ATHENA: Activity-awareness for Human Engaged Wellness Applications

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Contents

Chapter 1: Introduction

1.1 Abstract

To enable individuals as well as active lifestyle demands a smart and innovative way to stay active for a long time, prevent social isolation and motivation for performing daily life activities. In response to that, current advancement of information communication technologies (ICT), mobile solutions, wearable computing, and cloud computing infrastructure are expected to provide a cost effective solutions. To provide robust human engaged services and personalized recommendations; user daily life activity, emotions, and social interaction are the most important information sources. We proposed activity-awareness for human engaged wellness application (ATHENA) to provide wellbeing services. ATHENA can recognize the indoor/outdoor performed activities, emotion status, and social interactions. We are developing the core technology framework to process the sensory data and extract the above define primitive information. Furthermore, this information is utilized into high level context and predict the user's behavior. In order to provide customized services, we are managing the user's profiles along the subject's interest and preferences. Moreover, a complete system is proposed over these assistive technologies that can take care of mental health, physical health and social-wellbeing to provide a smart care for individuals as well as population levels. Finally, to make the ATHENA robust and flexible, we introduced the feedback mechanism that can take reflect the user's view about the personalized services.

For technological aspect, we are storing the massive amount of data into Hadoop distributed file system (HDFS) model. It gives us a reliable solution to meet the requirement of big data generation from sensor devices. We are also utilize the cloud infrastructure to reduce the cost and increase the utilization of the system.

This technical report presents our study and development of each component along our uniqueness and contributions. Our proposed ATHENA system can help in enhancing the capabilities and provides tremendous value by achieving efficient use of software and hardware investments.

1.2 Motivation of Research

Following are the motivations behind our research:

- We want to develop a proactive approach to adopt healthy lifestyle in our daily routines.
- Build a complete system over these assistive technologies that can take care of mental health, physical health and social-wellbeing to provide a smart care for individuals as well as population level.
- A common platform to process activities, emotions and social networks followed by the human behavior analysis.
- We want to utilize the cutting edge technology for storage and processing to solve the bottleneck issues of massive sensory data and processing.
- Make the proposed system available to the other developers through information sharing proper interface so that they can build and develop the services applications over the core technology framework

1.3 Abstract view of ATHENA

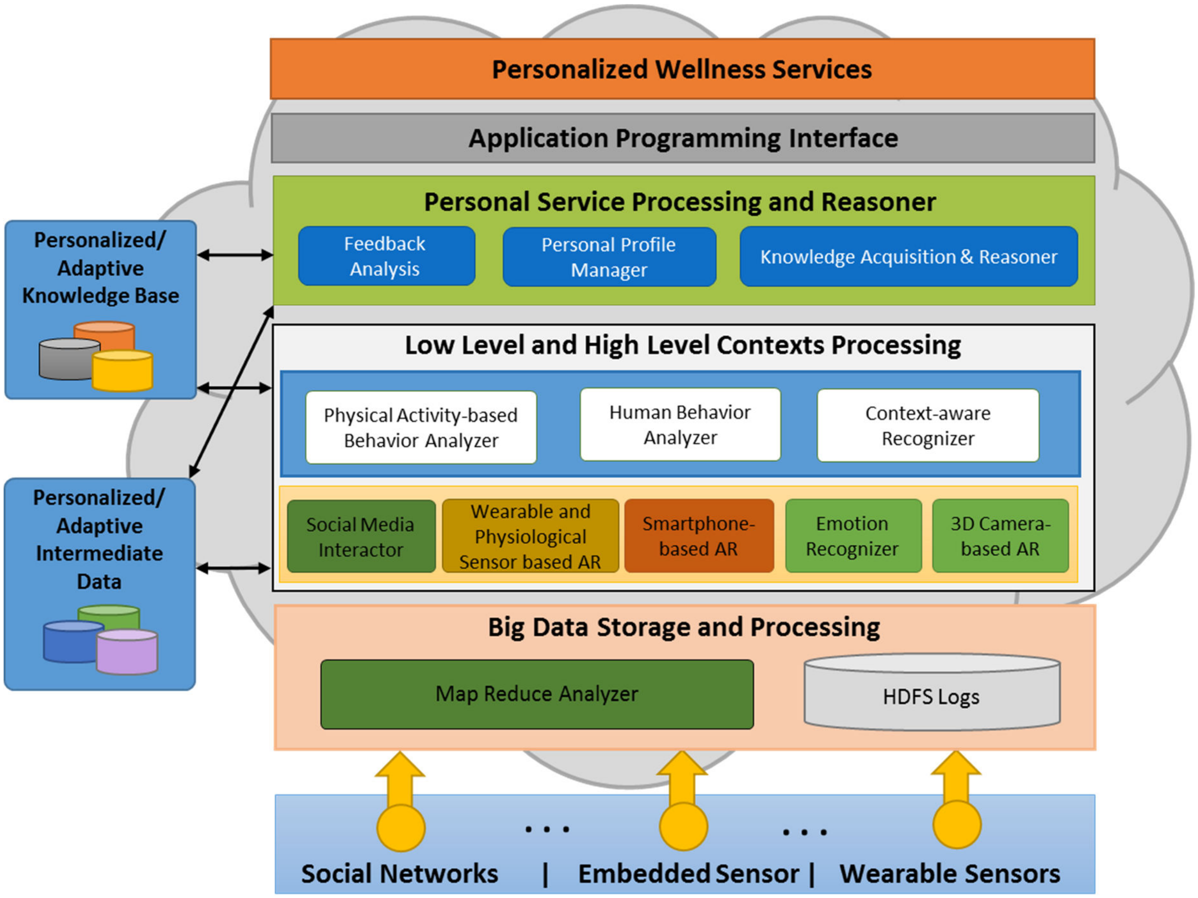


Figure 1 An overview of ATHENA

1.4 Uniqueness and Originality

- We are considering human activities, emotions and social activities all together for providing the well-being services.
- We are developing core algorithms to solve the primitive challenges of recognition rate, cost and processing overheads. In this regard, introducing novel light-weight classifiers that can work well inside the smartphone environments.
- The underneath component of the context-aware processing will be able to work independently and flexible, so that it can be tweaked according to the targeted application domain.
- We will embed the feedback methodology to re-train the context-aware processing module and increase the usefulness of our services on the user preferences and configurations.

- Storing data logs in Hadoop based infrastructure that are able to process the massive queries.
- Our proposed platform will be deployed over the cloud as a backbone infrastructure that can be accessed by different developers as well as users of the platform.

1.5 ATHENA Core Framework Components

Following are the core components of proposed activity-awareness for human engaged applications (ATHENA).

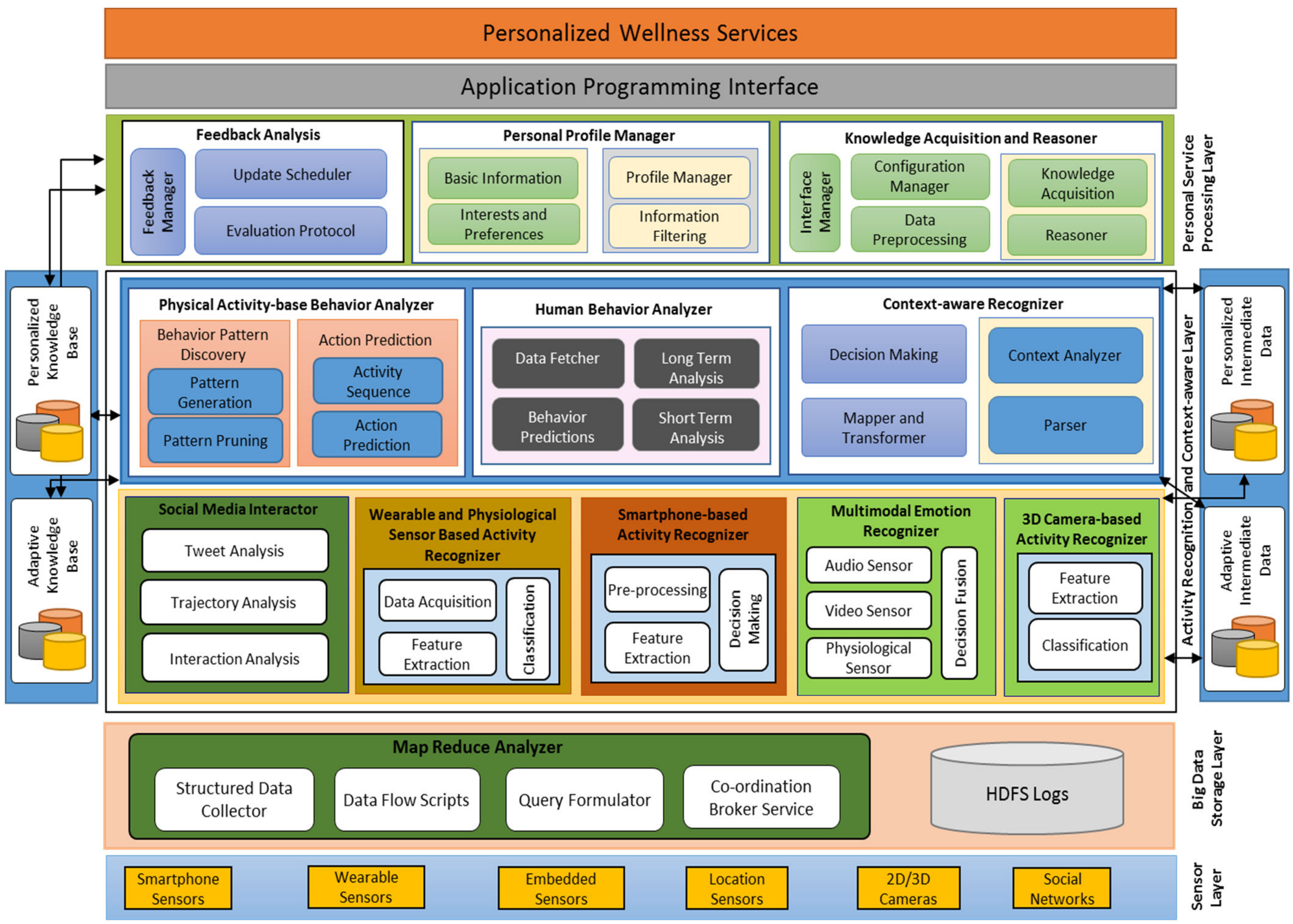


Figure 2 Core components of ATHENA

a. Sensor Layer

The sensor layer consists of multimodal physically sensors which based on embedded and different wearable devices such as smartphone and smart shirts etc. It also includes the social networks data that is considered as an input source to our platform. The input will be the raw data gathered and partially structured with respect to sensor categorization in a csv, xml, dat, or text files.

