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Mining Human Activity Patterns from Smart Home Big Data for Health Care Applications-A Survey

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Abstract - *Nowadays, there is an increase in the number of people migrating to urban places. So the need for health care resources is greatly affected by this vast influx of people moving to cities. As a result cities around the world are heavily investing in digital transformation in order to provide healthier ecosystem. In such a transformation millions of homes will be utilizing smart devices like smart meters, smart sensors and so on which can generate massive amount of data which can be used to support smart city services. This paper proposes a model that utilizes smart home big data in order to learn & discover human activity patterns for health care applications to detect health problems. The proposed model uses frequent pattern mining, cluster analysis and prediction processes. Since there is a strong relation between people's habits and every day activities, discovering these activities enable us to identify anomalous activities that may indicate people's difficulties such as not preparing food or not taking bath. This paper analyses temporal energy consumption patterns at the appliance level which can be directly related to human activities. The applications arise in the field of tracking individuals living alone or persons with self limiting conditions.*

Key Words: **Big data, smart home, smart meters, smart city, frequent pattern mining, cluster analysis, prediction, health care applications**

1. INTRODUCTION

In the proposed model [1], there is a smart home equipped with smart devices from which the data is collected by the smart meter placed in the smart home. Now the smart meter data is stored in various forms of databases like Mongo, Raw data and Time series. The Mongo database is a flexible and scalable document database. The data can also be stored in the raw data form without any transformation for the data. The time series database stores sequences of values or events obtained over repeated measurements of time (e.g., hourly, daily, weekly).The smart meter data from the database is taken for performing various processes. First it starts by cleaning which the noises and inconsistent data are removed. Then clustering of the source data occurs which the data having similar properties are grouped into classes of data called clusters. Next FP (Frequent Pattern) mining of the source data occurs. It is process of finding frequently occurring patterns in the source data. Through FP mining, the appliance to appliance association can be obtained i.e. which appliances are operating together. Next phase is incremental mining and clustering. The incremental mining is a form of mining which maintains the already discovered patterns with the existing patterns and newly discovered patterns whenever database gets updated. Then clustering happens to find the appliance to time association details i.e. which appliances are operating at what time. These associations are stored in the database. Then an inter appliance association can be inferred which helps to generate association rules among appliances. These association rules are a form of representing frequently associated patterns. The association rules are stored in the database. From the database the appliance to time associations as well as the association rules are taken up by a graphical probabilistic model called Bayesian network. This is a directed acyclic graph which consists of nodes and edges. The nodes represent random variables and edges represent probabilistic dependency. This network is used for prediction process which is a data analysis method. The process predicts the human activities inside the smart home. These activities are learned by specific health care application to detect the health problems in order to provide specific health care to the specific user.

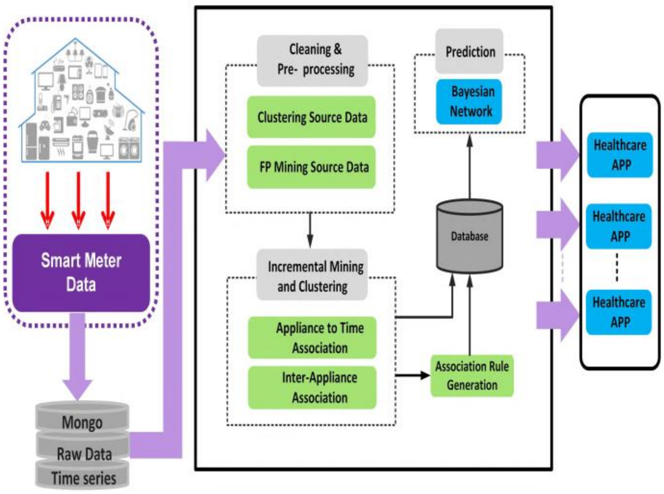

Fig-1: Architecture of the proposed system

This figure and the algorithm is taken from the paper Mining human activity patterns from smart home big data for health care applications proposed by Abdulsalam Yassine et.al [6]. This algorithm outlines the incremental frequent pattern mining process. It requires two kinds of databases like transaction database (DB) and frequent pattern discovered database (FP_DB).The DB stores the source data and FP_DB stores the frequently occurring patterns in the source data. During the incremental frequent pattern mining process it has to be ensured that while frequent patterns are discovered, it should be stored in FP_DB. The steps of the algorithm go like this. Initially for all transaction data in DB, the data has to be processed in the quanta of 24 hours. Then determine database size. Next mine the frequent patterns using the extended FP-growth approach. Further for all the frequent patterns found in the time slice of 24 hours, search for a frequent pattern in FP_DB. If a frequent pattern is found then update the frequent pattern in FP_DB or else if a new frequent pattern is found then add that frequent pattern to FP_DB. For all the frequent patterns in FP_DB, the database size has to be incremented by the size of the database for the quanta of 24 hours.

