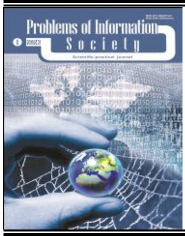
Problems of Information Society, 2023, vol.14, no.1, 75-84



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14 (1)
2023

Development of a model for the analysis of human behavior in a smart home environment

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ARTICLE INFO

http://doi.org/10.25045/jpis.v14.i1.08

Article history:
Received 16 August 2022
Received in revised form
21October 2022
Accepted 26 December 2022

Keywords:
Smart home
Behavior analysis
Sensor devices
Thermostat
Cyber-physical system
Data mining
Cloud computing

ABSTRACT

In modern times, it is impossible to imagine people's lives without information technologies. The Internet, mobile phones, remotely controlled devices designed to perform various operations have become ordinary for people. Concepts such as smart city, smart home, cyber-physical systems and cloud technologies become an integral part of the information society. The concept of a smart home can be seen as an environment equipped with sensors, cloud computing and user directives. A smart home works on the principle of collecting all information about the house and its inhabitants from the bottom up, that is, sensors monitor all the behavior of people in and around the house. The data collected in these sensors is collected and processed to identify and predict daily life activities of the people in the house. Evaluating and predicting human behavior in a smart home environment is both interesting and important in studying society, managing e-government and ensuring its security. The article studies the approaches related to the analysis of human behavior in the smart home environment, the influence of cyber-physical systems on the behavior analysis, and the role in the formation and functionality of smart homes. It defines existing problems related to the security of smart homes, and proposes a new model for analyzing human behavior based on the sensed data. The model reveals the main features of each citizen's behavior and allows for a more in-depth study of the socio-political and economic processes taking place in the society.

1. Introduction

Currently, proper management of e-state, protection of economic infrastructure, further s improvement of citizens' living conditions and information supply, provision of information security is the main task facing scientists and specialists working in the field of information communication technologies (ICT). A citizen of the 21st century lives in the era of Industry 4.0. The concept of the Industry 4.0 is based on close connection of the physical and virtual environment, big data, artificial intelligence and cloud computing [1, 2]. Social networks, Internet of Things (IoT), Cyber-Physical Systems (CPS) and cloud computing affect people's behavior and daily lives.

Industry 4.0 provides countries' movement to a new stage of economic development. Studies indicate that the main factor contributing to the full implementation of the Industry 4.0 concept is CPS and their role in people's daily life and behavior [2, 3]. In such a situation, there is a need to deeply study the impact of the smart home concept on people's behavior and the issues of behavior analysis through these systems.

CPS are systems unifying advanced technologies to provide intelligence in the field of control and management through modern communication systems, and to ensure the joint operation of physical systems functioning in the real world with the cyber aspects of computing [3].

Smart Home refers to an environment (apartment, office, etc.) equipped with various sensor technologies, devices working with intelligent algorithms, and additional services for the automatic performance of most tasks accomplished by a person in daily life. A smart home is a space equipped with an access control system, intelligent management systems of technical processes occurring in the apartment (lighting, temperature regulation, electrical devices, etc.) and designed to facilitate the life of the apartment resident.

A smart home is not only designed for the convenient use of household appliances by people, but it also creates prospects for adapting these appliances to people's behavior. Availablestudies in this field are mainly based on the analysis of data collected by sensors. Today, mining of sensed data is one of the most widespread research fields in ICT. The concept of smart home is based on equipping the home with various types of sensors measuring the physical parameters of the environment [4]. The sensor system is appropriate for intelligent and optimal realization of any work. For example, turning on the air conditioner according to the temperature sensors in the house, providing security for the house and lighting according to the motion sensors, etc. Here, it is necessary to mention the sensors recording the movement and the identification of radio frequencies (Radio Frequency Identification, RFID) reader.

RFID-radio frequency identification is an automatic identification system that collects information about people and objects through radio signals. Any RFID-system consists of a reader device and a transmitter [5]. According to the RFID context, the initial concept of a smart home is based on tracking systems. Nowadays, large scaled data collected in devices equipped with sensors are used in analytical studies, delivery of various additional services, and in healthcare.