b. Big Data Storage Layer

The partially structured sensory data is stored in the Hadoop distributed file system (HDFS). The structured schema will be passed on the map reduce analysis component. The output will be the sensor values of the user attributes and produce training data for the low level and high level context processing. This data will be stored into the personalized intermediate data for further processing and providing the fast access to the sub-modules of context-processing. Furthermore, the personalized knowledge base will store and retrieve the information for context-aware recognizer and inferencing.

c. Activity Recognition and Context Processing Layer

In proposed framework, user daily life activities, emotions, and social interactions are the most important informative and primitive sources. We process these sources individually and independently. The processed results are stored in the adaptive intermediate data for further processing. We divide this module into two level of processing that is low level and high level contexts processing. Low level context processing provides the primitive information about the activities, emotions and social interaction. While in the second step, we will find out the high level contexts and predict the human behavior.

d. Personal Service Processing Layer

We processed the user's generated sensory data and extract different meaningful contexts. In the next, we will do inferencing over the contexts for providing human centric services. To provide customized services, personal profile information along with interests and preferences plays an important role. We can provide different kind of customized services according to the user preferences and interests that are discussed in the later section of the proposal. To make the platform flexible and accurate feedback mechanism will be introduce to analyze the user's response over the provided services as well as improvement of the individual components of the platform.

e. Application Programming Interface

Due to its core technology development and exposed through information sharing API, it can be molded to diverse application domain. The developers will be able to use the proposed platform and provide diverse services over the better understanding of human. Furthermore, they can provide personalized recommendations and output information according to the user's interests and preferences.

f. Well-being Services

Smartphone, tablets and smart TV are selected as the end node to deliver the customized well-being services. Our proposed platform can provide tremendous valuable human centric services.

Chapter 2: Big Data Storage and Processing Layer

2.1 Introduction

Mobile technologies are increasingly jumping into the cloud computing technologies due to increased processing, storage and energy needed by today's application. Applications involved in generating huge data over a certain period of time by sensors can use big data for processing and find patterns. MapReduce [Dean2004] is one such big data technology that we are using to increase efficiency of the overall systems. It consumes unstructured, semi structured and structured data equally.

2.2 Related Work

Currently many large organizations like Google [Ghemawat2003], Yahoo [Kaushik2010], Oracle [Shankar2010], and Facebook [Borthakur2010] are introducing new tools and technologies for fast and parallel processing of BigData [Howe2008]. A new version of MapReduce (MR2.0 or YARN [Vavilapalli2013]) has been introduced by Apache Hadoop [White2012]. It has separated scheduling and resource management and introduced a global Resource Manager, per-application Application Master and per-node Node Manager. In this way it facilitates to run multiple applications alongside MapReduce. In an effort to incorporate enterprise data into BigData, Oracle has recently published a white paper [Dijicks2012], which integrates Hadoop, Oracle NoSQL and Oracle Data warehouse to provide BigData solutions. In database community, solutions are provided to implement MapReduce on the structured data such as HadoopDB [Zhou2012] and SCOPE [Kllapi2013].

2.3 Limitations

One of the limitations is the data redundancy in HDFS and DBMS. It is necessary because real time response is required in many cases. Extraction of data is dependent on the schema from the domain expert of the system which slows the overall process.

2.4 Proposed Methodology

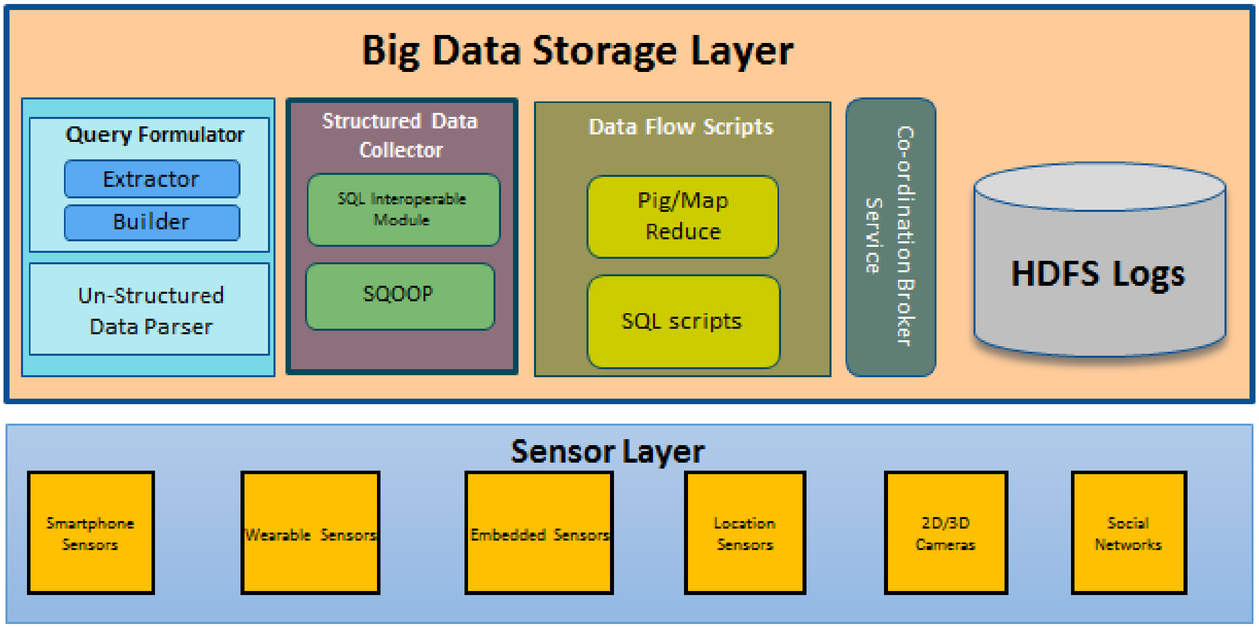


Figure 3 Proposed Methodology

- **Coordination Broker service**

This module will control the overall flow of the process and take care of the input and output of all the modules. It is a centralized service for maintaining configuration information, synchronization and distributed coordination. Apache ZooKeeper [Hunt2010] is one such service to develop and maintain an open-source server which enables highly reliable distributed coordination. ZooKeeper supports high availability through redundant services.

- **Parser Interface**

The Parser interface consists of a query formulator and the unstructured data parser. The query formulator consists of an extractor and builder module. Some of the engine in our system use BISE for storing their data in the life log repository. The parser interface maps the SQL queries to mapreduce jobs. The extractor module will extract the important conditions and restrictions of the query and pass it on to the builder. The builder will create a program/script to query the life log repository in HDFS.

- **Structured Data Collector**

This module turns the semi structured data into structured data by building a schema. Structured data is still needed by many systems to store information as many institutions and hospitals still use conventional database management systems. The structured information is passed on the institutions to align and update their systems. Apache Sqoop [http://sqoop.apache.org/] is a tool designed for efficiently transferring bulk data between Apache Hadoop [Bialecki2005] and structured data stores such as relational databases. SQOOP is a command line interface and it supports incremental loads of a single table well as saved jobs which can be executed again and again to import updates made to a database. Imports can also be used to populate tables in Hive or HBase.

- **Data Flow Scripts**

This module will help us write SQL like queries and execute them as MapReduce jobs. There are usually two scripting languages i.e. HIVE [Thusoo2009] and PIG [Olstion2008]. Hive is a system for Hadoop that facilitates easy data summarization, queries, and the analysis of huge datasets stored in HDFS. Hive provides a mechanism to map structure onto the data and query the data using a SQL-like language called HiveQL. Apache Pig is used for analyzing large data sets that consists of a high-level language for expressing data analysis programs. The language is called PigLatin which is simple but a powerful data flow language. . It is usually slower than MapReduce as Pig translates to MapReduce, so it cannot be faster than well implemented MapReduce code. You do not have to necessarily think in terms of map and reduce as the pig engine parses, optimizes and automatically executes PigLatin scripts as series of MapReduce jobs on Hadoop cluster.

Proposed Algorithm

Algorithm: : this mapreduce algorithm structures the data from

Input: a set of heterogeneous sensory data
Output: structured data

```
Begin
/*Map input=component schema for intermediate Database*/
/*Map output=Keys/column values*/
  1. Map Phase
        List=GetSchema(component)
        for(column=0;column<list.size;column++)
            key=searchlog(list[column])
            word.set(key)
/*Reduce input=Table, Column Name and the values*/
/*Reduce output=Queries which will populate the Intermediate DB*/
   2.Reduce Phase
 While(values.hasnext())
     createInsertQuery(column,Table,value)
End
```

2.5 UML Diagrams

- **Flow Chart**

The BISE module has two main objectives i.e. first to store data and secondly to generate insert queries for the relational database systems. If the data has come to be structured the first step is to formulate schema and create s structure. During the query a dataflow script is created in apache pig and result is sent.