Road map. The remaining of the paper is organized as follows. In Section 2, we review the literature survey. Finally, Section3 concludes this paper.

2. Literature Survey

Nowadays there has been a growing trend in utilizing smart home technologies in order to detect human activity patterns for health care applications. The main aim is to learn and discover human behaviors in order to predict the human activities inside smart homes that can help in identifying health issues.

2.1 Detecting Activities of Daily Living with Smart Meters

Detecting activities of daily living with smart meters [2] is a research work in which smart meters are used to provide information to analyze the energy consumption of buildings and to identify the usage of appliances. This helps the older people to stay longer independent in their homes by detecting their activity and their behavior models to ensure their healthy level. This paper can be used to analyze smart meter data to monitor human behavior in single apartments. There are two approaches focused by this paper. They are Semi Markov Model (SMM) and Influence based method. The Semi-Markov-Model (SMM) is used to analyze and detect individual habits to find unique structures representing habits. If the most possible executed activity (PADL) is evaluated then it can infer the currently executed activity (ADL) of the inhabitant. The impulse based method is used for the detection of ADLs by analyzing all parallel ADLs. Both approaches are based on smart meter events which help to detect which home appliance was switched. Thus, this paper will also give an overview of popular methods to detect the events on electricity consumption data.

2.2 The Elderly's Independent Living in Smart Homes: A Characterization of Activities and Sensing Infrastructure Survey to Facilitate Services Development

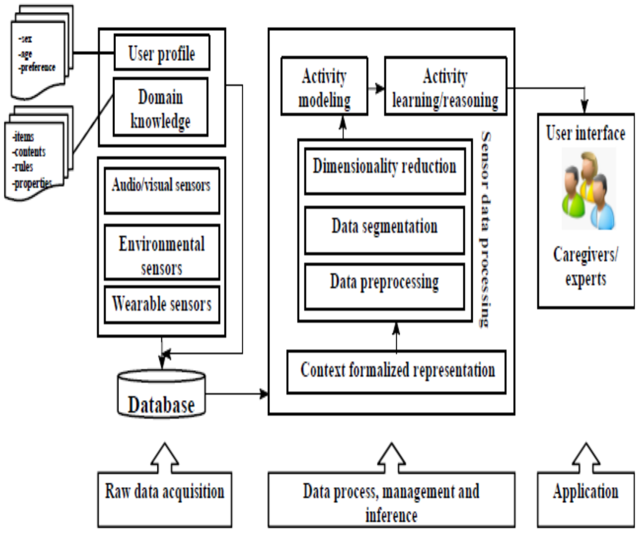

Fig-2: Stages in AAL

Q.Ni.A.B.G.Hernando et.al proposed The Elderly's independent living in smart homes: a characterization of activities and sensing infrastructure survey to facilitate services development [3] that involves the detection of human activities within smart homes in accordance with the wellness monitoring of a rapidly aging population in developed countries.

This is the architecture taken from the paper Elderly's independent living in smart homes: a characterization of activities and sensing infrastructure survey proposed by Q.Ni.A.B.G .Hernando et.al to facilitate services development. Such a living is termed as Ambient Assisted Living (AAL).The activity based AAL consists of three stages: Raw data acquisition, Sensor data processing and learning/reasoning by caregivers. In raw data acquisition stage, the user profile which consists of details of user like age and domain knowledge like items inside smart home are stored in database. There are various sensors like audio/visual, environmental and wearable sensors inside the smart home that collects data and this sensor data are also stored in the database. Next stage is sensor data processing in which the data from the database is taken and transformed into a context formalized representation. Now this data is preprocessed in order to remove noise. The preprocessed data is segmented to partition the data into groups of data having similar properties. The segmented data will undergo dimensionality reduction in which the dimensions of the data are reduced such that it is transformed into a form appropriate for mining. Then an activity modeling occurs in which a model is created based on the human activities inside the smart home. Further these activities are learnt by the caregivers/experts through the user interface of the health care applications in order to detect health problems of humans inside the smart homes.

