories: Recognition of 1) postures; 2) gestures; 3) right arm movements; 4) left arm movements; 5) right arm in interaction with objects; and 6) left arm in interaction with objects. Daily activities number 4 and 5 are used for testing. The result of human activity recognition is usually reported in the form of accuracy, F-measure, and AUC. F-measure, the harmonic mean of precision and recall, is the preferred measure for reporting performance in this work because the amount of data for different classes are mostly not equal, and the results that are benchmarked against the obtained results are also reported in F-measure (Chavarriaga et al., 2013; Fawcett, 2006).

When an activity does not fall into any category of predefined activities, it will be labeled as **null**. For example, when a subject is going to *stand up*, the period that he is in between the *sitting* and *standing* positions is labeled as null. An important issue in reporting the results is to clarify how nulls are treated in the classification phase. Nulls can be addressed using two different approaches. The first approach is to ignore them and omit them from training and test data, and the second approach is to consider nulls as a class. Because nulls are transitional states between the known activities, confusion of them with the activities occurs very often. Therefore, recognition is easier and F-measure for each activity is usually higher when they are excluded. However, because the frequency of occurrence of nulls is much more than other classes in hand-movements and object interactions, even though the recognition rate for non-null activities is lower, the total weighted average F-measure is higher when nulls are included. As the main objective of current research is to form a knowledge base for the whole activity session of all predefined activities as well as transitional activities, nulls are included and considered as a separate class for classification in the data that sent to the knowledge driven phase.

For hands' interactions and movements shown Figure 5.1, even though the object sensors are used to increase the recognition rate, the obtained results are not as accurate as posture and gesture according to Table 5.1. Similarity of the hand movements and the limited number of the training and test samples are the reasons for the obtained recognition rate; in most cases instances belonging to a class is less than 1% of the total number of samples. Furthermore, considering the priority of time consumption, to reach the scalability objective, this research did not applicate complicated and time-consuming signal transform methods.

Table 5.1 F-measure (average of four subjects) of hand object interactions and hand movement recognition; nulls included.

Subject	**Posture, Gesture, Hand object interactions (oi) and Hand movements (m)**					
	Posture	**Gesture**	**RH-oi**	**LH-oi**	**RH-m**	**LH-m**
S1	0.842	0.814	0.661	0.789	0.616	0.797
S2	0.829	0.848	0.693	0.677	0.647	0.651
S3	0.790	0.815	0.703	0.758	0.591	0.740
S4	0.800	0.720	0.617	0.770	0.552	0.762

For higher level activities, the recognition rate is lower. As shown in Figure 5.1, the recognition rate for cleaning table is low because from the sensor point of view, eating on the table and cleaning table are very similar. On the other hand, reasoning on this information will recognize high level activities efficiently, including cleaning time and breakfast time.

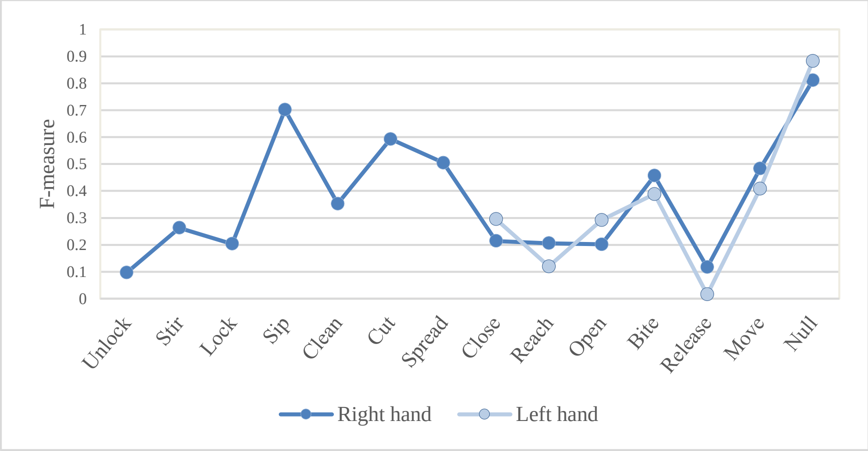


Figure 5.1 F-measure (average of four subjects) separated classes of hand movement recognition; nulls included.

There are different types of classification errors. Overfill and underfill occur when the beginning and the ending of an activity are predicted by the classifier earlier or later than is annotated. These errors are not recognition errors; they are due to not having clear boundaries between activities that happen naturally during daily routines, or due to manual annotation by different people who might have slightly different opinions about when an activity begins and ends. The other errors, which are the results of sensors' reports or classifications, are divided into three different types: 1) insertion: recognition of activity when the subject is idle; 2) deletion: recognition of idle state when the subject is engaged in an activity; and 3) substitution: misrecognition of an activity (Ward, Lukowicz and Gellersen, 2011). 4) Fragmentation, which occurs when during an activity or idle state, system faces few instances with irrelevant labels. In other words, fragmentation is an insertion, deletion or substitution occurring in a very short time span. Data smoothing is helpful for this problem. This technique is used in knowledge driven phase of study, but at this stage, just for comparing the proposed method with the other methods a simple, non-probabilistic, smoothing method is used to improve results. Since location tracking positions are not labeled in the dataset; there is no way to evaluate the predictions. Nonetheless, the integrity of the method and the correlation between high-level activities and locations, shown in Section 5.2.2, suggests the performance is acceptable.

5.2.1 Benchmarking

Benchmarking is not easy in human activity recognition area because different researches have used different datasets, in many cases made by themselves; therefore, results are not directly comparable. To benchmark the proposed method against the available methods, the most probable class is simply taken as the final choice before and after data smoothing. A subset of the Opportunity dataset has been used for a challenge competition (Chavarriaga et al., 2013). In the dataset for the challenge, there is no information from environmental and location sensors, Three sets of activities are fully labelled but no labels were declared for the sets 4 and 5 of activities for subjects, person 2, 3, and 4; these sets must be labelled by competitors of the challenge. Judgement is based on the obtained labels; however, there was no obligation to disclose the method they applied to obtain the labels. Meaning that some stages even might have been done manually.

There were 3 categories and each competitor was allowed to enter each one separately: Task A: recognition of postures; Task B: recognition of gestures; and Task C: recognition of gestures for one subject whose dataset has altered with missing data and rotated sensors in the middle of the activities. Eight research groups participated in this task, their results were published as well as the result obtained by the providers of the dataset, and tested with different classifiers, to establish the baseline. The best baseline performance was achieved by KNN (K=3) (Aloulou et al., 2015). For the challenge dataset, the same method is applied but using all features for classification. For subject 2, daily activities 1, 2 and 3 and the drill are used for training and activities 4 and 5 taken for testing. The same is applied to subject 3 but for the combination of subjects 2 and 3, all the data including activities 1 to 3, for subjects 1, 2 and 3 are used as the training data, to form an inter-subject validation.

The results have gone through a simple data smoothing method, replacing each instant with the mode of 5 instances in the interval. In Table 5.2, the results obtained for postures are promising, as the extracted features from sensors attached to the body are able to describe the situation relatively well. However, the gesture results are comparable but not that high, regarding the fact that for time efficiency complicated feature calculation and classification techniques are avoided. All researchers did not report the processing time but for instance, Yang et al (2015), the winner of competition in gesture who used deep learning techniques spent about 1 hour for training and 8 minutes for testing. In current research the training time is about 30 seconds for posture and 90 seconds for gesture and the testing time is less than 1 second (for about 90 minutes of training and 35 minutes of testing data). A recent research, Palumbo et al. (2015), who applied neural networks reported a near real-time, testing time is near testing data length, performance. For batch processing the system is supposed to recognize a large amount of activities in a reasonable time.

Table 5.2 Benchmarking using F-measure: the proposed method before and after data smoothing compared with the best results in the challenge and baseline.

Method	Posture w Null			Posture w/o Null			Gesture w Null			Gesture w/o Null		
	S2	S3	[S2 S3]	S2	S3	[S2 S3]	S2	S3	[S2 S3]	S2	S3	[S2 S3]
UP	0.58	0.62	0.60	0.88	0.80	0.84	0.64	0.64	0.64	0.23	0.19	0.22
CStar	0.60	0.65	0.63	**0.90**	0.83	0.87	0.88	**0.87**	**0.88**	**0.72**	**0.80**	**0.77**
MI	0.85	0.81	0.83	0.87	0.86	0.86	-	-	-	-	-	-
MU	0.57	0.68	0.62	0.86	0.87	0.87	-	-	-	-	-	-
Baseline	**0.86**	**0.83**	**0.85**	0.86	0.85	0.85	**0.89**	0.86	0.85	0.53	0.58	0.56
Proposed	0.84	0.77	0.81	0.88	0.87	0.87	0.82	0.77	0.79	0.56	0.61	0.59
Smoothed	**0.86**	0.80	0.83	**0.90**	**0.90**	**0.90**	0.82	0.78	0.78	0.61	0.68	0.58

Two highly cited methods are applied on the current database: Chen et.al (2008) and Altun et al. (2010) and compared with the proposed feature selection and calculation method with regards to the number of features, calculation time and F-measure of classifier results. Chen et al. proposed a method for accelerometer sensors and Altum et al. method is for IMUs which include accelerometer, gyroscope and magnetic sensors. The applied dataset includes 19 body sensors: 12 accelerometers and 7 IMUs. In Table 5.2, benchmarked with the challenge, the proposed method benefits from all sensors. Although, in the results shown in Table 5.3, only signals from accelerometers are used for comparing the proposed method with Chen et al. and IMU signals compared with Altun et al. At this stage, this research aims to compare methods in terms of feature selection, therefore, data smoothing is not applied.