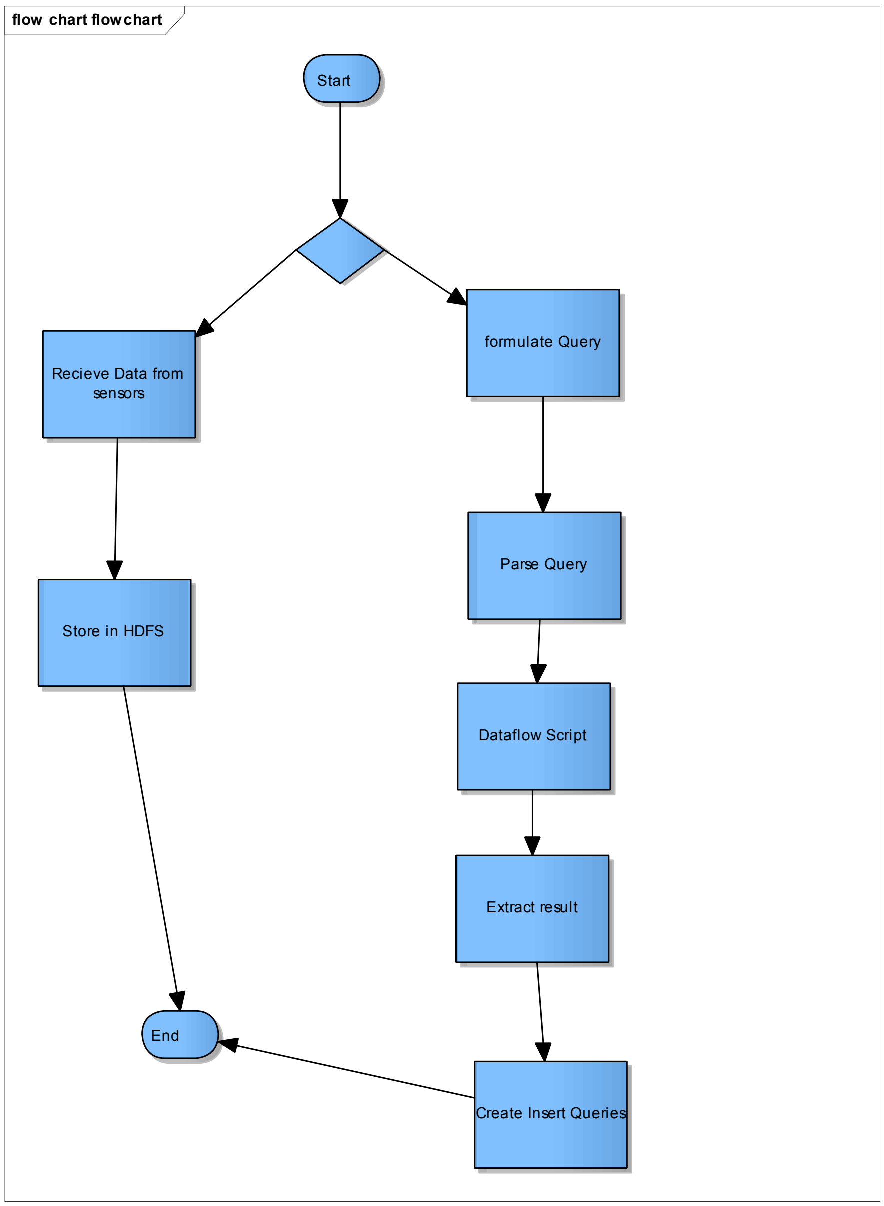


Figure 4 Complete flow chart of BISE

- **Use Case Diagram**
  - Following figure shows the interaction of the component to construct the activities and emotion profile.

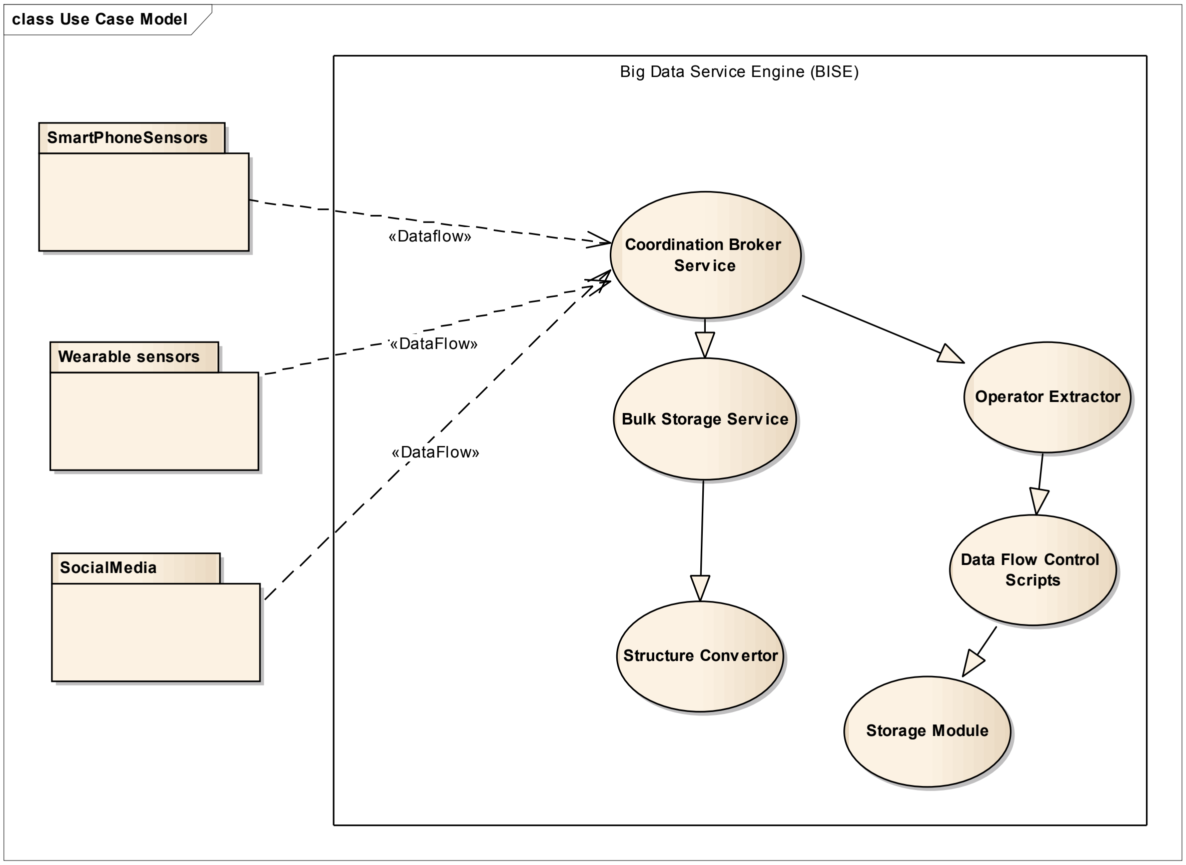


Figure 5 Use Case diagram of BISE

- **Use case Description**
  - Different kind of sensor interface will be communicating with big data engine.
  - The coordination broker service will communicate a control the internal as well as external communication.
  - The bulk storage API will transfer the data in HDFS for processing.
  - The structure convertor will structure and create a schema for the data.
  - Operator extractor will extract the user query operator to construct the apache pig query
  - Data flow control scripts will create a query for the storage module to convert into mapreduce.

- The storage module will convert the query in mapreduce jobs and retrieve the results from HDFS

- **Sequence Diagram**

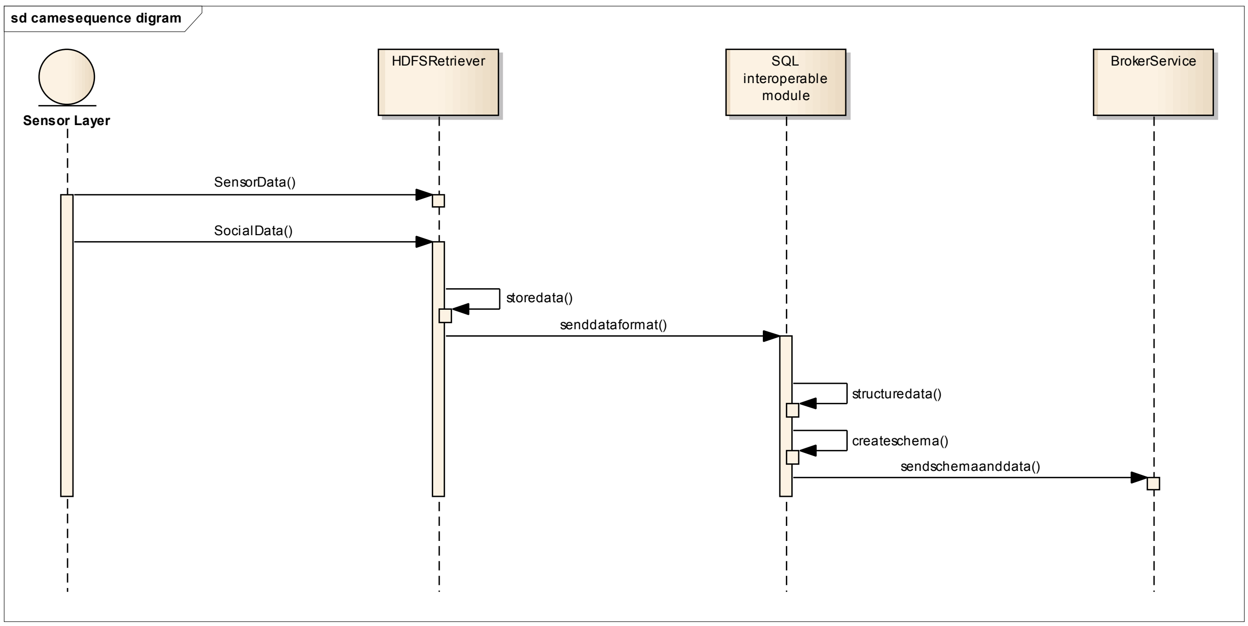


Figure 6 Processing sensor data into structured form

- The sensor layer will pass the sensory logs to the virtual file system
- The HDFS retriever will store the data and send the rough data format to the SQL interoperable module.
- The SQL interoperable module will structure and create a schema depending on the data format.
- The structured data is sent to broker service.