It is impossible to imagine the concept of a smart home without the concept of IoT. Today, IoT is applied to security and control systems, equipping the buildings with sensor devices (smart home), transport, trade, healthcare, agriculture, military and many other fields. Thus, IoT is a dynamic distributed environment that combines many smart devices to understand procedures around them and perform appropriate operations. Such devices monitor the state of the environment, collect information about procedures in the environment and provide sensed data processing in cloud computing. It should be noted that these computing systems create a CPS environment by ensuringconnection with other devices regardless of the location of each sensor-equipped device.

CPS is the deep integration of cyber computing into sensor devices and human activities, that is, CPS refers to the close interactions and relationships between sensor and cyber components constituting the basis of IoT. Physical components refer to thedifferent information systemsand people [6]. The main areas covered by CPS are the automation of transportation, energy and industry, healthcare, critical infrastructures andIoT. Since CPS is a system capable of processing different types of large scaled data collected from the environment, it accelerates the realization of smart home and smart city concepts by enabling more efficient and beneficial use of big data [2, 6].

According to the International Telecommunication Union, IoT is a global infrastructure that provides a wide range of services through the interaction of physical and virtual objects intended for the information society [7]. Analytical processing and decision-making systems have asignificantrole in CPS and IoT systems [8]. It can be concluded that both CPS and IoTconsist of logical, physical, transmission and human components that interact with each other and are designed to work with logical and physical systems. CPS is related to artificial intelligence (machine learning, etc.), IoT (network infrastructure, network of things, sensors, etc.), intelligent services and applications, information security, cloud computing, and social networks. Therefore, there is a growing demand for research related to CPS modeling, design, simulation, and verification before being applied to smart homes, manufacturing, transportation, and many other fields. In addition to these technological aspects, the realization of CPS depends on the skills, willingness and capabilities of the stakeholders [9].

2. The main devices controlling smart homes

For the efficient management of smart homes, stationary and remote-controlled systems are offered by various companies every year, which are more improved and adapted to new technologies. These include management through cloud technologies and mobile devices [10]. However, as the number of household items increases, new programs for additional services are downloaded, more costs are required, and the management of smart homes requires certain competence, knowledge and experience from the user.

In recent years, with the wide application of data mining technologies, manufacturers have been analyzing the behavior of citizens and offering various household products adapted to it. For example, Amazon, Ecobee, Honeywell, Nest, Sensi and other smart thermostats [11]. The thermostat is a Wi-Fi enabled, programmable and self-learning electronic device that optimally regulates the heating and cooling of homes and businesses while saving energy. The device learns the temperature adjustment performed by the user during a certain time, for example, per week, creates a personalized schedule according to this behavior, and continuously adapts to the changing behavior of the user [12, 13].

Some smart thermostats also use presence sensors to detect whether the user is at home or not and automatically change the temperature according to the situation [14]. Thermostats automatically switch between "home" and "away" modes depending on the location of the mobile phone, making a decision according to the mode. Generally, smart thermostats do more than just control the heating, cooling, and lighting of a house. Consequently, a smart thermostat has software that performs various functions. Many thermostats are controlled from a compatible smart display or speaker with voice commands via Alexa, Google Assistant or Siri.

One of the intelligent devices offered by Google is a voice-activated device called Google Nest (or Google Home). This device allows the user to give voice commands to household devices through the Google Assistant program. Google Home can be connected to a mobile phone or special speakers. It can also be seen as the central network of a smart home. It provides information about the weather forecast, latest news, and can also function as a memory book [15]. Google Assistant is based on artificial intelligence and even has the ability to participate in two-way conversations [16].

One of the main platforms of the smart home is the Amazon Alexa intelligent device. It is also widely used for voice control of household devices like Google Home, but unlike Google Home, it can also control orders on Amazon. It also has the ability to determine the mood of the user from the voice rhythm. For example, if the user is speaking too slowly or excitedly, Amazon Alexa will respond in a quiet and whispery manner, depending on the tonality of the voice. However, Google Home understands natural language better and can execute multiple commands within an app. According to the reports for 2022, Amazon Alexa controls about 100,000 household items, and Google Home about 50,000 [17].