The number of features proposed in this research is considerably less compared to aforementioned researches. Chen et al. calculated 24 features for each sensor but the current research, as explained in section 4.3, has only 2. For IMU sensors, Altum et al. calculated 234 features per sensor while this research has 5. According to their method, for each sensor there are 3 (ACCEL, GYRO, Magnet) 3-axis equal 9 and from each one 5 simple features therefore it will be 45 signals. These signals (45), their Fourier peaks (45) and the frequency values correspond to these peaks (45) and eleven autocorrelation samples placed in the feature (11*9=99). After that PCA, principal component analysis is used, which reduced features to 30 but at the cost of losing some F-measure. The number of features not only affects feature calculation and classification time but also requires more storage space as it is preferable than saving raw signals data. Even though the proposed method is considerably faster and less storage consuming, the final classification results are comparable with Chen et al., very near to Altum et al. without applying PCA and better than it with PCA. Having fewer features not only save memory and CPU for batch processing but also, if they relatively simple, they can be extracted in a simple micro-controller system located in the sensing end and then be transmitted to the computer node for signal processing: it is more energy and bandwidth efficient (Ghayvat et al., 2015). The proposed method that avoids complicated calculations, like Fourier transform, and has fewer number of features is suitable for this purpose especially when the amount of collected data is huge and there is no fast and persistent connection to transmit them.

Table 5.3 Comparing the proposed feature extraction method with Chen et al. 2008 and Altun et al. 2010 in terms of the number of features, calculation time and F-measure.

		Features			**Posture**				**Gesture**			
Sensors	**Method**	**Number**	**Time***	**Time****	**S1**	**S2**	**S3**	**All**	**S1**	**S2**	**S3**	**All**
12x ACC w/o Null***	Chen et al.				90.5	87.0	83.8	85.4	49.6	30.4	48.5	79.5
	Proposed				87.1	82.4	77.8	81.4	49.5	38.2	46.4	43.0
12x ACC w Null	Chen et al.	24 * 12	52	31	85.8	78.4	80.3	71.1	55.3	62.9	58.6	83.5
	Proposed	2 * 12	33	1.5	77.8	70.5	66.7	69.8	68.3	76.3	37.6	74.1
7x IMU w/o Null	Altun et al.				90.6	90.0	88.1	83.5	51.4	46.3	52.3	47.4
	Altun (PCA)				89.8	88.8	85.3	81.8	48.8	40.3	50.2	44.1
	Proposed				90.9	87.2	87.4	86.9	50.4	44.2	51.3	45.9
7x IMU w Null	Altun et al.	234 * 7	414	238	85.3	84.8	80.3	82.7	62.8	69.2	65.8	67.9
	Altun (PCA)	30	610	351	82.4	84.2	78.0	80.5	50.8	67.1	44.6	63.2
	Proposed	5 * 7	45	2	84.3	78.7	77.9	78.1	74.5	77.1	73.6	74.3

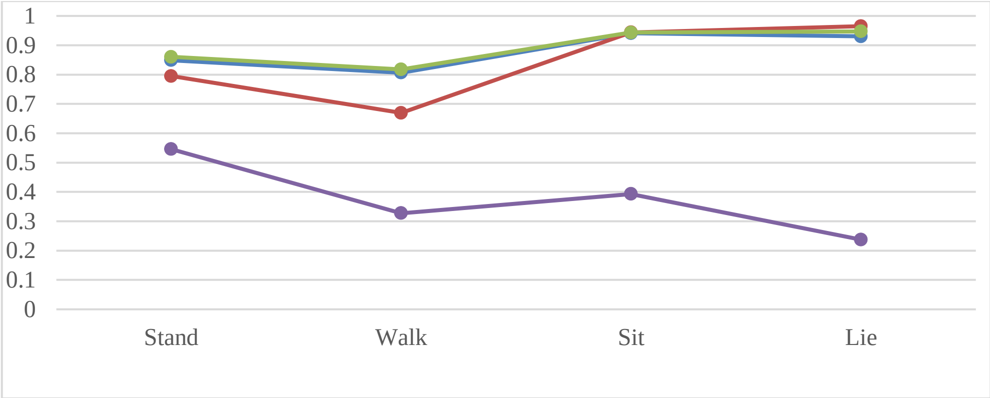
* Time= Calculation time of features for all activities of subject 2, in seconds.
** Time= Average calculation time for one instance, in milliseconds.
*** nx ACC/IMU n= number of sensors, ACC=Accelerometer, IMU=Inertial Measurement Unit

5.2.2 Performance of Different Assemblies of Sensors

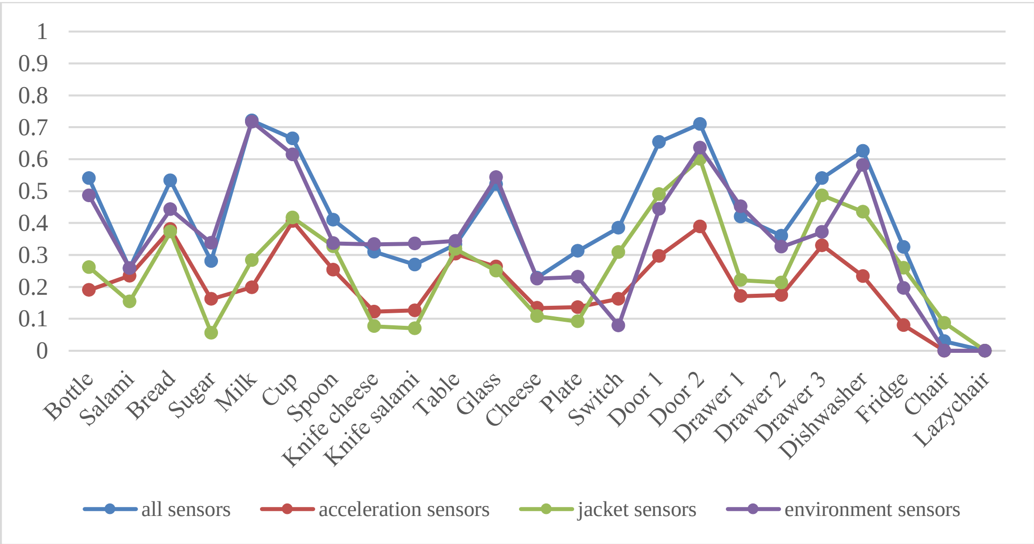
Chavarriaga et al. (2013), who creates Opportunity dataset, have used sensors excessively; that includes four sets of sensors: (a) 12 ACCEL on subjects' body, (b) 7 IMUs on subjects' jacket and shoes, and (c) Various sensors on environmental objects. (d) Indoor positioning tags. Although this arrangement makes the dataset very flexible for different usage, it is costly to use all the sensors for practical systems.

In this section, the recognition rate for different assemblies of sensors are compared. As it can be seen in Figure 5.2, red (accelerometers) and green (IMUs on jacket) have similar functionality of different classes but green has a better performance. Indeed, in most cases after dismissing red, nothing will be lost, while set B is present. For posture recognition, purple (environmental) has no positive effect and maximum performance can be reached with green. In reverse for gesture recognition, purple (environmental) has a critical role, but red or green sets (body) also increase the performance. Magnetic field signals from IMU on the back and electronic compass from IMU on the shoes provide almost same information, but the second one is more accurate. None of aforementioned are used in classification phase, however; coded information from shoes compass is directly stored in the knowledge base.

Excluding some sensors in each of these sets is not studied, as sensor configuration is out of scope of this research. Nevertheless, for commercial implications, it must be done to reach a tradeoff between performance from one side and cost and cumbersomeness from other.



(a)



(b)

Figure 5.2 Average F-measure of different assemblies of sensors for (a) postures and (b) hand-object interactions, nulls excluded.

5.2.3 Final Probabilistic Ontology Triples

The following sets of "probabilistic ontology triples" have been generated; they can be chosen to be the foundation of an ontology for recognition of high-level activities. (1) Postures (2) Gestures (3) Hand-object interactions for both right and left hands (4) Hand movements for both right and left hands (5) Compass, coded and non-probabilistic (6) Location positioning. Since 5 and 6 are not manually labeled in the dataset, the labels are generated for both training and test sets for them. All triples are produced from the information made by data driven phase and before data smoothing, which can be done in knowledge driven stage; null classes are included.

It should be taken into consideration that not always the most probable class is the actual target. Therefore, this research benefits from the second and the third probable class as well, including the other two most probable choices could drastically increase the chance of finding the actual target. Figure 5.3 shows how probable it is that the actual target is the first choice, is one of the first or second choices, or is among the first three choices, for the gesture with 18 different targets.