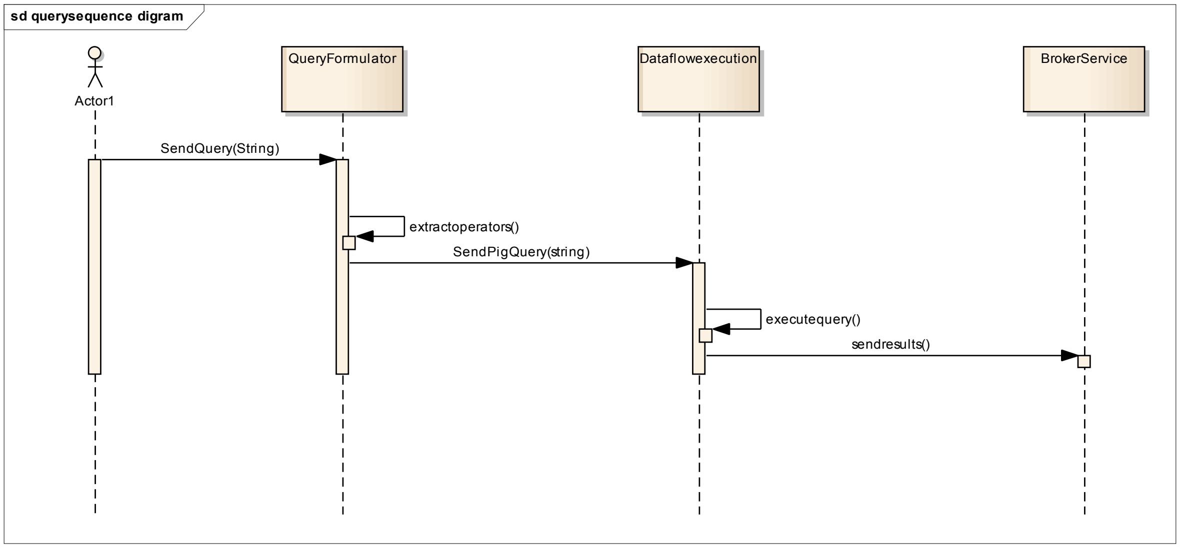


Figure 7 Execute query in big data

- A user sends the query to get some results from the big data.
- It is passed to the query formulator to convert into the Apache PIG query by extracting the operators and other key information from user query.
- The data flow execution class than executes the query by converting it in Hadoop jobs and sends the result to broker service.

- ## Class Diagram

It consists of the main class that interacts with the internal classes of the component.

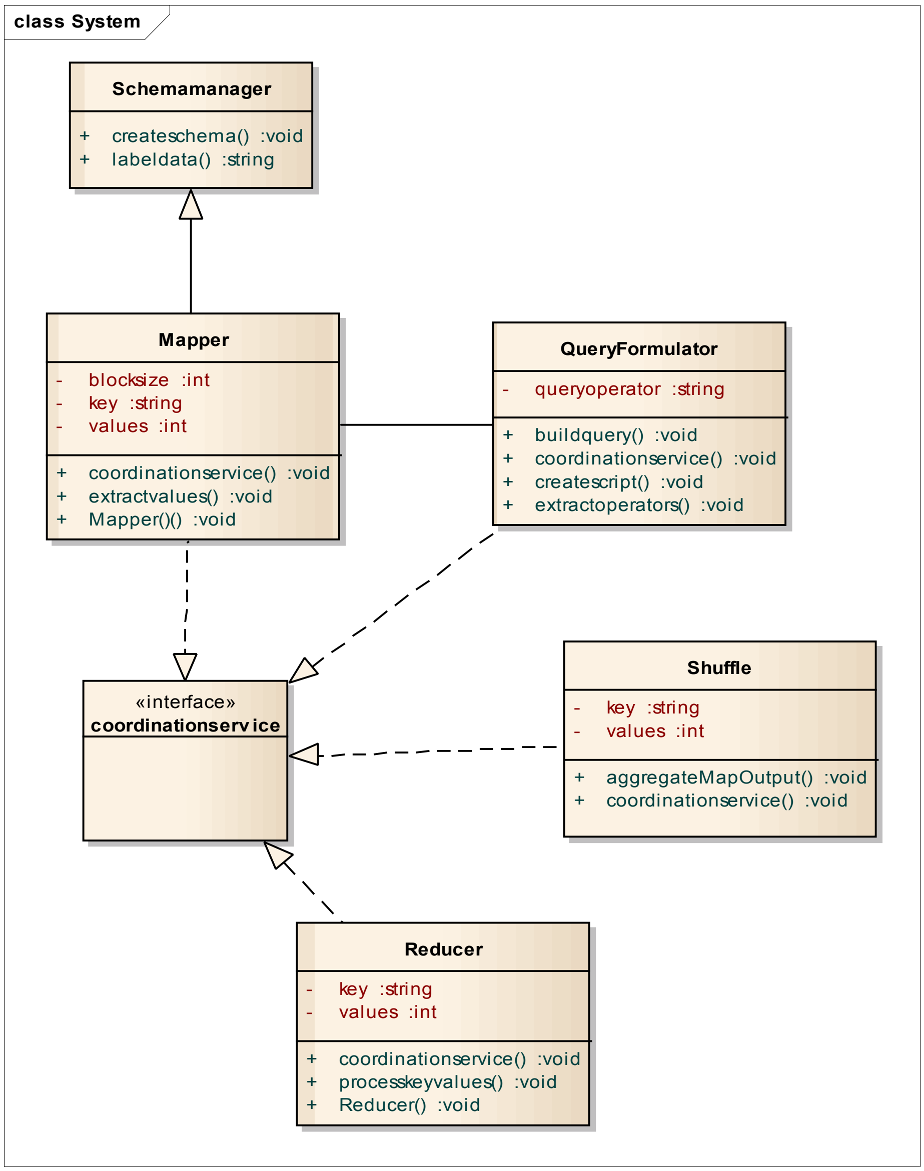


Figure 8 Class diagram of the overall module

- **Component Diagram**

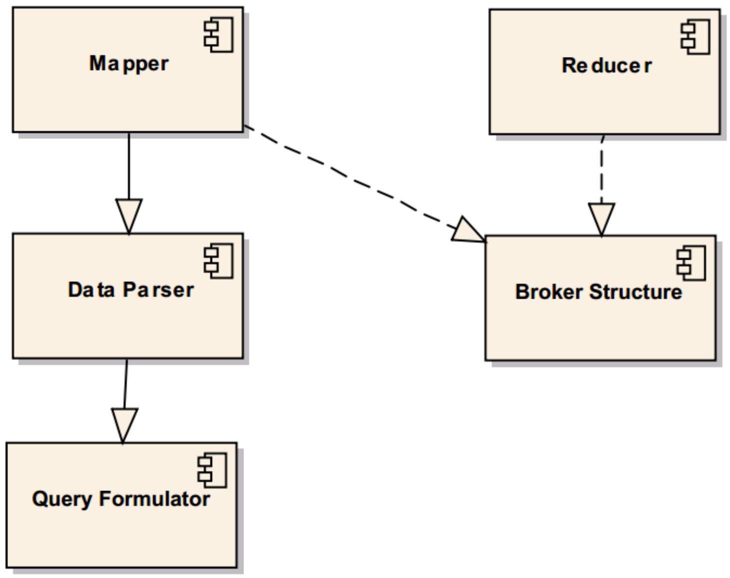


Figure 9 Component Diagram of BISE

- The component diagram shows different components and their relationships with each other. Mainly there are three main components and are explained below.
- Mapper component will store extract values of labels through a data parser and passed the data through broker service.
- Reducer component will process the key values and also execute some part of queries being requested by the user
- The query formulator will be used to create mapreduce compliant query to be executed on Hadoop
- Fusion Component: calculate the accuracy matrix for assigning the weights to extracted rules.

2.6 Contribution and Originality

Different kind of inputs from different engines in the system will be coming in the big data. The input information varies from emotion labels, activity labels, action loggers and social media input. The big data will store and process most of the input given to it.

One of the main functions is to process the sensory inputs from the sensor layer. The output will range from smartphone sensors to wearable sensors to social media data. These inputs will then be arranged in a structured format in structured data collector module. This structured information will be in a tabular format for KARE to process it for wellness recommendations.

One of the unique attribute is to structure the information fed to big data storage processing engine so that it can be passed on to the KARE for easy processing. This is one of the novel techniques as the output for the system is generated so it can easily process information for efficient response.

2.7 Conclusion

Big Data has a very important role to play in health and wellness systems as constant monitoring and social media have created a data deluge. The data generated is usually in semi structured or unstructured data and there is no querable schema. So we are applying mapreduce which is the most popular big data technology.

Chapter 3: Low-level and High-level Context Processing Layer

In the following section we briefly described the technical details and proposed methods and models in each sub component.

Multimodal Emotion Recognizer: In this module we are taking care of audio, video and heart rate sensor. Following is the detail of each component while heart rate sensor processing module is processed by Dr. Leon (Tecnalia Research Institute, Spain).

3.1 Audio-based Emotion Recognition

3.1.1 Introduction

- Emotion is a mental state that arises spontaneously. In daily life, emotion is not only an effective way to convey our intention in communication but also a good indicator of our mental health. That is the reason why automatic detection of human emotions is an important factor to enhance the quality of the service provided by the computer such as human-computer interaction [Cowie2001, Schuller2004], lifestyle monitoring in ubiquitous health care systems [Tacconi2008].

- Emotional speech is one of different ways people use to express their psychological states. In face to face conversation, emotional speech, facial expression and body gestures convey mostly implicit information of speaker to listener. However, in some situations, speech is only way that can be used to convey human messages such as blind people or call center system. While human emotion can be expressed by a variety of physiological changes such as speech, blood pressure, heart rate, facial expression, etc.; many researchers prefer acoustic speech as a source of emotion [Ayadi2011, Bitouk2010, Iliev2010, Lee2005] because speech signal is the most commonly used and most natural method of human communication.

- Finding the best feature extraction and classification for emotion recognition from speech signal still are the current challenge for researchers.

3.1.2 Related Work

- Since speech signals are not stationary even in wide sense, it is common in speech processing to divide a speech signal into small segments called frames. Within each frame the signal is considered to be approximately stationary. Prosodic speech features such as pitch and energy are extracted from each frame and called local features. On the other hand, global features are calculated as statistics of all speech features extracted from an utterance [Ayadi2011].