A smart home is also provided with warning systems against various emergency events. The task of these systems is to notify owners about water or gas leakage, flood, smoke, fire and short circuit, as well as malfunction of engineering network mechanisms, for example, sewage or submersible pumps. These systems have the ability to prevent an incident. For example, if a water pipe bursts, the water pipe is automatically shut off, or if there is a short circuit in the electrical network, the power supply of the corresponding part of the house is automatically cut off.

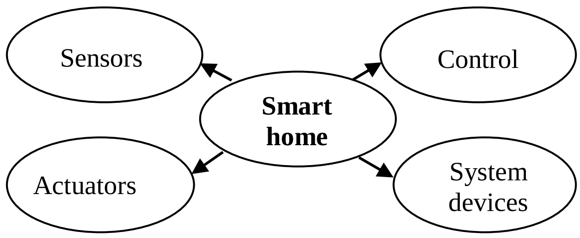

Fig. 1. Key components of a smart home environment

Sensors are the key components of a smart home system that detects changes in controlled devices and programs. Another component of a smart home is an actuator (a functional element of automatic control systems; a mechanism that allows changing the flow of energy or matter entering the object) (Fig. 1). It provides appropriate management to incoming signals from sensors or control devices according to a pre-programmed scenario. For example, the simplest actuator's function is to regulate the lighting of the rooms according to the signal from the light sensor, or to open/close the blinds, etc. Tracking devices are programmable control modules of a smart home that receive signals from sensors, compare, process them and give commands to actuators according to the script (Script language contains all the codes of the program and is written in any programming language). System devices are the elements of a smart home that provide power to the system and connect sensors, trackers and actuators into a single smart home system. By monitoring people's daily activities at home and outside the home with the help of sensors, it is possible not only to timely solve problems related to their comfort and health, but also to determine their interests and predict their behavior. Such tasks are performed by activity recognition systems equipped with sensors.

3. Related works

Various approaches have been proposed for collecting data from sensors and analyzing behavior based on this data in the context of a smart home. In some researches, the model of a person's behavior and activity is built on the basis of the devices he/she wears (smart watch, devices measuring pulse and steps, etc.) and information obtained from the environment [18]. In other cases, the interaction between people and objects is detected by sensor devices, and the nature of the behavior is recognized by the frequency and sequence of these interactions [19, 20].

Machine learning and deep learning models are mainly used to detect anomalous behavior. In some approaches, researchers classify behavior as normal and abnormal behavior within certain rules [21].

Other studies define a regular pattern of "activity" by the sequence of events occurring in a given time interval and develop a schedule of rules. If there is a deviation from the rules, it is considered an anomalous behavior. Such approaches mainly use hidden Markov models [22], machine learning models and graph theory [23, 24]. For example, [23] uses two machine learning methods to learn human behavior in a smart home environment and detect any behavior that deviates from normal behavior. These are the autoencoder and the one-class support vector system. Correspondingly, the study uses Samsung Smart Things, an open platform, as a real-time behavior detection and notification mechanism.

[25] applies neural networks to analyze and predict human behavior in a smart home environment. The main goal here is the automatic regulation of the heating system of the house by studying human behavior.

The study in [26] is analogous to the previous study. Here, it proves that by learning human behavior, the intelligent system can adjust the smart home according to the human's daily behavior. A hierarchical model according to human behavior is created, and this model learns and executes each human action. For example, it determines the optimal temperature parameters for maximum comfort, etc. The researchers note that a slight change in the human model system can cause the system to behave completely opposite. These changes are made according to the behavior of the user of the intelligent system. That is, if the user's behavior changes, the "human model" system begins to learn the new behavior and updates its activity. Research applies Markov chain and fuzzy set theory.

Another study proposes using the "Ecobee" smart home thermostat to assess behavior [27]. It is noted that it will be possible to predict user behavior based on data mining in sensor devices controlled by the Ecobee thermostat. This approach uses an unsupervised neural network model to detect abnormal activity.

A major challenge in studies regarding to human behavior is the possibility of unpredictable actions in behavior. For example, [28] records all information sharing between portable devices and home devices order to determine human behavior during the day and predict its demand. A demand matrix is then constructed to predict the user's demand for the home environment. The data processed includes all data on the connected devices, starting from the date of activation of the device. The study develops two simulation systems to demonstrate user behavior identification.