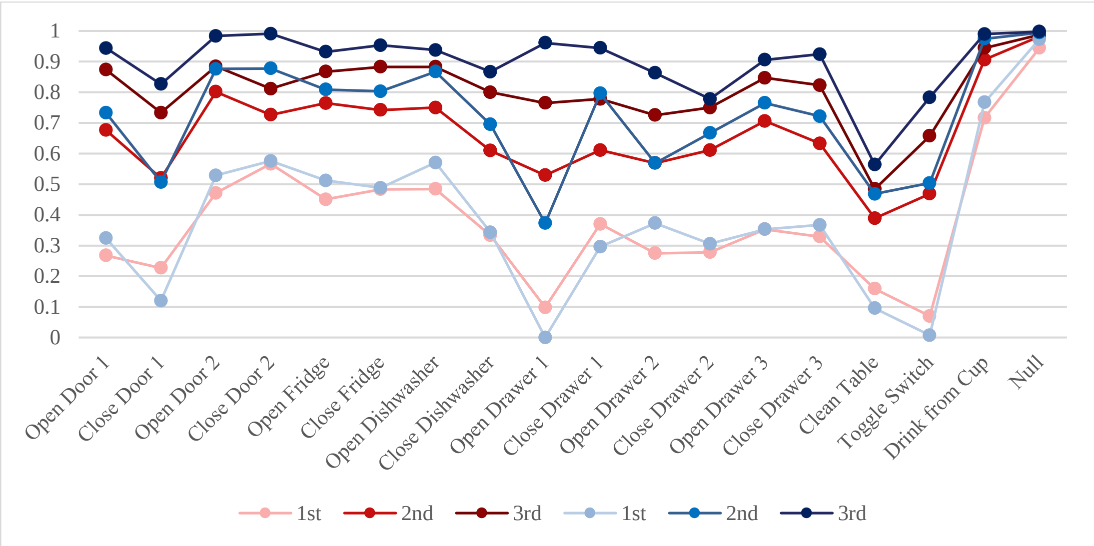


Figure 5.3 Probability of detection in the first, first two and the first three choices of "hand interactions with objects", nulls included, RED first results, BLUE after smoothing.

In this part of research, the first outcome of the classifier and normalized values of locations, and all of these after data smoothing, are accompanied with values which are called "probability" in the classification tools and methods. These values are between 0 and 1, outcome of the classification method, and the higher they are it means more certainty for that activity or location is assured. They are slightly different from classic probability that is defined as exact number of true predictions divided to number of all cases. Nevertheless, the obtained results can be treated as probabilistic information and stored in the form of a probabilistic ontology triples.

5.3 Evaluation of the Knowledge-Driven Methods

In this section the model, the time performance, and the accuracy performance of the knowledge-driven methods are presented and compared with the well-known methods in this area. To the best of our knowledge, this is the first ontology-based knowledge driven work for human activity recognition that makes use of probabilistic observations from sensors.

5.3.1 Model Evaluation

To evaluate and compare human activity recognition models, Zolfaghari et al. (2017) proposed six criteria. Here, these benchmarks are exploited to show the advantages and drawbacks of the proposed ontology-based, fully probabilistic, scalable system for human activity recognition.

(a) Ability to handle uncertain, noisy data and incomplete ambiguous information: The proposed model is fully probabilistic in all stages, which provides a very high ability in dealing with uncertainty including imperfect data from sensors and non-deterministic axioms.

(b) Ability to model complex activity correlations: Unlike OWL based models, in the proposed model, axioms are not limited to a tree-like schema. Relational model empowers the system to store and manage complex correlations in the form of tuples.

(c) Supporting temporal reasoning: In the proposed system, instants are not isolated islands; the value of one instant is related to the values of instances before and after and the duration of activities is involved in the inference process. If the dataset contains real-time stamps, SQL is able to store and process this type of data.

(d) Expressive representation: As the method is not implemented based on the knowledge representation languages, the expressive representation benchmark cannot directly apply to it. On the other hand, almost all queries, with more or less effort for query designing, are expressible using SQL. There are just some exceptions like recursive queries that cannot be written in SQL.

(e) Reusability: The proposed framework is highly reusable; it does not depend on any particular subject, environment and activity set. In case of changing the location, e.g. from the kitchen to workhouse, the only necessary change is to redesign the interface of the application of defining LAP axioms.

(f) Ability to model complicated activities: The proposed system does not model concurrent, parallel, and multi-subject activities. The applied dataset, Opportunity, does not contain such data and is limited to “daily morning activities” and not full day activities. Nevertheless, the proposed framework is extendable to model more complex activities. It is discussed in future works.

5.3.2 Accuracy Performance Evaluation

In this section, the impact of the proposed methods are evaluated. The first proposed method is probabilistic data smoothing. It is applied to LAP (Location, Angle, Posture) and BHO (Both Hands Object interactions); however, because there is no manual label for location and angle of the subject, the correctness of the predicted labels for LAP cannot be measured. Labels for right and left hands interactions with objects are available and can be compared with predicted labels, before and after data smoothing.

There are 24 different states for each hand, which means there are 24*24=576 possible states for both hands but in the dataset, there are 479 available states. The predictions are evaluated using a simple metric, hit rate: number of correctly predicted instances to the number of all instances, not only because of numerous classes but also because the first, second and third probable predictions are important in evaluation. The under/over fill window is assumed 1 second. In about half of instances, both hands are idle, and the value is null. The evaluation is done once with and once without null values. The results are shown in Table 5.4.

Table 5.4 Hit rate of BHO, before and after the probabilistic data smoothing.

	Including nulls		Excluding nulls	
	bf/smoothing	**af/smoothing**	**bf/smoothing**	**af/smoothing**
1st prediction	0.680	0.717	0.478	0.513
1st or 2nd prediction	0.781	0.807	0.627	0.658
1st, 2nd or 3rd prediction	0.832	0.850	0.710	0.730

bf: before / af: after

This part of research aims to correctly predict the high-level activities. The evaluation of the results of this part reveals the total performance of the proposed system including obtaining the assertion axioms and the inference process. Since the manual labels are in the form of fixed length instances, the final ontology is converted to this format. The assertion axioms are automatically obtained. Some apparent manual modifications in LAP axioms, using the application, led to some improvement of results, but because of difficulties in documenting the details of modifications, the results are ignored.

Figure 5.4 depicts F-score for predicting high-level activities; (a) First choice: considering only the most probable choice or the first reported choice, which means using non-probabilistic input data, (b) Probabilistic: considering 1st,2nd and 3rd most probable choices and their probability values. In both a and b, selection of the target is done with naïve Bayes method, (c) Final: after three-step of removing the short length activities, (d) Under/over fill effect is eliminated.

As shown in Figure 5.4, three most probable choices are more informative, and the proposed system take advantage of this fact to improve results from (a) to (b). After three-step of removing the short length activities which are most likely to be errors, explained in section 4.4.5, the results are again improved from (b) to (c). As the manual labels are assigned by a human observer, the boundary between activities, e.g. from *sandwich time* to *cleaning*, are not very clear and even different human observers may choose a different time. The automatic system also may determine the starting time of the activity a bit earlier, underfill, or a bit later than what the observer labeled, overfill. In such situation, the performance of the system is estimated lower than what is. To negate this effect, a window is defined; in (d) if the correct answer is not in the exact place that is predicted, but it is still inside the window, the predicted answer is supposed to be correct. Since the usual length of high-level activities are several minutes, the window size is 30 seconds. In short, in each step, the obtained results are improved.

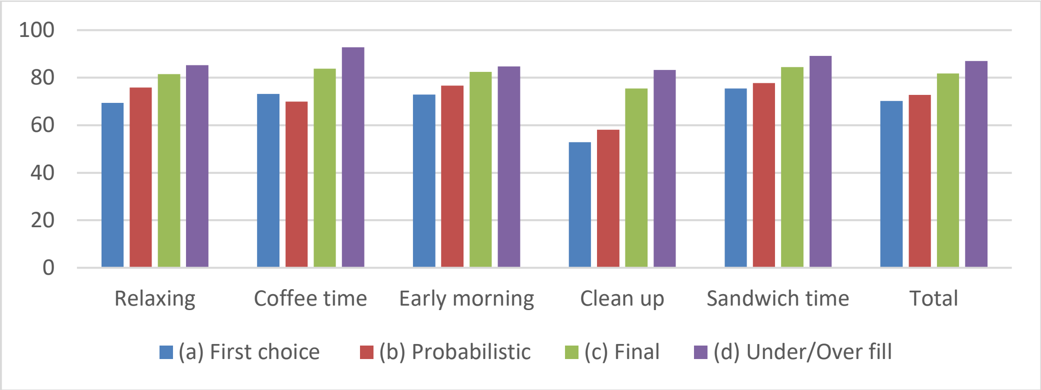


Figure 5.4 F-score for prediction of high-level activities; (a) First choice (most probable), (b) All probable choices, (c) Final, after three steps of removing short activities, and (d) After eliminating the under/over fill effect.

Figure 5.5 compares the actual labels that are made manually by video checking, with the labels made by the system that implements the proposed method before and after three steps of removing short activities, in three consecutive lines.