- Various types of classifiers have been used for the task of speech emotion recognition HMM, GMM, SVM, artificial neural networks (ANN), *k*-NN and many others. In fact, there has been no agreement on which classifier is the most suitable for emotion classification. It seems also that each classifier has its own advantages and limitations [Ayadi2011].

- Matching pursuit is an iterative algorithm has been used to decompose an input signal into a block of atoms which are chosen from predefined complete redundant dictionary [Mallat1993]. For each step, the most appropriate atom is selected that minimizes the residual energy. Once the process is stop, selected atoms and corresponding coefficients represent an approximation of input signal.

- Matching pursuit can be considered as a preprocessing step before feature extraction step. After decomposition of input signal into a block of atoms by using matching pursuit, we can apply different methods for explorer information from selected atoms and corresponding coefficients. Several existing works have applied matching pursuit for the task of recognition. In [Umapathy2005a, Ummapathy2005b, Chu2009], matching pursuit was applied for recognition of environmental sounds, musical instrument and classification of pathological voices respectively.

3.1.3 Limitations of Existing Work

- Many feature extraction and classification methods that have been proposed to extract more and more useful features and classify emotional state from speech signal [Cowie2001, Lee2005, Banse1996, Gobl2003, Nwe2003]. But we still don't know what the best features and classifiers for this task of recognition are.

- Most of spectral feature extraction method such as Mel-Frequency Cepstral Coefficient (MFCC) are using Fast Fourier Transform (FFT) to transform input signal from time domain into frequency domain. However, information is lost due to poor representation in time of FFT. So it needs a more flexible representation of signal to exploit more information such as matching pursuit decomposition.

- Original matching pursuit didn't take into account spectrogram information which help to improve efficiency of decomposition [Mallat1993, Umapathy2005a, Ummapathy2005b, Chu2009].

3.1.4 Proposed Methodology

- The main function of this component is recognizing emotional content of unknown speech signal. It takes a speech sentence from audio sensor as input and then process to classify to one of different emotions. The output emotion has the form of text label such as anger, happiness, boredom, sadness, normal, etc.

- This AER component has 4 main sub-components called:
  - Data Acquisition
  - Feature Extraction
  - Feature Selection
  - Classification

- Each of them has a unique important role in the whole process of this component. It shares the similar architecture with almost classification applications that need to have at least three parts including of collecting data, extracting features, selecting features and classifying.

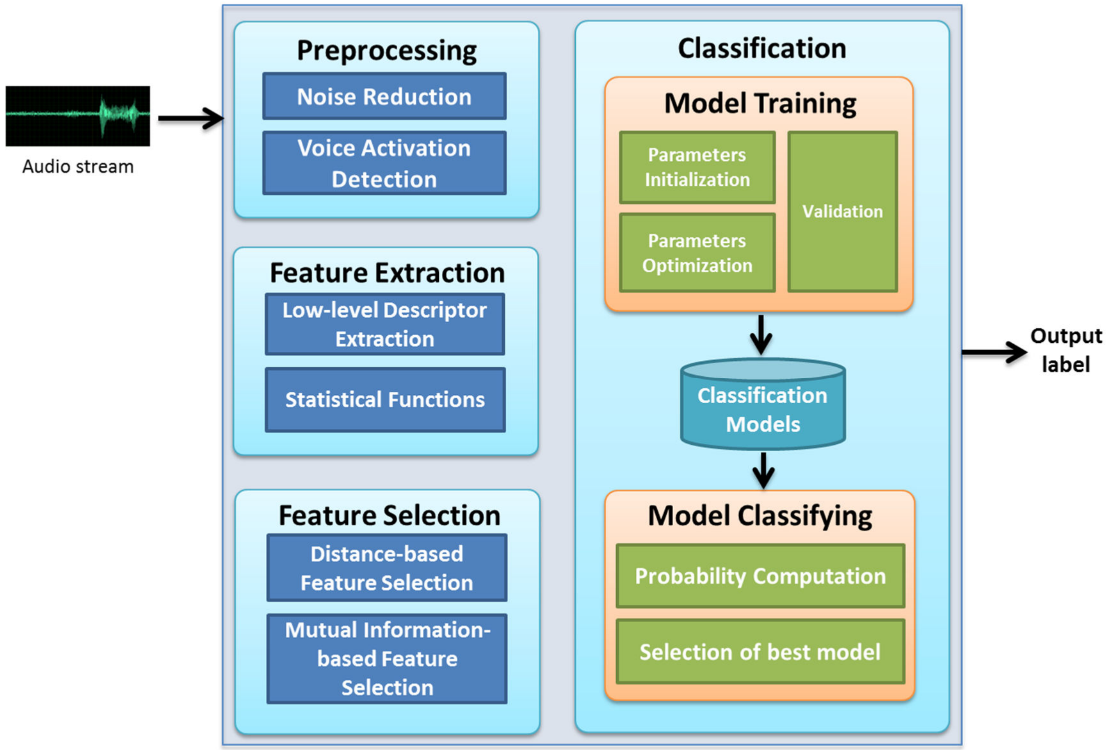


Figure 10 General architecture of audio-based emotion recognition engine

- **Data Acquisition:** The main purpose of this sub-component is to detect and record audio data for further process. Input audio stream from sensor is continuous and contains audio and speech signal as well.
    - We need to detect when speech signal appears in audio stream so that we can record speech signal. To reduce the complexity of this process, we can assume that the audio stream contains speech signal only, so we just need to detect speech signal by using energy threshold.
    - Whenever the average energy is larger than threshold, the audio recording module is activated to start recording speech signal. If average energy becomes lower than threshold, it means a sentence is completed, recording module is stopped, and then recorded speech signal is stored as a file.
- **Feature Extraction:** This is one of two most important parts that takes a speech sample as input and then generates a feature vector or a sequence of feature vectors. The main purpose of this process is extract the most relevant features that can describe clearly about the

processing signal, and can be used to classify between different classes of signal. Specially, we need to extract the most valuable features that can classify emotional states from speech signal. Depend on what kind of signal and application, there are different processes inside feature exaction component. In this architecture, we have:

- Signal Preprocessing: to reduce noise that can affect to quality of signal and reduce the accuracy of classification. In this process, we can apply spectrum subtraction to reduce background noise.
- Signal Decomposition: Matching Pursuit is applied to decompose the input signal into a block of atoms that are small-predefined signals [Mallat1993, Umapathy2005a, Ummapathy2005b, Chu2009]. And then depend on the distribution of these atom we can extract different features.
- Time feature and frequency features are extracted from output block of atoms by using temporal and spectrum histogram.

- **Feature Selection:** In feature extraction stage, we can use different kind of features, some of them are good, but some of them are not good, they affect to accuracy of classification. We apply feature selection here to reduce the irrelevant features in order to increase the accuracy. Two type of considered criteria here are distance-based feature selection and mutual information feature selection.
  - Distance-based feature selection: features are selected so that they maximize distance between classes and increase the dissimilarity of classes.
  - Mutual information feature selection: features are selected based on the mutual information between features and features, between features and classes so that they maximize the relevance and minimize the redundancy.
- **Classification:** In this stage, a machine learning algorithm is applied to learn the properties of processing signal, and to differentiate between different classes of signal. To make balance between simplicity and performance, we apply Gaussian Mixture Model (GMM) as classifier to recognize different emotional states in speech signal. GMM is a lightweight classification

algorithm, so that it is easier to apply on smartphone that have limited computational resources. Similar with other classification, there are 2 main processes training and classifying.

- **Training process:** This training is used to learn properties of each class of signal by group all training data of class and apply Expectation Maximization to generate the parameters of GMM model. Each emotional class of speech signals is used to generate a GMM model. For example we have 4 classes Normal, Angry, Happy and Sad, so 4 GMM models are trained in this step.

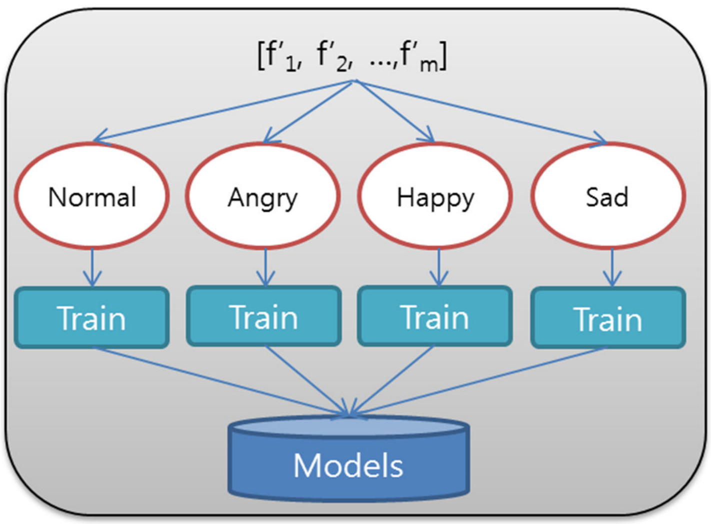


Figure 11 GMM Training process for 4 emotional classes

- GMM Parameters Initialization: we initialize parameters for each GMM model randomly

- GMM Parameters Optimization: in this process, EM algorithm is used to optimize parameters of a model. This is a recursion process to fit parameters of GMM model with distribution of training data in iteration. The process is stopped when it reaches to a number of iterations or is below a threshold.

- Validation: This process is to validate predefined parameters of a model by using them to recognize a set of validating data. Which parameters have better performance and accuracy are chosen for classifying stage.

- All trained models are stored in a local database or provided to mobile side for further process.

- **Classifying stage:** This process is deployed at PC side or mobile side as well depending on what kind of application. The main purpose of this process is to find from all trained models the best model that has the largest probability with unknown input feature vector compare with other ones.