The research revealed that there are many international practices and approaches for determining and predicting human behavior through the analysis of data from sensor devices. Studies related to the analysis of behavior in the smart home environment suggest that 5 areas constitute the basis of the smart home concept:

1. Tracking devices that track the trajectory of people and objects and determine their physical location.
2. Interactive systems that measure environmental variability and interact between the environment and humans.
3. Systems that collect data obtained through sensors into a database.
4. Decision systems based on data mining.
5. Auxiliary devices providing communication between physical systems and computing technologies.

The fourth industrial revolution, the use of artificial intelligence in social, economic and other fields, big data and IoT have led to the complexity of methods of analyzing citizens' behavior not only in the smart home environment, but also in other fields (production, transport, social relations, etc.). It should be noted that nowadays the capabilities of CPS, mainly cloud technology, create new opportunities for the analysis of human behavior in the smart home environment.

Taking these into account, the study suggests the use of distributed parallel processing systems to get more efficient, flexible and quickresults, as well as to solve big data problems.

Research indicates that machine learning, fuzzy computing methods and cloud technology are mainly used for behavior analysis in the smart home environment. Behavior analysis approaches in smart homes can be divided into two classes: sensed data-based approaches and knowledge-based approaches [29]. In data-based approaches, data analysis is performed by using statistical and probabilistic methods to learn behavior models. These datasets are mainly used for training models that identify connections between events and behaviors. Training models may be generative and discriminative according to the modeling strategy. The data collected from the sensor devices provides a complete imagination of the events taking place in the smart home along with the operation of these devices. The knowledge obtained from data analysis allows us to determine both the subject of requests and commands, the time of execution, and thedevices between which the related operation is performed.

Training mechanisms are often based on data mining and machine learning methods, depending on the modeling strategy applied. Depending on the modeling strategy applied, maps are created that fully describe the relationship between events and the behaviors corresponding to these events. These maps identify the most likely behaviors to occur based on a set of observations. Such studies mainly use Hidden Markov models, Naive Bayes classifier, and neural networks.

Generative approaches face challenges from the availability of big data to generate the full set of possible states to ensure good functionality. Discriminative approaches, as shown in [30], can achieve high results using fewer datasets than those of generative approaches. These approaches mainly use artificial neural networks and focus primarily on matching input states (sensor data) to action processes. A general advantage of input-based approaches is that they allow modeling of uncertainty and time parameters. Their disadvantagesare the need for a big data base for training. Furthermore, the reusability of these models is limited to the environment and scenarios generating the dataset. Knowledge-based behavior recognition does not require a large number of sensors and activity records. Knowledge-based approaches are generally logical or ontological.

The study identifies the research fields and the main challenges and determinesthe widespread application ofmachine learning, rule-based approach and artificial intelligence for the analysis of human behavior in the international practice.

Studies showthat although smart homes are designed to improve people's living conditions and ensure their safety, they also cause certain problems. These problems can be divided into four categories:

1. Information security: a) data privacy; b) software security of smart home devices. The first problem is related to personal data. Thus, the data collected in the sensors is considered the personal data of the user, and their unauthorized transfer and processing must be carried out in accordance with the law on personal data of each country. The problem of inviolability of the user's personaldata remains in smart homes. Studies show that the protection and stability of most sensor devices against information attacks is not at the required level [31, 32]. Even, in order to offer more effective and necessary services according to the user's behavior, in many cases, unauthorized transfer and processing of data from sensor devices is carried out by individual companies. As a result, the data privacy is potentially violated by behavioral recording [32, 33]. In terms of software security, threats to sensors and their networks can come from different sectors: software vulnerabilities, legacy network infrastructure, protocols, etc. [34].

2. Digital diversity. A smart home requires a large number of sensor devices to work efficiently. This, in addition to affecting the environment in wide use, creates conditions for further increasing the digital diversity among people.

3. Financial costs. Equipping homes with a large number of sensors requires large financial costs. These sensor devices also require maintenance, which can lead to additional costs.