As shown with magnifier with more clarity, sometimes the predicted labels differ from the actual labels, as there are some wrong predictions. The proposed technique of removing short activities in three steps could successfully correct some of these wrong predictions. For instance, the bottom timeline of subject 1 in Figure 5.5 shows that the predicted labels are disturbed with wrong predictions when compared with actual labels. The middle line of the same subject shows that many of these wrong predictions are corrected using the proposed method. What is reported as “Final” in Figure 5.5 is the same as “Final” in Figure 5.4, and “Predicted” in Figure 5.5 is the same as “Prob” in Figure 5.5. Target wise, the highest improvement with more than 17% goes to *cleaning up* with this method, which is depicted with green lines in Figure 5.5.

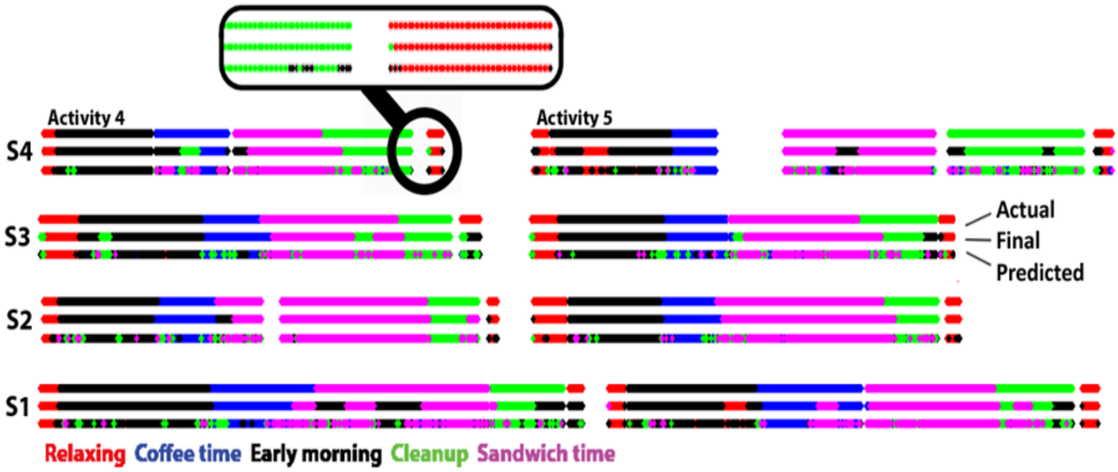


Figure 5.5 Comparison of actual, manually labelled, activities with predicted labels by the proposed system before and after three steps elimination, for four persons (S1-S4) each perform two testing activities.

According to Manzoor et al. (2010 KNN has relatively the best performance on the same dataset. KNN is employed in the same way that they used on the training and testing sets. In addition to KNN classifier, the current approach is compared with previously research done in this area, a research that applied the same dataset that is used by this research), discussed in section 2.3.5. They employed neutrosophic lattice and fuzzy lattice methods for activity recognition (Mittal, Gopal and Maskara 2015); all of these three methods are using manual labels of low-level activities provided by the dataset developers. In contrast, the fully probabilistic method, proposed by this research, used probabilistic predictions computed from sensors data. In other words, for proposed method the input data is not error-free, but it is for three other methods.

As shown in Figure 5.6, although the proposed method is dealing with uncertain data from sensors, it could surpass the other methods. For all the targets, the fully probabilistic method showed a considerable improvement. Target wise the highest improvement, comparing the average performance of the other two methods, goes to *cleaning up* with 30% and the lowest goes to *early morning* with 10% improvement. Moreover, the proposed method has less deviation; the performance is almost the same for all targets of high-level activities. The results could be improved even more if temporal and order-based probabilistic reasoning had been done. Although in the applied dataset, as shown in Figure 5.5, all subjects perform activities in the same order.

The recognition rates are not relying only on HAR techniques, they also depend on how subjects perform their activities. For example, as shown in Figure 5.7, the proposed method, comparing other methods, has much better recognition rate for subject 2. Also, for the subject that performs in more uncertain condition, with sensor failure and relocation, the proposed method performs better than others, particularly for activities which interacts with objects: *cleaning* time and *sandwich time*.

All the Confusion matrixes are reported in Figure 5.8. It illustrates details of classification data and how the performance is improved in four stages: a) Classifying isolated instances without smoothing. b) Data smoothing algorithm is applied but there are no probabilistic candidates and only the most probable choice is used. c) Probable choices are used and the algorithm for removing short activities is applied. d) Under/over fill effect is eliminated.

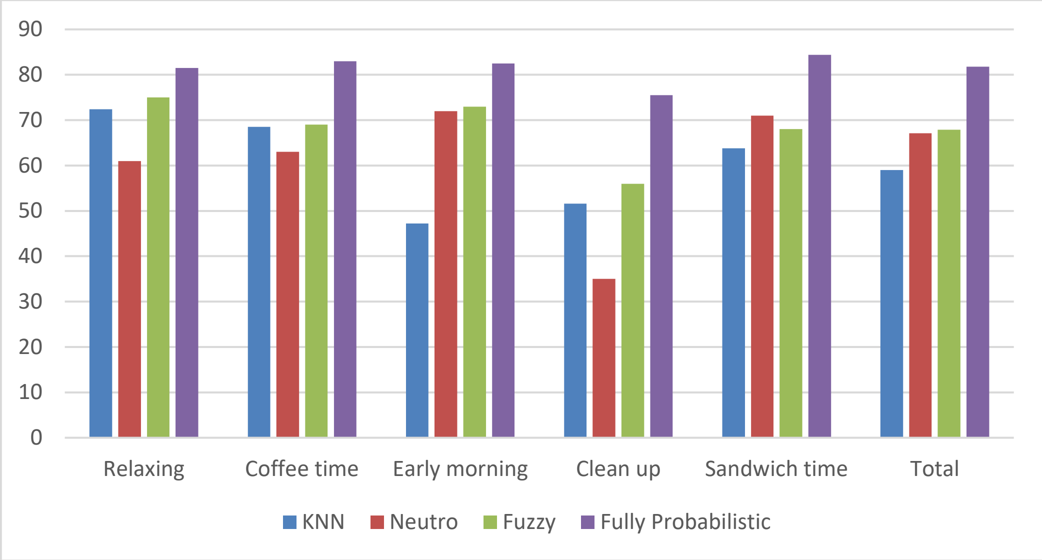


Figure 5.6 The performance (F-score) of KNN, Neutrosophic lattice, Fuzzy lattice, and the proposed method: Fully Probabilistic, for 5 targets of high-level activities.

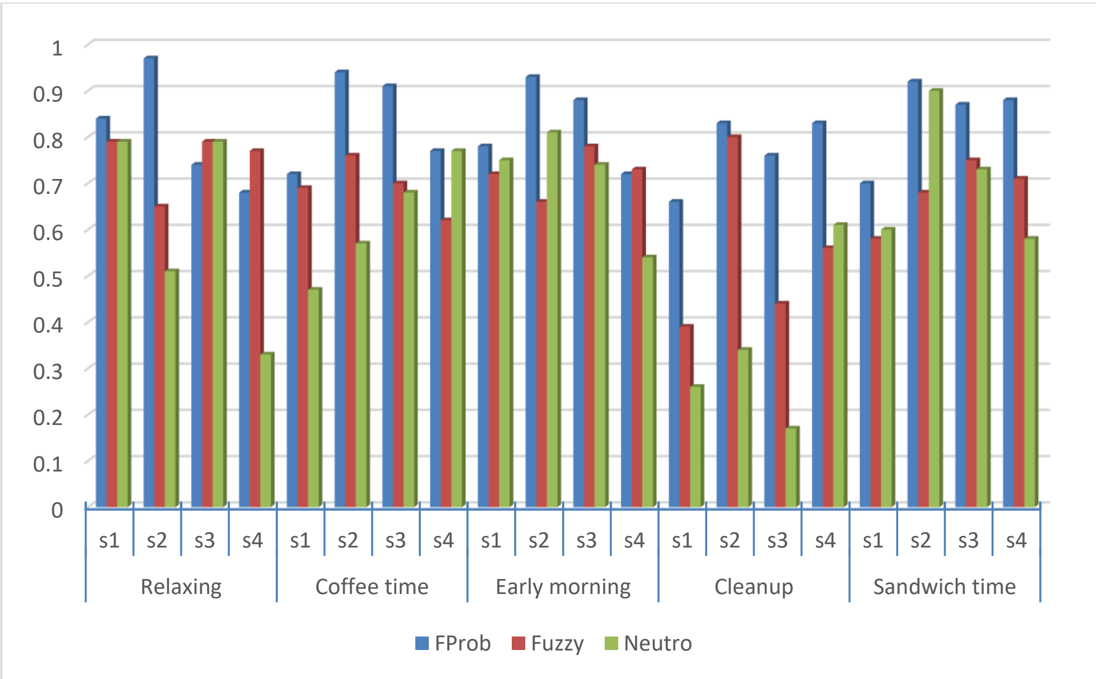


Figure 5.7 The performance of Neutrosophic lattice, Fuzzy lattice, and the fully probabilistic, proposed, for 5 targets of high-level activities separately for each subject.