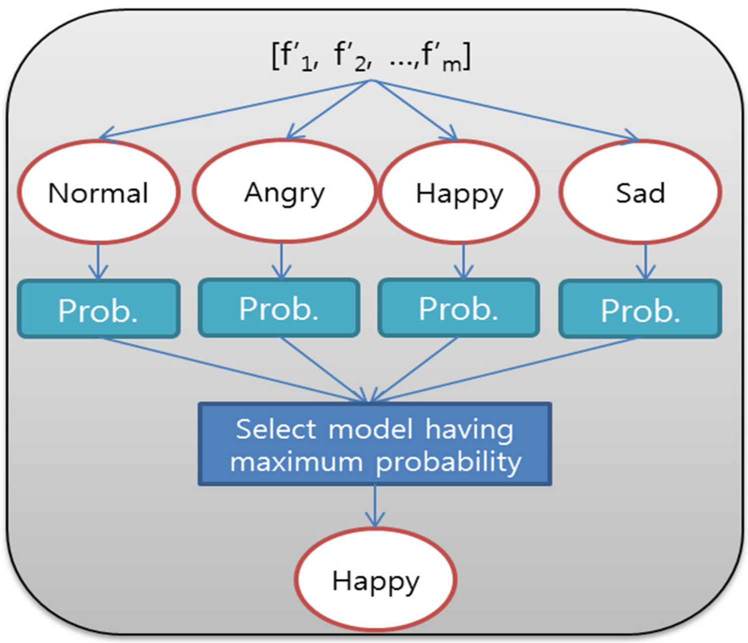


Figure 12 Classifying of unknown input signal given 4 GMM models

Probability Computation: when the input feature vector is available, its probability with each GMM model is computed using Gaussian distribution. All probabilities are compared to select the largest one. And then we consider the model with the largest probability is the output of classifying stage.

3.1.5 UML Diagram

- **Overall System Flowchart**

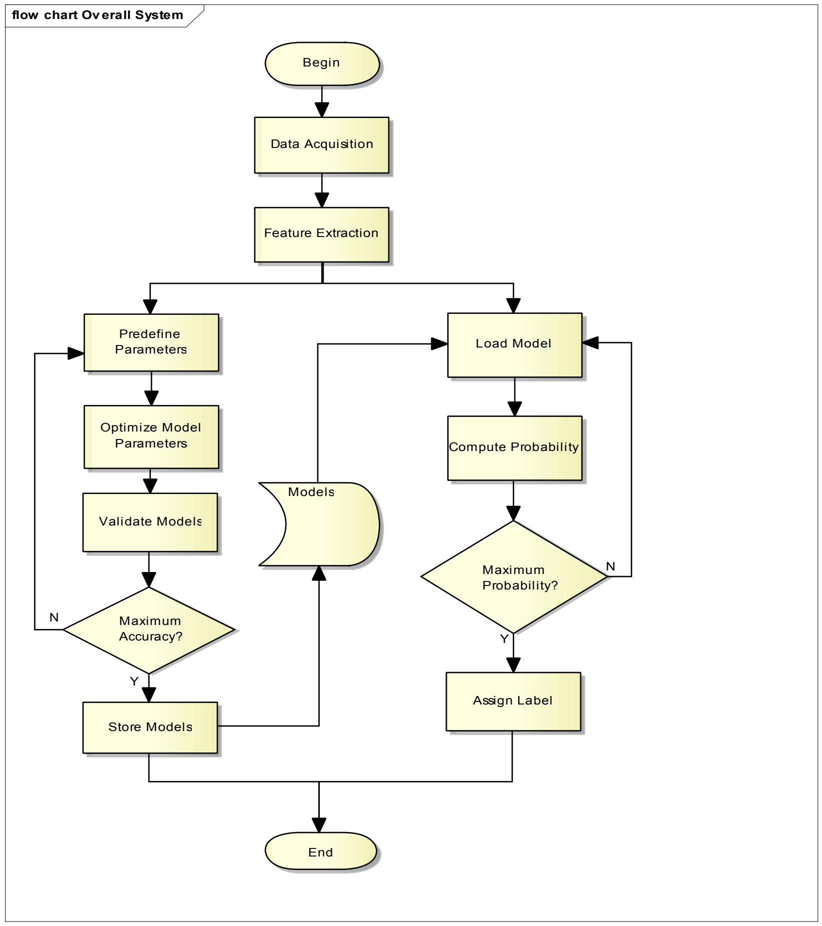


Figure 13 Flow chart of the system

- It contains two phases: training and testing.
- This shows that how different components work together and how the output of one component flows to the other component where it is used as input for further processing.

- **Use case diagram**

Following diagram shows the interaction between activities in training and classifying stages.

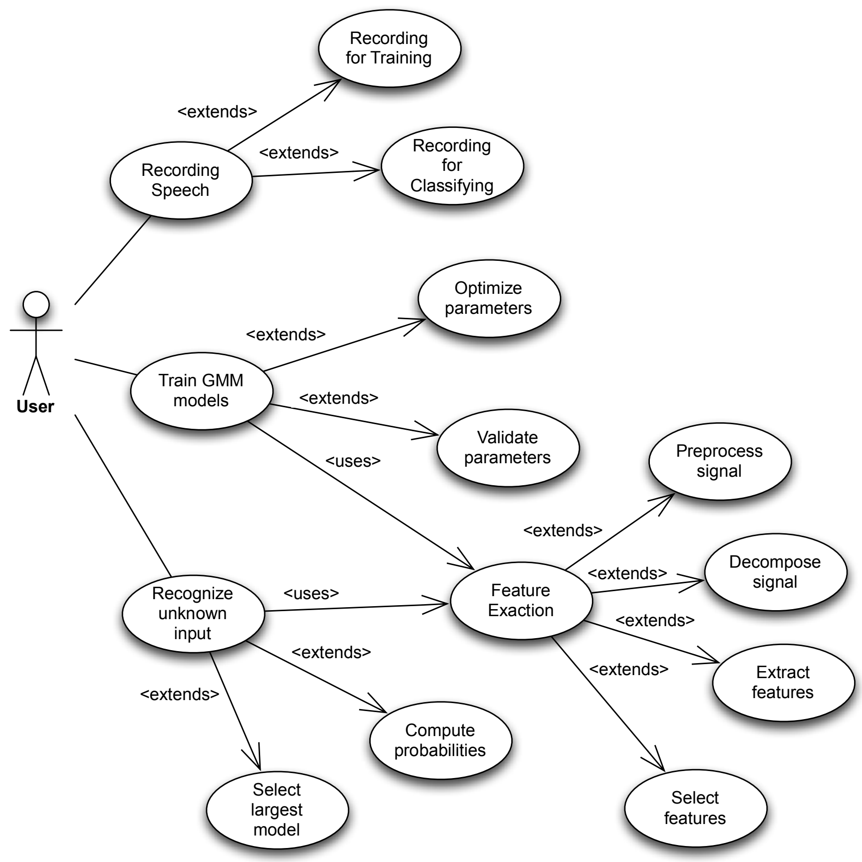


Figure 14 Use case diagram of Training and Recognition

User/Actor can interact with the system in 3 use cases: Recording Speech, Training GMM Models, and Recognizing Unknown Input

- Recording Speech: is required to record speech signal for training and classifying.
- Training GMM Models: is used to train GMM models, this use case need Feature Extraction to generate training feature vectors, and Optimize Parameters to estimate parameters of GMM model, and Validate Parameters to tune the values of those parameters to best fit the training data.

- Recognizing Unknown Input: this use case requires Feature Extraction also, and then it computes the probabilities of classifying signal with trained models to select the model that has the largest value of probability.

• Sequence Diagram

Following training and testing phase sequence diagrams show the sequence of message between objects in an interaction.

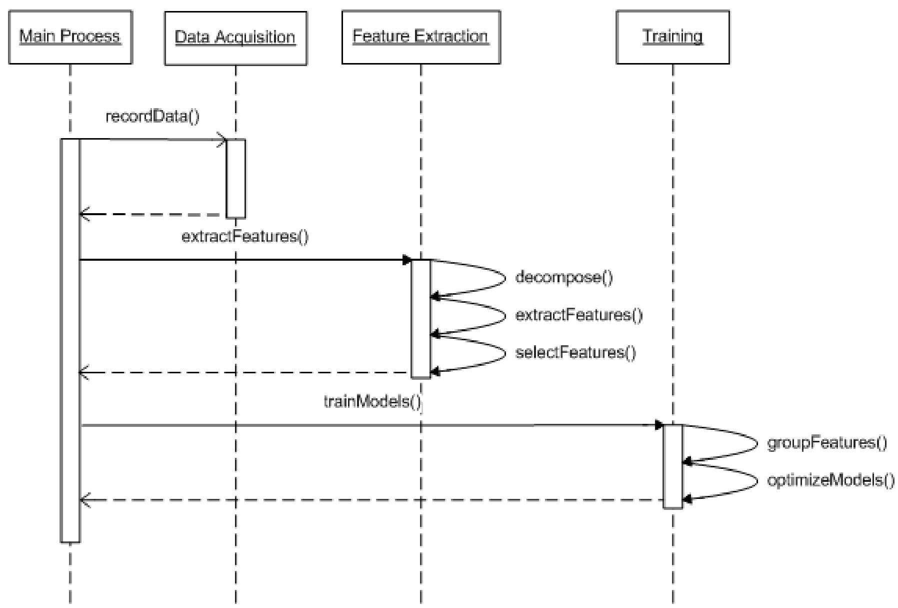


Figure 15 Sequence diagram of training stage

- Initially, Data Acquisition is called to detect and record speech signal from audio stream.
- Main Process requests Feature Extraction to extract feature for all training speech signal. Inner processes are called to generate feature vector following Matching Pursuit algorithm.
- Finally, training stage of GMM algorithm is used to train models for all emotional classes.

Following diagram show the recognizing phase sequence diagram.