4. People's capacity to deal with modern ICT and sensory devices. Using new devices requires additional knowledge and experience.

Research reveals that most of the proposed approaches to human behavior in a smart home environment are based on a specific cause. For example, identifying anomalous actions in human behavior, providing human comfort or home security, etc. As a rule, the proposed model cannot fully cover the causes and types of human behavior. This complicates predicting and making decisions about human behavior. Taking this into account, the study proposes a three-stage analysis model for the mining of human behavior based on the data collected in sensor devices.

4. Three-stage behavior analysis model based on smart home data

The sensor network of a smart home can be viewed as a general system that performs four main tasks: creating a list of tasks to be done based on user commands, creating a list of tasks performed based on this list, monitoring the operation of the sensor network, and analyzing sensor data. The interaction of these four processes and the mining of all the data collected at the end of the process is the basic condition for determining and predicting behavior. Comparative analysis of tasks to be done and tasks performed based on user commands first of all defines the effectiveness of sensor devices and hardware-software problems that may arise in the work process. The main problem here is the heterogeneous and distributed nature of the sensor devices in the smart home environment and the sensitivity of the interacting sensor devices.

Fivefields should be taken into account in the analysis of behavior based on smart home data (Fig. 2). The proposed model is based on the bottom-up principle for analyzing behavior in a smart home environment. User requests or commands (e.g. via mobile phone) are sent over the Internet to a smart home hub (e.g. Google Home). Cloud database stores all requests and orders. The metadata of the cloud collects information on data sending location, time etc. Sensor devices record all events occurring at home based on the user's request or commands. Sensors connect to devices in the home to collect internal and external data about the home and measure the smart home environment. Sensor data is collected and continuously transmitted over the local network to the smart home server. Sensor data is processed by a local server. The server, in turn, works in connection with the cloud, data from the server is transmitted to the decision system for mining.

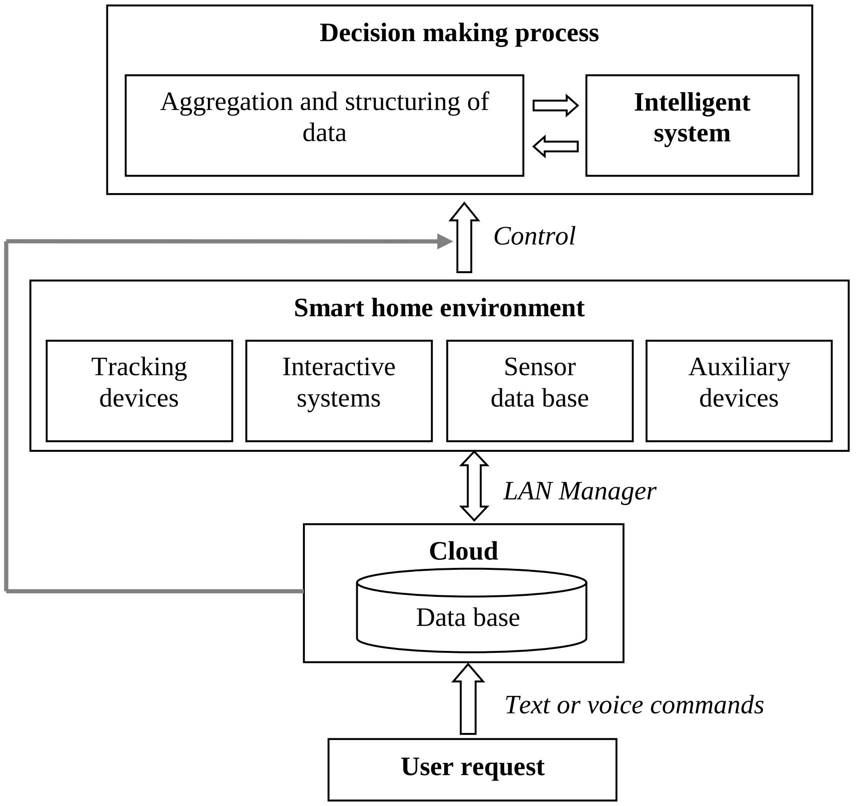

Fig. 2. Bottom-up principle for behavior analysis in a smart home environment

Application Programming Interfaces which include software components can control processes at home by processing sensor data. Connecting new devices to the smart home network, managing them, and downloading data from sensors areperformed using API [35]. Owing to the API, various wireless network standards can be used by devices connected to the network. For example, the Mystrom API receives user commands via the http protocol using GET and