	Relaxing	Coffee time	Early morning	Cleanup	Sandwich time	Classification overall	Producer Accuracy (Precision)
Relaxing	1233	20	373	58	6	1690	72.959%
Coffee	0	2102	273	306	447	3128	67.199%
Early m..	322	80	4243	317	97	5059	83.87%
Cleanup	0	293	526	1922	571	3312	58.031%
Sandwich	9	388	590	700	4903	6590	74.401%
Truth overall	1564	2883	6005	3303	6024	19779	
User Accuracy (Recall)	78.836%	72.91%	70.658%	58.19%	81.391%	F-score = 72.64	

(a)

	Relaxing	Coffee time	Early morning	Cleanup	Sandwich time	Classification overall	Producer Accuracy (Precision)
Relaxing	1019	46	578	35	12	1690	60.296%
Coffee	1	2328	281	216	302	3128	74.425%
Early m..	213	81	4307	256	202	5059	85.135%
Cleanup	4	346	712	1565	685	3312	47.252%
Sandwich	8	435	880	540	4727	6590	71.73%
Truth overall	1245	3236	6758	2612	5928	19779	
User Accuracy (Recall)	81.847%	71.941%	63.732%	59.916%	79.74%	F-score = 70.20	

(b)

	Relaxing	Coffee time	Early morning	Cleanup	Sandwich time	Classification overall	Producer Accuracy (Precision)
Relaxing	1278	0	339	72	1	1690	75.621%
Coffee	0	2385	207	77	459	3128	76.247%
Early m..	170	36	4794	59	0	5059	94.762%
Cleanup	0	0	510	2244	558	3312	67.754%
Sandwich	0	145	713	181	5551	6590	84.234%
Truth overall	1448	2566	6563	2633	6569	19779	
User Accuracy (Recall)	88.26%	92.946%	73.046%	85.226%	84.503%	F-score = 81.81	

(c)

	Relaxing	Coffee time	Early morning	Cleanup	Sandwich time	Classification overall	Producer Accuracy (Precision)
Relaxing	1347	0	302	40	1	1690	79.704%
Coffee	0	2710	49	77	292	3128	86.637%
Early m..	126	0	4874	59	0	5059	96.343%
Cleanup	0	0	510	2608	194	3312	78.744%
Sandwich	0	0	713	181	5696	6590	86.434%
Truth overall	1473	2710	6448	2965	6183	19779	
User Accuracy (Recall)	91.446%	100%	75.589%	87.96%	92.124%	F-score = 86.97	

(d)

Figure 5.8 Confusion matrix and F-score for prediction of high-level activities (a) isolated instances (b) without different probable candidates (c) after three steps of removing short activities (d) after eliminating the under/over fill effect.

5.3.3 Time Performance

A HAR system is scalable if it is able to process a big amount of data in a reasonable time. CPU time usage in an efficient way does matter and the system fails if it is not ready for being scalable to perform on big data. One of the key advantages of the proposed system is time performance that enables it to perform batch processing. Unlike real-time activity recognition systems, the system must be highly scalable to process the activity data in a much shorter time than the activity performing time.

The experiment is carried out on Dell Precision 3620 machine, which is equipped with 3.6GHz Intel i7-4790 quad-core processor and 16 GB RAM running Microsoft SQL Server 2016 express edition, the free version, 64 bits.

Table 5.5 The running time of procedures in hours, minutes and seconds, the time length of the activity of the processed data and ratio of processing to activity time length.

Procedure	Activity length	Processing time	Ratio
BHO data smoothing	2:02:42	0:02:40	0.0217
LAP data smoothing	5:30:00	0:05:25	0.0164
3-Step elimination of HL	1:49:53	0:01:02	0.0094

The running times of queries which are reported by SQL Server are recorded. The training data is about 3 hours and a half and there is about 2 hours of testing data. With this amount of data, for all queries, including obtaining the assertion axioms and inference process, the running time is reported as zero which means it is less than one second. There are only three exceptions: 1) running time of procedures for data smoothing of LAP (for all available data, interval size three) 2) and for BHO (for testing data, interval size five) and, 3) the three-step elimination of High-level activities. They are reported in Table 5.5 to illustrate an overview of time performance of the system. In short, the processing time for preprocessing, obtaining axioms and inference are very short; however, the applied techniques for the improvement of the system performance are relatively time-consuming. The current system running on the former mentioned computer for processing the testing data is 27 times faster than a real-time system and processing the training data is 61 times faster.

5.4 Chapter Summary

This chapter was about the obtained results and model evaluation. For Data driven methods the results are compared with methods that used the same dataset and also some highly cited methods were implemented with the applied dataset to be comparable with the proposed methods and algorithms in this research. The obtained accuracy in some cases is higher and, in some cases, very close to them. In the case of the processing time, the proposed methods in the current research could perform much faster. For knowledge-driven the model is assessed using criteria for ontological models for HAR, and the results were compared with other methods that applied non-probabilistic methods. The performance of the proposed system was relatively higher compared to the benchmarked methods. The processing time of the knowledge-driven phase is also reported in detail.

CHAPTER 6

CONCLUSION AND RECOMMENDATIONS

6.1 Overview

Sensor-based HAR has been around for a few years. These methods focused on accuracy, not on processing time; what they aimed, in the most difficult conditions, is a real-time system: if the actual activity time is one hour the processing time should be one hour or less. One of the goals of this research is scalability. If the activity time is only ten minutes the system should process it, if there are several recordings with hundreds of hours of activities, again the system should be able to process them in a reasonable time. In other words, the proposed system is supposed to process big data while the accuracy is still important.

6.2 Research Outcomes

In this research, several methods/algorithms are proposed and tested to make probabilistic ontological reasoning for a realistic sensor-based human activity dataset with uncertain observations a possibility; while improving the performance. To reach this goal, the following conclusions, based on the research objectives, are achieved:

In the data-driven part of research, a set of human activity recognition methods are proposed to extract probabilistic information, including low-level activities and location, from sensor data, electric signals from sensors attached to body of person, subject, or to environmental objects, for example door of fridge. The extracted information will be low-level activities, for example open the fridge door with the right hand, body postures, for example standing, body direction, using compass, and the location of person in the room. It provides information for a probabilistic knowledge base on human daily activities recognition. Time efficiency and the scalability for big data, batch processing, were the top priority in this research, while the accuracy is still important. Comparison of the results of this research, in terms of time and efficiency, shows this phase of the research was relatively successful in terms of accuracy and it is performing significantly faster in terms of processing time. The number of features is also less than pure statistical, non-semantical, methods; therefore, those extracted features are easier to store.

Developing the ontology model that is able to reason about the information, knowledge-driven methods, is another part of the study. The obtained information is formed as a fully probabilistic ontology, which has probabilistic observations and probabilistic axiom rules. The ontology can automatically learn the axioms and do reason and recognize high level activities, for example *sandwich time*, from *early morning* activities that is in the scope of the dataset. According to outcomes of the research, the ontology model passes all criteria for HAR ontological models, qualitative evaluation, and the activity recognition performance is relatively high compared to other proposed methods that do not use probabilistic information from sensor readings, quantitative evaluation.

A new method for transforming probabilistic ontologies in SQL based relational DBMS and reasoning about them, is also designed in this research. In other words, the proposed ontology is defined and implemented in a commercial relational database management system to ensure the commercial grade performance. The major advantage of this is ease of use by software application and the required time to perform that make it highly scalable for batch processing of big data; it has been confirmed according to the obtained results of the research.

6.3 Findings and Contributions

This section aimed to present the contribution of our research study. The major contributions of this research study are outlined as follows:

i. **Extracting meaningful, semantic features from raw sensor signals.**

As the raw data are not informative enough, the data-driven phase of the research applied several signal processing methods to compute meaningful and applicable features. Unlike most of previous researches who extracted simple statistical or transformational features from all signals, this research tried to extract more meaningful, semantic, features while aimed to have a minimal number of them. These features are more effective in case of time and accuracy when they are used in a classifier and more suitable if stored in a knowledge structure. Then, employed a classifier for calculation of the probability of different targets of postures, gestures, hand-object interactions and hand-movements. Besides, a method introduced to find the most probable locations of the subject in the room using four noise prone location tracking tags attached to his body. The results of applying these methods on Opportunity dataset, an EU project for benchmarking human activity recognition methods, generated a new probabilistic dataset which is publicly accessible for download[2].

ii. **Developing an ontological activity recognition work with probabilistic observations.**

The knowledge-driven phase of study presented a set of methods to recognize coarse-grained, high level, human activities from probabilistic fine-grained, low-level, activities that are obtained from location, body and environmental sensors. The model is able to deal with uncertainty, e.g. sensor failure and it is reusable for different subjects, environments and activities. To the best of our knowledge, this research is the first ontological activity recognition work that uses probabilistic observations from sensors as input.

[2] http://dx.doi.org/10.17632/ny4y6mctbm.1

iii. Transforming the probabilistic ontology into a relational database.

Prior to this research, there were few research on transforming simple ontologies into relational databases, very limited researches on classification and doing reasoning using relational databases and no effort on storing probabilistic ontologies in relational databases. This research is an attempt to consider applying the above strategies to improve execution time and storage.