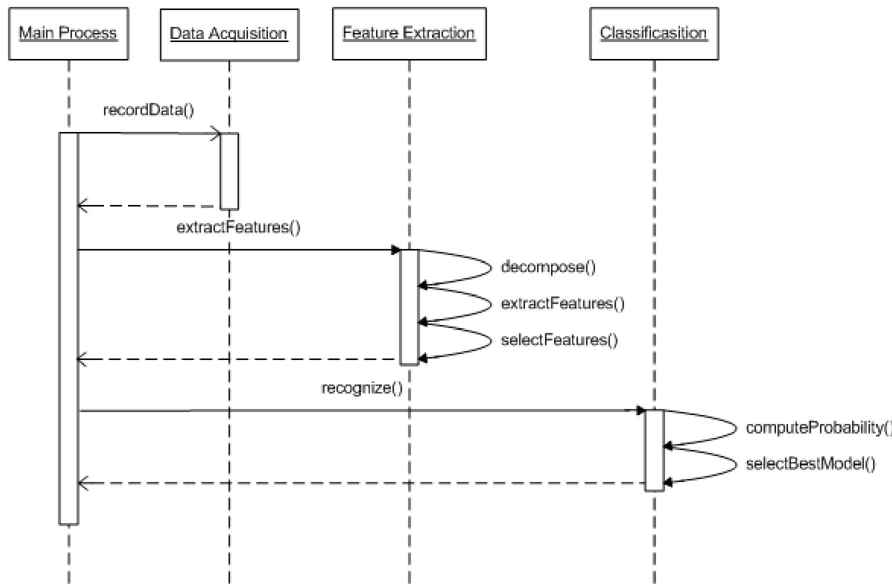


Figure 16 Sequence diagram of classifying stage

- Similar with training, Data Acquisition is called to record unknown signal.
- Feature Extraction is applied for unknown signal also.
- GMM classifier takes feature vector from Feature Extraction and compute probability with all models to find the model that has the largest probability value and then assigns according emotion as output label.

- **Class Diagram**

Following diagram shows structure of classes and relationship between them.

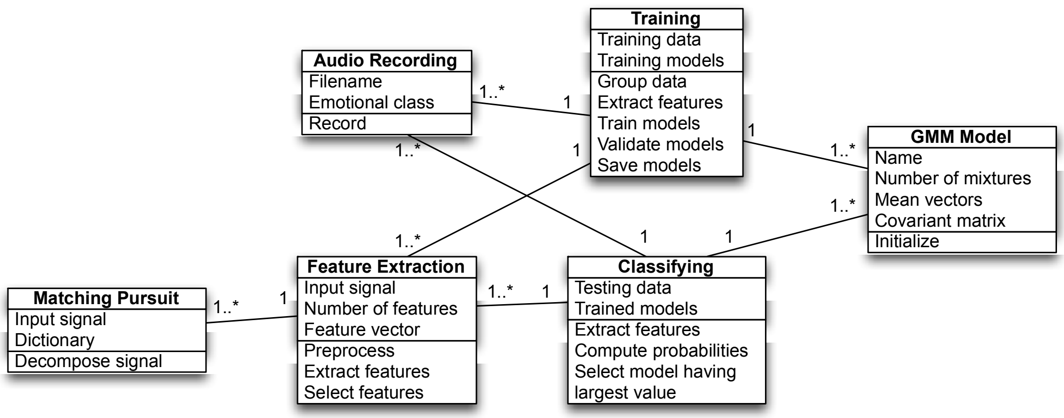


Figure 17 Class diagram of the system

There are two main classes of Training and Classifying. In structure of those classes, appropriate attributes and methods are defined according to training and classifying purpose. They use other classes of Audio Recording, Feature Extraction and GMM Model for different processes.

Matching Pursuit class is used for signal decomposition using MP algorithm and Feature Extraction class utilizes this class.

3.1.6 Contribution and Originality

- Propose algorithm to improve matching pursuit decomposition (MPD) based on weighted dictionary of atoms to increase the speed of decomposition and reduce the time consumption.
- Apply MPD to extract features in time and frequency domain simultaneously.
- Combine with other feature extraction methods to find relevant features.

Apply feature selection based on scatter matrix and mutual information in combination with Gaussian mixture model classifiers to make the combination of discriminative (feature selection) and generative (classification) methods.

3.1.7 Conclusion

- We provide a flexible ACCESS engine for the task of emotion recognition from speech signal that can be applied easily in different system such as personal computer, smartphone, robot or home appliances.
- The ACCESS engine can be combined with other emotion recognition method using different signal such as facial expression or physiological signal to provide a more general framework for classification emotion.
- Our engine can be extended more valuable and efficient by taking into account emotional speech recognition with independent language and in natural communication.

3.2 Video Based Facial Expression Recognition

3.2.1 Introduction

Facial Expressions are a universal mean of communication which can be expressed non-verbally without any language constraints. They are recognized through facial expressions, voice tones, speech and physiological signals. Communication through facial expressions plays a significant role in social interactions. Over the last decade, automatic facial expressions recognition has become an important research area for many applications such as child development, neuroscience and psychology, access control and surveillance and human behavior understanding.

Anytime and anywhere, people have the ability to sense and express emotion, which can help make decisions, handle crises, and maintain relationships. Plentiful words and phrases are used to express moods and feelings. The ability of sensing and expressing emotion in a machine is often a luxury, considered unnecessary and functionless in basic computer intelligence. Programmers hardly encode emotion descriptions into computers. Why are people still trying to give computer emotional ability? [Malika2009].

When a human user interacts with a computer agent, emotion expressed by the agent affects the emotional response from user. In a study of game agent, if the virtual game agent opponent behaves “naturally" in that it follows its own goals and expresses associated positively or negatively affect behaviors, users will be less stressed than when the agent does not do so [Prendinger2006]. A frustrating interaction with a computer system can also leave a user feeling negative toward the system and its maker [Klein2002], so the consideration of emotion for computers and agents becomes important.

Before giving computer emotion ability, recognizing human emotion is a preliminary requirement. A computer agent needs to know how a person feels via emotion recognitions, and then the computer agent can perform a reasonable emotional feedback to the person. This feedback of computer is a design of human computer interaction. In the design of human computer interaction human desire and feeling should be considered. Furthermore, it needs to obtain the emotion via contain electronic media before it recognizes such emotion [Malika2009].

The study of facial expression recognition (FER) has consistently been an active and exigent research area in recent years, which has a significant contribution in many applications such as communication, personality and child development [Bartlett1999], neuroscience and psychology [Mehrabian1968], access control and surveillance [Bettadapura2009] and human behavior understanding. There are three basic modules in FER systems, face detection, feature extraction and recognition as shown in Figure 11.

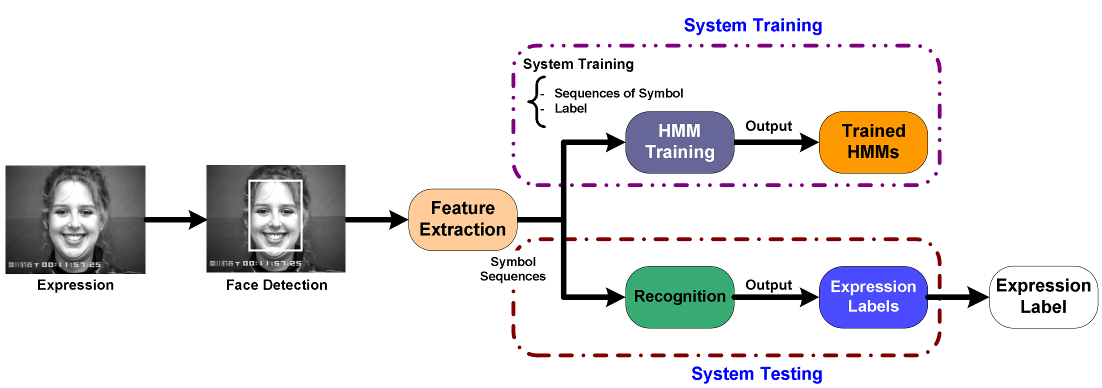


Figure 18 General architecture of video-based emotion recognition system

3.2.2 Related Work

Essentially, face detection is the first-step for automatic Facial Expression Recognition (FER) systems, with the purpose of localizing and extracting the face region from the background. It has several applications such as content-based image retrieval, video coding, video conferencing, crowd surveillance, and intelligent human computer interfaces. The human face is a dynamic object and has a high degree of variability in its appearance, which makes face detection a difficult problem in computer vision. A wide variety of techniques have been proposed, ranging from simple edge-based algorithms to composite high-level approaches utilizing advanced pattern recognition methods.

Though, there lots of works have been done for face detection; however, most of them have their own limitations. Neural Network (NN) has been exploited by [Rowley1998] for face detection that divided the facial frame in small windows in order to find the location of the face. A robust geometrical method has been proposed by [Rezq2011] for face detection; however, this method does not has the capability to represent the global face structure. Some factors such as illumination, head pose and occlusion might reduce robustness of the FER systems; therefore, [Tripathi2011, Song2007] employed the combination of skin-color and template matching methods in order to detect the face.

Feature extraction is one of the most important modules for Facial Expression Recognition (FER) systems, which deals with getting the distinguishable features each expression and quantizing it as a discrete symbol. Many of the existing works have been investigated new algorithms to extract good features. A complete approach has been proposed by [Wu2010] for extraction the facial features. They employed canny edge detection and a well-known statistical approach such as Principal Component Analysis (PCA) for features extraction. Gabor filter has been employed by [Liu2008, Schels2010, Tian2005] in order to extract the facial features from expression frame. Most of the significant facial expressions information can be extracted from lips, nose and eyes known as local features that have an important role in achieving the best accuracy of recognition. Therefore, to extract the local features, one of the higher order feature extraction techniques such as Independent Component Analysis (ICA) has extensively employed by [Bartlett2002, Chuang2006, Buciu2003] for local facial feature extraction. Another method like Local Binary Patterns (LBP) has been exploited by [Shan2009] for feature extraction. In this method a 3 x 3 operator is used in which each pixel is compared with its eight neighbors by subtracting the center pixel value. The resultant positive values are encoded to 1 otherwise encoded to 0. To solve the problem of LBP and to extract the best local features, high order local pattern descriptor such as Local Directional Pattern (LDP) has been presented by [Jabid2010] and [Jabeed2010]. By using LDP, we can extract best local features that will further be used for recognition.