POST requests. GET is used to read information about the device, and POST request is used to update device settings. It is important to have actuators to provide and execute commands on the server or other control devices. It converts the requested process into command syntax. In the course of processing the received sensor data, the program checks whether the corresponding rule has started to be executed. In this case, the system sends a command to the processor of the corresponding device. A database for storing data collected from sensors and cloud services is an important component of a smart home. It is also involvedin data analysis, data presentation and visualization. The processed data is stored in the database for further use.

The Local Area Network (LAN) Manager determines which request/response authentication protocol to use to access the network. LAN Manager is a network operating system that combines Microsoft client and server software enabling the users to connect home devices on the same network. The protocol selected by LAN Manager affects the level of authentication protocol used by the user, the level of session security, and the level of authentication by servers.

The following technologies should be considered in research on decision-making based on behavior analysis. Without these technologies, it is impossible to effectively analyze behavior based on smart home data. These technologies are as follows:

-*Technology for efficient collection of sensor data.* The methods and algorithms used for datacollection by bringing them to a common base require the integration of various information sources, as well as the correct assessment of environmental events in real time. Obviously data is stored in sensors and various tracking, facial recognition and other devices that collect data. In order to take full advantage of availableequipment in data collection, thisequipment should be provided with additional capabilities (technology to perform data cleaning, aggregation and structuring). At this stage, two main factors should be taken into account:a) Considering its variety, performing the operation of data collection and transmission to the central server without obstacles and in a given time interval; b) correcting thedata source selection.

-*Sensor-control technologies.* CPS, consisting of many non-homogeneous elements, requirescomplex models that control the operation of each subsystem. There are dynamic interactions between the subsystems that organize the work of CPS and control objects that regulate these relationships. Interrelationships of subsystems vary over time due to factors such as data distribution conditions and traffic load. In subsystems that make up CPS, information is carefully controlled in advance, synchronized between physical systems and cyber-computing systems. Using simulation and virtual reality technologies in the development of control systems enables obtaining more accurate information. The processing of data about each user from tracking devices equipped with virtual reality technologies provides new opportunities for sensor-control technologies.

-*Data Mining technologies*. Deep learning, knowledge extraction, artificial intelligence and other technologies are widely used to understand socio-economic processes in the world and reduce risks in this field. Intelligent system or Data Mining technologies create new opportunities for knowledge acquisition, analysis and training [36].

The intelligent system leads to a comprehensive analysis of the controlled system, i.e., the control system of the sensor devices of the smart home. The correct presentation of the acquired knowledge to skilled experts confirms that the decision to be made is correct. Since the information about the condition of each device is important, a decision can be made about the priority issues for the optimization of service processes. Fig. 3 shows the general scheme of the intelligent system.

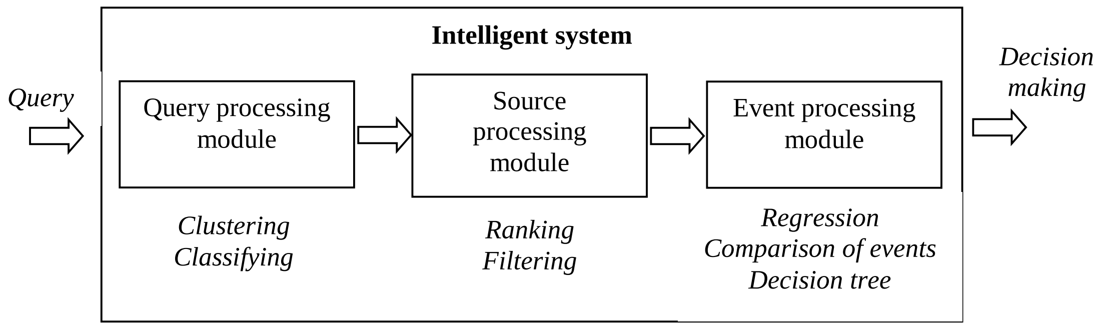

Fig. 3. General scheme of the sensed data mining based on user queries

As can be seen from the figure, intelligent analysis consists of query, source and event processing modules. The difference between the proposed approach and other approaches is that the work of the intelligent system includes three stages. This approach allows for a more in-depth study of human behavior and can determine the causes of the behavior.