6.4 Future Works

The direction of future work of data-driven phase is to make use of all the obtained results, the published probabilistic dataset, as building blocks for a probabilistic ontology, besides that is made in knowledge-driven phase. The ontological knowledge base will use the probabilistic predictions for subjects' low-level activities and location. The semantic rules can be defined according to human knowledge or can be learnt from data, and then system will be able to make prediction for high-level morning daily activities. Combining these with other kinds of activity recognition methods, including camera based HAR, is another direction of future research. In this case the higher recognition rate can be reached with less installed sensors, but at the cost of more complexity and processing time. The signal processing algorithms and feature selection methods are subject to be improved, particularly if they are designed to work state of art, more accurate, sensors.

The proposed model in knowledge-driven part of the research is capable to be extended to deal with complex high-level activities, to discover order and relationship between them and do temporal reasoning about instances with real timestamps. For example, using a real-world whole day recording with clock time stamps aimed to be used for psychological studies, the system is able to discover habits of the specific person for order and time of activities. The chosen dataset for this research, Opportunity, had specific merits but also limitations. Near real-world circumstances, fully covered with sensors with some controlled sensor faults and failures beside favorable assortment and labeling facilitate the researchers to develop a reusable, fully probabilistic ontology-based system for HAR. However, on the other hand, it is limited to short period daily activities from waking up in the morning until finishing the breakfast. Even though subjects are free to do each activity in the desired timespan, all high-level activities are performed in the same order. To develop more advanced practical activity recognition systems, there is a need for superior datasets that are recorded in enough sensor coverage, in a near real-life conditions and with proper labeling; they also should contain activities of whole or a major part of the day, for example a long working day that includes resting times, performed on various orders, and including clock time. In such a dataset and HAR system, high-level activities are not obtained from low-level activities only; they also can be obtained from real time and order and relationships between activities.

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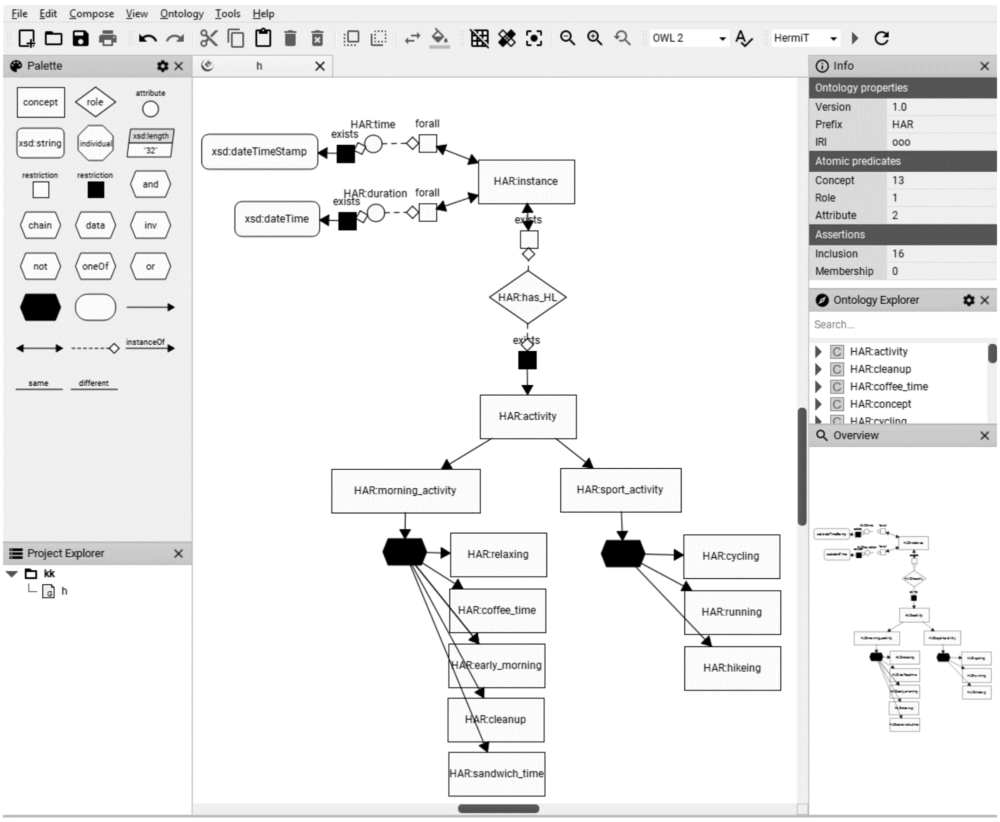
Appendix A Ontology Manual and Details

Here is the description of ontology nodes and edges in Eddy and Graphol, that used for illustration of the ontology of the current research.

Symbol	Name	Symbol	Name
	Concept node		Role node
	Attribute node		Value-domain node
	Individual/ Value node	Restriction type	Domain restriction node
Restriction type	Range restriction node		Inclusion edge
and	Intersection node	or	Union node
not	Complement node		Input edge
inv	Inverse node	oneOf	One-of node
chain	Role chain node		

GRAPHOL predicate nodes, constructor nodes, and edges.

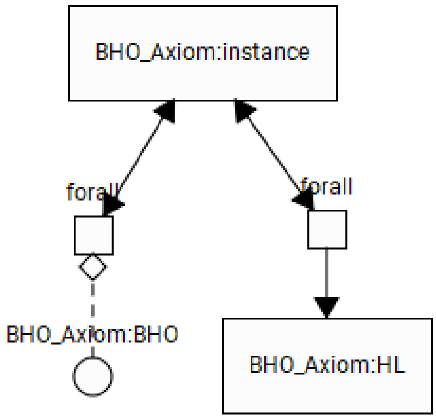


Eddy's user interface with an example

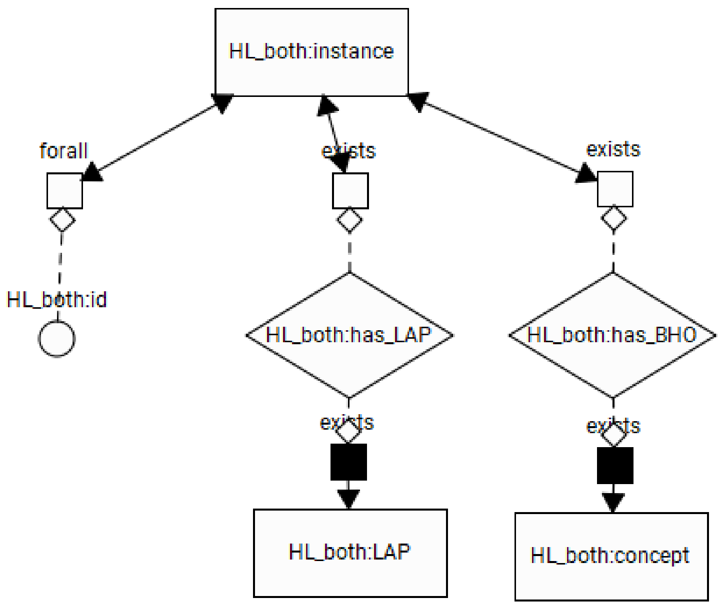
The primary ontology, from triples coming from signal processing is shown in Figure 4.11. Here the further steps of ontology population are illustrated:

1- **Smoothing of LAP and BHO.** This procedure does not change the structure of the ontology, but it increases the accuracy. It just updates the data.

2- **Automatic and manual development of assertion axioms.** For each value for LAP and BHO, available on training dataset or defined by user, there will be an instance on axioms. Each instance has a class of HL activity (because the system is probabilistic, the number of classes can be more than one, each has a probability and sum of them is 1). BHO is shown here, LAP has the same structure.



3- **Suggestion of HL activity for each instance, based on LAP and BHO.** At this stage, the reasoning process using values of instances and axioms, populates ontology with new instances, each has two high level activities, one from LAP and one from BHO (Again, both of them are probabilistic with up to five classes).



4- At this stage, the reasoner combines both probabilities and decides about the high-level activity of the particular instance. High-level activity was in primary structure, Figure 4.11; for training instances it already has value but for testing instances, the recognized value is placed in the ontology at this stage.

5- Three-step elimination changes the values of HL activity for some instances, but like step 1, it changes the data only.