2.3 Detecting Household Activity Patterns from Smart Meter Data

In the paper, Detecting Household Activity Patterns from Smart Meter Data [4] an algorithm is proposed for identifying domestic activities from the aggregate data collected by the smart meter . There are two types of activities: Type I activities are those that can be identified by the smart meter data and Type II activities can be identified from the smart meter data and environmental sensing (temperature and humidity). For identifying the individual activities, y disaggregate the total power usage down to individual electrical appliances. Then, an activity model is created to reason the domestic activities. This reasoning is done with the help of Dempster-Shafer theory of evidence. The theory states that we can combine evidence from different sources and arrive at a degree of belief that takes into account all the available evidence. Identification of domestic activities inside a smart home has many applications for example, healthcare and elderly care. However, other applications go far beyond healthcare. For example, support home automation and energy savings in smart homes.

2.4 Smart meter profiling for health applications

C. Chalmers et.al proposed Smart meter profiling for health applications [5] in which the smart meters are used to monitor electricity usage and recognize sudden changes in the behavior of humans inside smart homes. Its applications come in the field of tracking individuals suffering from Alzheimer's disease, Parkinson's disease and clinical depression. This focuses on data classification techniques which detect anomalies in behavior by analyzing personal energy usage patterns. Here the infrastructure is termed as Advanced Metering Infrastructure (AMI).

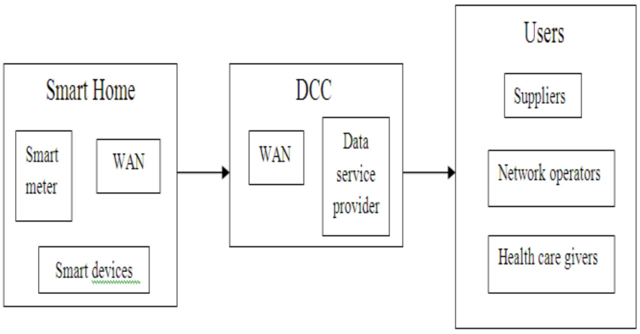

Fig-3: Advanced Metering Infrastructure (AMI)

This is the AMI in which there is a smart home equipped with smart devices like smart meter gas, smart meter electricity and there is a smart meter that collects data from all the smart devices. The smart meter data is transferred to Data and Communications Company (DCC) via a Wide Area Network (WAN) module which acts as a communication service provider between smart home and users. There is a data service provider inside DCC which collects data from WAN in DCC and provide it the specified users like suppliers, network operators and other authorized parties like healthcare givers/experts.

2.5 Smart energy group anomaly based behavioral Abnormality detection

The paper, Smart energy group anomaly based behavioral abnormality detection [6] deals with a data analytic approach which detect the energy usage anomalies and thus identify behavioral abnormality of residents. Here the smart meter is used to detect everyday appliance usage. This work follows a hierarchical probabilistic model.

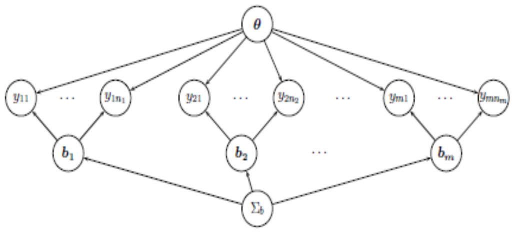

Fig-4: Hierarchical Probabilistic Model

This figure shows the hierarchical probabilistic model in which observations are grouped into m clusters. The model is used for group anomaly detection which detects the behavioral anomalies over a set of energy source data points. The hierarchical form of analysis and organization helps in the understanding of multi parameter problems and also plays an important role in developing computational strategies.

3. CONCLUSIONS

This survey has been performed for monitoring the human activities inside a smart home which can be utilized by health care applications to detect health problems. It was found that the former research works does not consider appliance level patterns which are a critical factor to determine human activity variations. This paper proposes a model which is used for recognizing human activities patterns from smart meters data. The human habits and behavior follow a pattern that could be used in health applications to track the health problems of individuals living alone or those with self-limiting conditions. These human activities can be inferred from appliance-to- appliance and appliance-to-time associations. An incremental frequent mining and prediction model is proposed based on Bayesian network. In the proposed work, 24-hour period was found to be optimal for data mining, but the model can operate on any quantum of time. The applicability of the proposed model was to correctly detect multiple appliance usage and make short and long term prediction. The output of the system is utilized by specific health care applications depending on the intended use. For example, a health care provider might only be interested in knowing activities related to cognitive impairment where tracking the sequence of daily activities is crucial for reminding the patient when abnormal behavior is detected.

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