Any system can be used as an event source once the correct architecture is established. Credit card systems, phone networks, and websites are just a few examples of real event sources. The next step is to analyze the events. Analyzing events means controlling the data stream about events in the smart home environment, making decisions as a result of mining. The goal is to identify events and behavior from sensed data.

Such an approach is appropriatefor the analysis of data stream that is continuously increasing and generating big data. The approach applies k-means for clustering, k-nearest neighbor or Naïve Bayes for classification. This approach depends on two phases: training and testing phase. The training phase is based on mathematical functions and algorithms that learn the characteristics of any environment using ordinary data such as benchmark input data. These features are then used for detection and classification in the second stage.

5. Results of the study

The study confirmed that the smart home is created from the concepts of IoT and CPS, and the interaction of logical and physical components of both systems provides interactive data mining about these objects, processes and events. That is, most devices in the smart home are equipped with sensors, which are an important component in the collection of big data. Sensors also determine the physical environment, organize a network for data transmission, measure the physical condition of the environment in which a person and object are located by conducting remote analysis, and make a decision based on the received result. A device or system can be used for different purposes at the same time. For example, a mobile phone performs functions such as tracking an object, creating social relationships, establishing information relationships between a person and a device, and collecting, changing, and transmitting data.

Stating the importance of the proposed model, its flexibility and comprehensiveness should be considered first. The data entered in the system can be in any format around a certain scheme. Cloud computing replaces thousands of processors to process data more accurately and quickly.

As a result of distributed data analysis, the intelligent system processes different types of data (voice, text, video) simultaneously, which ensures faster smart home service. Since the user-server architecture is used here, the server and user ports of the system are located on separate servers. This, in turn, provides the reliability and transparency of the system.

Big data analysis can only be completed by applying sensor devices and special technologies that ensure efficient use of parallel data. Significant parameters specific to big data should also be taken into account during analysis. For example, the intensity of interaction in the network, processing speed, etc.

Analysis and evaluation of human behavior will create new opportunities for more efficient implementation of electronic services in the e-government environment, health, financial affairs, business, commerce, education and many other fields. Considering the complexity and versatility of social and economic processes occurring in human behavior and society in general, the study actually suggests a distributed data analysis system. Methods based on Data Mining algorithms are an integral part of big data analysis. Thismethodsobtain new knowledge in the analysis of human behavior and increasing the efficiency of research.

6. Conclusion

This study showed that smart homes can improve security, automate tasks, remotely monitor household chores, improve energy efficiency, and provide user convenience. A smart home is rich in sensors that generate large scaledinformation in the form of data or events. Analyzing this data is beyond human capabilities. As a result, event and behavior analysis systems are used to identify anomalous behavior and respond to unusual events more quickly.

Smart home, IoT and cloud computing are not just combinations of technologies, but rather a balance between local and central computing, means of optimizing resource consumption. Smart home systems still require further research in terms of providing strong security for all connected elements, finding effective ways to minimize the digital diversity and take faster and more efficient measures in improving citizen' knowledge and skills in this field.

The article proposed a new model for learning and recognizing human behavior using data from sensor devices in a smart home environment. This approach was based on the mining of data collected from all devices in the smart home environment, including text, audio and video data. The proposed approach mainly considered two objectives: sensor data processing ensured offline analysis of human behavior and enabled online detection of learned behavioral patterns.

In a smart home environment, a human behavior analysis system can process a large number of events and perform real-time process monitoring, navigation, and optimization functions. It can detect anomalies or exceptions in behavior, conduct analysis, issue warnings, and take damage prevention measures. The proposed model for human behavior analysis can be easily integrated into a distributed and service-oriented processing platform, and the computational tasks can also be performed on IoT and smart home devices.

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