Appendix B SQL Codes

Part 1. Preparation and smoothing of BHO

10_triples_obj

```
SELECT        [triples_or].id, 'h' + iif([ro] = '0', '00', RIGHT([ro], 2)) +
iif([lo] = '0', '00', RIGHT([lo], 2)) AS cd, iif(dbo.[triples_ol].pr < 0.01,
0.01, dbo.[triples_ol].pr) * iif(dbo.[triples_or].pr < 0.01, 0.01,
dbo.[triples_or].pr) AS prb
FROM          [triples_or] INNER JOIN
                       [triples_ol] ON [triples_or].id = [triples_ol].id
```

11_cods_obj

```
SELECT        COUNT(id) AS num, 'h' + iif(Lrightobj = '0', '00',
RIGHT(Lrightobj, 2)) + iif(Lleftobj = '0', '00', RIGHT(Lleftobj, 2)) AS cod
FROM          tr_lab_train
GROUP BY 'h' + iif(Lrightobj = '0', '00', RIGHT(Lrightobj, 2)) + iif(Lleftobj
= '0', '00', RIGHT(Lleftobj, 2))
HAVING        (COUNT(id) > 9)
```

14_ranked_obj

```
SELECT        [nbrfull].iid AS id, [nbrfull].accod, [nbrfull].pr AS mxpr,
RANK() OVER (PARTITION BY iid
ORDER BY pr DESC) AS rnk
FROM          [nbrfull]()
```

15_testlabs_obj

```
SELECT        id, 'h' + iif(Lrightobj = '0', '00', RIGHT(Lrightobj, 2)) +
iif(Lleftobj = '0', '00', RIGHT(Lleftobj, 2)) AS codt
FROM          tr_lab_test
```

```
ALTER FUNCTION [dbo].[nbrest] (@id int)
RETURNS @trackingItems TABLE (
accod    varchar(5)   NOT NULL,
pr       float        NOT NULL
)
AS
BEGIN
declare @temp table (acv varchar(5),prr float)

insert into @temp select cd,prb from dbo.[12_m]  where id between (@id - 3)
and (@id + 3)
insert into @trackingItems select top 3 acv,sum (prr)/count(prr) as E1 from
@temp group by acv ORDER BY E1 DESC

declare @sm float
set @sm = (select sum(pr) from @trackingItems)
update @trackingItems set pr = (pr / @sm)
RETURN;
END;
```

```sql
ALTER FUNCTION [dbo].[nbrfull] ()
RETURNS @t TABLE (iid int not null, accod   varchar(5)   NOT NULL, pr
float        NOT NULL)
AS
begin
declare @c int

set @c = 11066
while (@c < 17062)
begin
set @c = @c + 1
insert into @t select @c, * from nbrest (@c)
end

set @c = 32183
while (@c < 38316)
begin
set @c = @c + 1
insert into @t select @c, * from nbrest (@c)
end

set @c = 52051
while (@c < 57185)
begin
set @c = @c + 1
insert into @t select @c, * from nbrest (@c)
end

set @c = 72929
while (@c < 77749)
begin
set @c = @c + 1
insert into @t select @c, * from nbrest (@c)
end

RETURN
end
```

Part 2. Preparation and smoothing of LAP

21_avg_arc

```
SELECT        iid, pr, accod
FROM            dbo.arcfull() AS arcfull_1
```

23_mixed_arc

```
SELECT        [21_m].iid, [21_m].accod AS arc, [21_m].pr AS mxpr, rank() OVER
(partition BY iid
ORDER BY [21_m].pr DESC) AS rnmx
FROM            [21_m]
```

24_finalfr_arc

```
SELECT          dbo.triples_main.id, MAX(dbo.[23_mixed_arc].arc) AS arcc,
MAX(dbo.[23_mixed_arc].mxpr) AS pr
FROM            dbo.[23_mixed_arc] RIGHT OUTER JOIN
                         dbo.triples_main ON dbo.[23_mixed_arc].iid =
dbo.triples_main.id
WHERE        (dbo.[23_mixed_arc].rnmx IS NULL) OR
                         (dbo.[23_mixed_arc].rnmx = 1)
GROUP BY dbo.triples_main.id


ALTER FUNCTION [dbo].[arcest] (@id int)
RETURNS @trackingItems TABLE (
accod    varchar(5)   NOT NULL,
pr       float        NOT NULL
)
AS
BEGIN
declare @temp table (acv varchar(5),prr float)

insert into @temp select arc,iif(id<@id, pr, pr+0.01) from dbo.[triples_arc]
where id between (@id - 5) and (@id + 5)
insert into @trackingItems select top 3 acv,sum (prr)/count(prr) as E1 from
@temp group by acv ORDER BY E1 DESC

declare @sm float
set @sm = (select sum(pr) from @trackingItems)
update @trackingItems set pr = (pr / @sm)
RETURN;
END;


ALTER FUNCTION [dbo].[arcfull] ()
RETURNS @t TABLE (iid int not null, accod   varchar(5)   NOT NULL, pr
float        NOT NULL)
AS
begin
declare @c int
```

```
set @c = 0
while (@c < 17062)
begin
set @c = @c + 1
insert into @t select @c, * from arcest (@c)
end

set @c = 22415
while (@c < 38316)
begin
set @c = @c + 1
insert into @t select @c, * from arcest (@c)
end

set @c = 43478
while (@c < 57185)
begin
set @c = @c + 1
insert into @t select @c, * from arcest (@c)
end

set @c = 64115
while (@c < 77749)
begin
set @c = @c + 1
insert into @t select @c, * from arcest (@c)

end
RETURN
end
```

Part 3. Preparation of train and test sets

3_tr_ar

```
SELECT        dbo.triples_main.id, dbo.[24_finalfr_arc].arcc
FROM            dbo.[24_finalfr_arc] RIGHT OUTER JOIN
                         dbo.triples_main ON dbo.[24_finalfr_arc].id =
dbo.triples_main.id
WHERE        (RIGHT(dbo.triples_main.subject, 1) = '1') OR
                         (RIGHT(dbo.triples_main.subject, 1) = '2') OR
                         (RIGHT(dbo.triples_main.subject, 1) = '3')
```

3_tr_ho

```
SELECT        id, 'h' + iif(Lrightobj = '0', '00', RIGHT(Lrightobj, 2)) +
iif(Lleftobj = '0', '00', RIGHT(Lleftobj, 2)) AS codt
FROM            tr_lab_train
```

3_ts_ar

```
SELECT        dbo.triples_main.id, dbo.[23_mixed_arc].arc AS arcc,
dbo.[23_mixed_arc].mxpr
FROM            dbo.[23_mixed_arc] RIGHT OUTER JOIN
                         dbo.triples_main ON dbo.[23_mixed_arc].iid =
dbo.triples_main.id
WHERE        (RIGHT(dbo.triples_main.subject, 1) = '4') OR
                         (RIGHT(dbo.triples_main.subject, 1) = '5')
```

3_ts_ho

```
SELECT        TOP (100) PERCENT dbo.triples_main.id, dbo.[141_rank_obj].accod,
dbo.[141_rank_obj].mxpr, dbo.[141_rank_obj].rnk
FROM            dbo.[141_rank_obj] RIGHT OUTER JOIN
                         dbo.triples_main ON dbo.[141_rank_obj].id =
dbo.triples_main.id
WHERE        (RIGHT(dbo.triples_main.subject, 1) = '4' OR
                         RIGHT(dbo.triples_main.subject, 1) = '5') AND
(dbo.[141_rank_obj].rnk < 4) AND (dbo.[141_rank_obj].mxpr > 0.1)
```

Part 4. Generating assertion axioms for BHO

4_101

```
SELECT        COUNT(dbo.[3_tr_ho].id) AS c101, dbo.[3_tr_ho].codt
FROM            dbo.[3_tr_ho] INNER JOIN
                         dbo.tr_lab_train ON dbo.[3_tr_ho].id =
dbo.tr_lab_train.id
WHERE        (dbo.tr_lab_train.Lhlev = N'101')
GROUP BY dbo.[3_tr_ho].codt
```

4_102 …. 4_105 are similar to 4_101

4_tot

```
SELECT        COUNT(dbo.[3_tr_ho].id) AS ct, dbo.[3_tr_ho].codt
FROM            dbo.[3_tr_ho] INNER JOIN
                         dbo.tr_lab_train ON dbo.[3_tr_ho].id =
dbo.tr_lab_train.id
WHERE        (dbo.tr_lab_train.Lhlev <> N'0')
GROUP BY dbo.[3_tr_ho].codt
```

4_hrul

```
SELECT        dbo.[4_tot].codt, CAST(ISNULL(dbo.[4_101].c101, 0) AS float) /
CAST(dbo.[4_tot].ct AS float) AS p101, CAST(ISNULL(dbo.[4_102].c102, 0) AS
float) / CAST(dbo.[4_tot].ct AS float) AS p102, CAST(ISNULL(dbo.[4_103].c103,
0) AS float)
                         / CAST(dbo.[4_tot].ct AS float) AS p103,
CAST(ISNULL(dbo.[4_104].c104, 0) AS float) / CAST(dbo.[4_tot].ct AS float) AS
p104, CAST(ISNULL(dbo.[4_105].c105, 0) AS float) / CAST(dbo.[4_tot].ct AS
float) AS p105
FROM            dbo.[4_tot] LEFT OUTER JOIN
                         dbo.[4_101] ON dbo.[4_tot].codt = dbo.[4_101].codt
LEFT OUTER JOIN
                         dbo.[4_102] ON dbo.[4_tot].codt = dbo.[4_102].codt
LEFT OUTER JOIN
                         dbo.[4_105] ON dbo.[4_tot].codt = dbo.[4_105].codt
LEFT OUTER JOIN
                         dbo.[4_104] ON dbo.[4_tot].codt = dbo.[4_104].codt
LEFT OUTER JOIN
                         dbo.[4_103] ON dbo.[4_tot].codt = dbo.[4_103].codt
```

Part 5. Generating assertion axioms for LAP

5_101

```
SELECT        COUNT(dbo.[3_tr_ar].id) AS c101, dbo.[3_tr_ar].arcc
FROM            dbo.[3_tr_ar] INNER JOIN
                         dbo.tr_lab_train ON dbo.[3_tr_ar].id = 
dbo.tr_lab_train.id
WHERE        (dbo.tr_lab_train.Lhlev = N'101')
GROUP BY dbo.[3_tr_ar].arcc
```

5_102 …. 5_105 are similar to 5_101

5_tot

```
SELECT        COUNT(dbo.[3_tr_ar].id) AS ct, dbo.[3_tr_ar].arcc
FROM            dbo.[3_tr_ar] INNER JOIN
                         dbo.tr_lab_train ON dbo.[3_tr_ar].id = 
dbo.tr_lab_train.id
WHERE        (dbo.tr_lab_train.Lhlev <> N'0')
GROUP BY dbo.[3_tr_ar].arcc
```

```
5_arul

SELECT        dbo.[5_tot].arcc, CAST(ISNULL(dbo.[5_101].c101, 0) AS float) / 
CAST(dbo.[5_tot].ct AS float) AS p101, CAST(ISNULL(dbo.[5_102].c102, 0) AS 
float) / CAST(dbo.[5_tot].ct AS float) AS p102, CAST(ISNULL(dbo.[5_103].c103, 
0) AS float)
                         / CAST(dbo.[5_tot].ct AS float) AS p103, 
CAST(ISNULL(dbo.[5_104].c104, 0) AS float) / CAST(dbo.[5_tot].ct AS float) AS 
p104, CAST(ISNULL(dbo.[5_105].c105, 0) AS float) / CAST(dbo.[5_tot].ct AS 
float) AS p105
FROM            dbo.[5_tot] LEFT OUTER JOIN
                         dbo.[5_101] ON dbo.[5_tot].arcc = dbo.[5_101].arcc 
LEFT OUTER JOIN
                         dbo.[5_102] ON dbo.[5_tot].arcc = dbo.[5_102].arcc 
LEFT OUTER JOIN
                         dbo.[5_105] ON dbo.[5_tot].arcc = dbo.[5_105].arcc 
LEFT OUTER JOIN
                         dbo.[5_104] ON dbo.[5_tot].arcc = dbo.[5_104].arcc 
LEFT OUTER JOIN
                         dbo.[5_103] ON dbo.[5_tot].arcc = dbo.[5_103].arcc
```

6_1_predict

```
SELECT         TOP (100) PERCENT dbo.tr_lab_test.id, dbo.tr_lab_test.Lhlev,
ISNULL(dbo.[3_ts_ar].mxpr * dbo.aruled.p101, 0) AS p101,
ISNULL(dbo.[3_ts_ar].mxpr * dbo.aruled.p102, 0) AS p102,
ISNULL(dbo.[3_ts_ar].mxpr * dbo.aruled.p103,
                         0) AS p103, ISNULL(dbo.[3_ts_ar].mxpr *
dbo.aruled.p104, 0) AS p104, ISNULL(dbo.[3_ts_ar].mxpr * dbo.aruled.p105, 0)
AS p105, ISNULL(dbo.[3_ts_ho].mxpr * dbo.hruled.p101, 0) AS h101,
                         ISNULL(dbo.[3_ts_ho].mxpr * dbo.hruled.p102, 0) AS
h102, ISNULL(dbo.[3_ts_ho].mxpr * dbo.hruled.p103, 0) AS h103,
ISNULL(dbo.[3_ts_ho].mxpr * dbo.hruled.p104, 0) AS h104,
ISNULL(dbo.[3_ts_ho].mxpr * dbo.hruled.p105, 0)
                         AS h105
FROM                dbo.[3_ts_ar] LEFT OUTER JOIN
                         dbo.aruled ON dbo.[3_ts_ar].arcc = dbo.aruled.arct
RIGHT OUTER JOIN
                         dbo.hruled RIGHT OUTER JOIN
                         dbo.[3_ts_ho] ON dbo.hruled.codt =
dbo.[3_ts_ho].accod RIGHT OUTER JOIN
                         dbo.tr_lab_test ON dbo.[3_ts_ho].id =

dbo.tr_lab_test.id ON dbo.[3_ts_ar].id = dbo.tr_lab_test.id
```

6_2_mixhoar

```
SELECT         id, Lhlev, 1 - (1 - 0.7 * p101) * (1 - 0.7 * h101) AS v101, 1 -
(1 - .7 * p102) * (1 - .5 * h102) AS v102, 1 - (1 - .4 * p103) * (1 - .5 *
h103) AS v103, 1 - (1 - 0.9 * p104) * (1 - .7 * h104) AS v104, 1 - (1 - .6 *
p105)
                         * (1 - .5 * h105) AS v105
FROM                dbo.[6_1_predict]
```

6_2

```
SELECT         id, Lhlev, MAX(v101) AS v101, MAX(v102) AS v102, MAX(v103) AS
v103, MAX(v104) AS v104, MAX(v105) AS v105
FROM                dbo.[6_2_mixhoar]
GROUP BY id, Lhlev
```

6_3_selected

```
SELECT         id, Lhlev, CASE WHEN v101 >= v102 AND v101 >= v103 AND v101 >=
v104 AND v101 >= v105 THEN '101' WHEN v102 >= v101 AND v102 >= v103 AND v102
>= v104 AND v102 >= v105 THEN '102' WHEN v103 >= v101 AND
                         v103 >= v102 AND v103 >= v104 AND v103 >= v105 THEN
'103' WHEN v104 >= v101 AND v104 >= v102 AND v104 >= v103 AND v104 >= v105
THEN '104' WHEN v105 >= v101 AND v105 >= v102 AND v105 >= v103 AND
                         v105 >= v104 THEN '105' END AS pred
FROM                dbo.[6_2]
```

Appendix C   Dataset Labels

"Properties of instances":

id	Instant serial number
subject	A two-digit number. Left digit number of subject (1-4), right digit number of activity (1-5)
time	Time in seconds

"Labels":

Angle (a):

a0	0 - 59.99
a1	60 - 119.99
a2	120 - 179.99
a3	180 - 239.99
a4	240 - 299.99
a5	300 - 359.99

Locations (t):

t11 .. t88	Location in the chessboard divided room

Postures (l):

l0	None
l1	Stand
l2	Walk
l4	Sit
l5	Lie

Hand movements (o left-hand, p right-hand):

o/p00	None
o/p01	unlock
o/p02	stir
o/p03	lock
o/p04	close

o/p05	reach
o/p06	open
o/p07	sip
o/p08	clean
o/p09	bite
o/p10	cut
o/p11	spread
o/p12	release
o/p13	move

Hand object interactions (m left-hand, n right-hand):

m/n00	None	m/n12	Table
m/n01	Bottle	m/n13	Glass
m/n02	Salami	m/n14	Cheese
m/n03	Bread	m/n15	Chair
m/n04	Sugar	m/n16	Door1
m/n05	Dishwasher	m/n17	Door2
m/n06	Switch	m/n18	Plate
m/n07	Milk	m/n19	Drawer1 (top)
m/n08	Drawer3 (lower)	m/n20	Fridge
m/n09	Spoon	m/n21	Cup
m/n10	Knife cheese	m/n22	Knife salami
m/n11	Drawer2 (middle)	m/n23	Lazychair

Activities (high-level):

000	None
101	Relaxing
102	Coffee time
103	Early morning
104	Cleanup
105	Sandwich time

LIST OF PUBLICATIONS

Journals

1. Foudeh, P., & Salim, N. (2019). An Ontology-Based, Fully Probabilistic, Scalable Method for Human Activity Recognition (Under review).

2. Foudeh, P., Khorshidtalab, A., & Salim, N. (2018). A probabilistic data-driven method for human activity recognition. Journal of Ambient Intelligence and Smart Environments, 10(5), 393-408. doi:10.3233/AIS-180496 (ISI indexed, Q3, IF 2019: 1.595)

Indexed Conference Proceedings

1. Foudeh, P., Khorshidtalab, A., & Salim, N. (2016, November). Testing and analysis of the proposed data driven method on the opportunity human activity dataset. In Proceedings of the 2nd International Conference on Communication and Information (pp. 6-10). Nanyang Executive Centre, Singapore. Publisher: ACM doi:10.1145/3018009.3018011 (ACM & Scopus)

2. Foudeh, P., & Salim, N. (2012, December). A Holistic Approach to Duplicate Publication and Plagiarism Detection Using Probabilistic Ontologies. In International Conference on Advanced Machine Learning Technologies and Applications (pp. 566-574). Cairo, Egypt. Publisher: Springer doi:10.1007/978-3-642-35326-0_56 (ISI & Scopus)

3. Foudeh, P., & Salim, N. (2011, November). Probabilistic ontologies and probabilistic ontology learning: Significance and challenges. In International Conference on Research and Innovation in Information Systems (ICRIIS) 2011 (pp. 1-4). Kuala Lumpur, Malaysia. Publisher: IEEE doi:10.1109/ICRIIS.2011.6125727 (IEEE & Scopus)

Non-Indexed Conference Proceedings

1. Foudeh, P., & Salim, N. (2010, July). Information Extraction from Handwritten Medical Records and Assigning ICD-10 Codes. In Proceeding of International Workshop of Extraction of Structured Information from Texts in the Biomedical Domain ESIT-BioMed 2010 associated with the 18th International Conference on Conceptual Structures ICCS'10, Kuching, Malaysia ISBN:978-983-41371-3-7