3.2.3 Limitations of Existing Work

However, the performance of NN is completely reliant on the number of hidden layers and nodes and learning rates, and also to get an optimum performance, the network has to be comprehensively adjusted [Kakumanu2007]. Similarly, the skin-color methods have difficulties to get the faces robustly under varying lighting conditions and especially in the presence of complex background [Hsu2002]. Moreover, template methods are correlation-based, which computational wise much expensive and also a huge amount of storage are required [Garcia1999].

Moreover, canny edge detection computational wise very much expensive, and some time it is not particularly successful technique because mostly the edges are not continuous and serious edges might be presented due to noise, which might a complex task for canny edge detection. On the other hand, PCA yields uncorrelated components. If the data have a Gaussian distribution, the uncorrelated components are independent. However, if the data are merged of non-Gaussian components, then PCA fails to extract components having non-Gaussian distribution [Buciu1999]. Furthermore, Furthermore, PCA is an unsupervised technique that locates PCs at the optimally diminished dimension of the input. For facial expression recognition, it only focuses on the global information and extracts the global features from the whole face image, which results in low accuracy. The major drawback of Gabor filters is that they are computationally much expensive. The peak state of the facial expression was proposed to recognize the facial expression images; however, the localized features were ignored [Kim2009]. Furthermore, ICA is slow to train when the dimension of the data is bulky. Moreover, these features are receptive to decipher and scaling of human facial expressions which concerns the feature extraction procedure. Also, ICA is very weak in managing the inputs. If there are plenty of video frames, exploited as input, ICA does not have the capability to organize it, due to which some time ICA cannot retrieve the desire features. Likewise, the dominant features cannot be extracted by 3 x 3 LBA operator. Also it does not provide directional information of the facial frame because it only captures the relations with its surrounding eight neighbor pixels. Moreover, LBP uses first order local patterns and cannot extract more detailed information. Similarly, computational wise, LDP is much expensive. Moreover, lots of memory size is required for LDP to store the binary codes that is four times bigger than LBP [Rosdi2011].

3.2.4 Proposed Methodology

Some environmental factors such as lighting effects might reduce the accuracy of the facial expression systems; therefore, in preprocessing class, these illumination and lighting effects are diminished to increase the recognition accuracy, using techniques like morphological filters, homomorphic filters, or median filters.

In order to detect faces, two improved key methods were used, simultaneously: gray-level and skin-tone-based. To attain the best performance, the similarity angle measurement (SAM) method (a method that compares the found and actual facial signatures) has been introduced, which extracts the most accurate face location in a video frame, obtained by using gray-level and skin-tone methods concurrently. In the face tracking model, facial geometry structure was used for feature extraction and comparison. The proposed face detection system is based on multiple cues from a face image/frame. When a rough face image is presented to the system, an improved gray-level and skin-tone model is adopted to locate the face region. Very often, hairs were included in the detected head contour. The second step is to find the precise face geometry using a facial geometry operation. To locate the exact face region, three cues were used: the face intensity (because the intensity of the eye region is relatively low); the direction of the line joining the center of the eyes, which is determined on the face edge image; and the response of convolving the proposed facial geometry variance filter with the face image. We have developed a facial geometry filter for extracting potential face windows, based on similarity measurements of facial geometry signatures. This process generates a list of possible face signatures, since each face feature has unique identification, or signatures, and these signatures can be compared with stored face signatures. However, in some cases, the detected face boundary usually might consist of hair. Hairstyles are different from person to person. Therefore, in the next step another technique such as face skin region has been employed in order to locate the skin region from the detected face region and to get rid of the problem of different hairstyles. Under normal illumination, the facial features such as nose, mouth, and eyes possess relatively lower gray levels. We can always plot the intensity histogram of the face image, because skin color has a relatively high gray intensity, while other facial components have relatively low intensities. In this way, it is easy to find a threshold value for face detection under normal illumination. In most images, the number of possible cases for the second loop case was less than two. For each possible case, the similarity measurement function was adopted for face detection, tracking, and verification. If the face was detected in the face frame, the detection process completed; if not, next possible case was tested. Details of each block are presented in Figure 12.

We employed the well-known statistical approaches, PCA and ICA, to extract local and global features, respectively. Since most expressions share high similarity, their features overlap significantly in the feature space. This can result in the presence of very low between-class and high within-class variances in the feature space, which in turn can lead to low recognition accuracy. Numerous methods have been presented in the machine learning literature to solve this problem, such as LDA. However, our experiments showed that applying LDA directly to the whole feature space failed to resolve the overlap or low between-class variance among facial expressions. This failure could be attributed to the fact that LDA is a linear technique, which limits its flexibility when applied to complex datasets. Moreover, the assumption made in using LDA that all classes share the same within-class covariance matrix is not valid in this case.

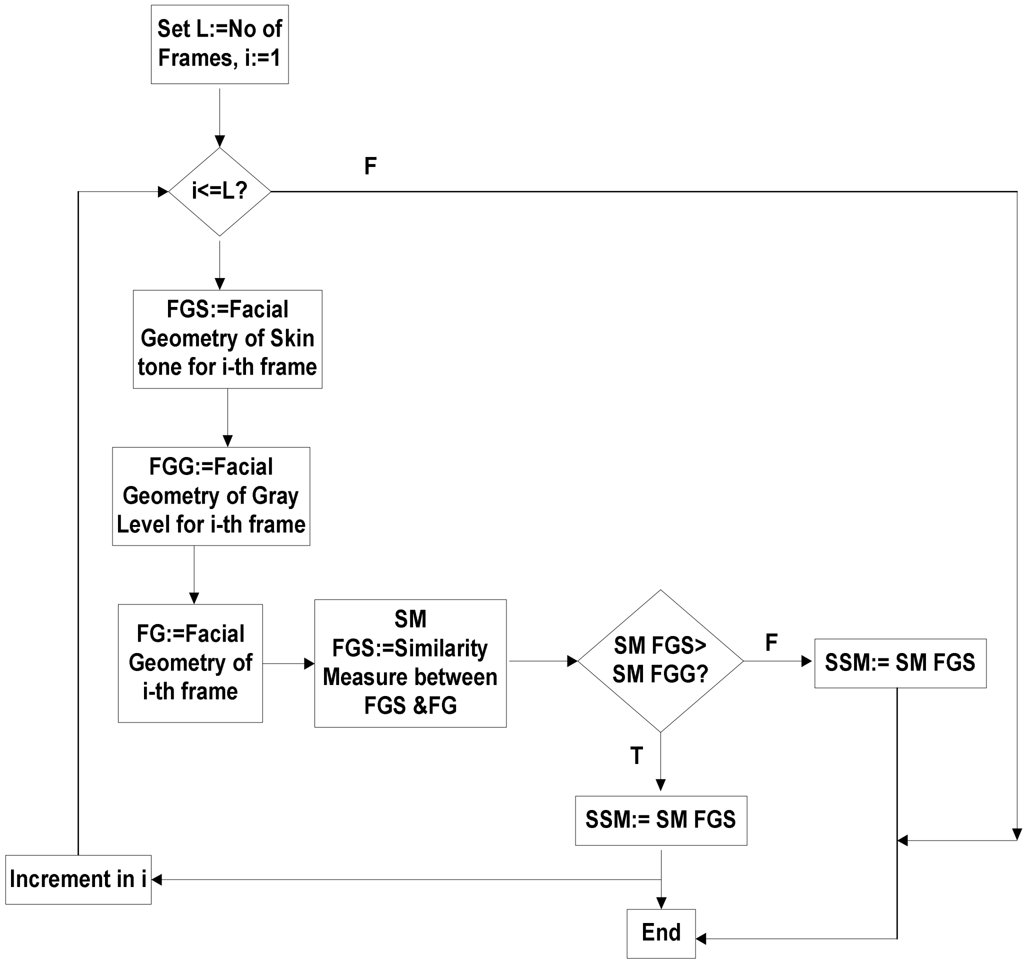


Figure 19 The architectural diagram for the proposed face detection system

To overcome the problem of single-HMM, we proposed a hierarchical recognition scheme that is a combination of PCA, ICA, LDA, and HMMs. Based on the parts of the face that create an expression, expressions were divided into three categories: lips-based, lips-eyes-based; or lips-eyes-forehead-based expressions. At the first level of the proposed hierarchical recognition scheme, LDA was applied to the features (PCs and ICs), and the resulting LDA features were fed to a single HMM to recognize the category for the given expression (as shown in Figure 13). Once the category of the given expression was determined, the label for the expression within the recognized category was recognized at the second level by again feeding the features to a combination of LDA and HMM, trained specifically for the recognized state as shown in Figure 14.

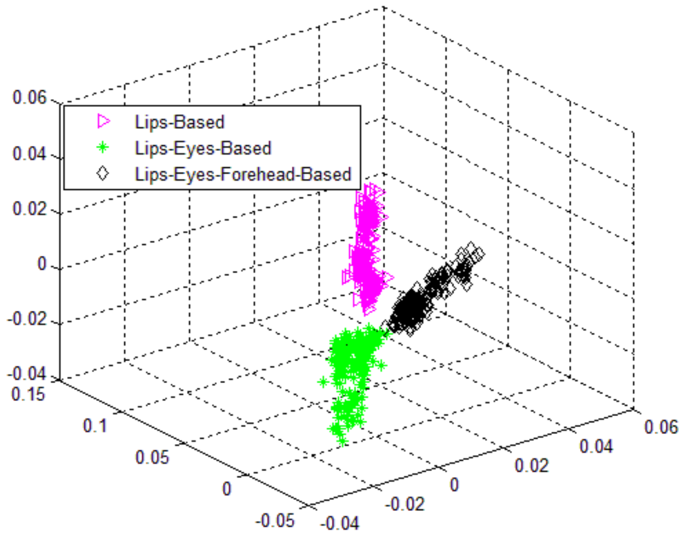


Figure 20 3D feature plots for the three expression-categories after applying LDA at the first level

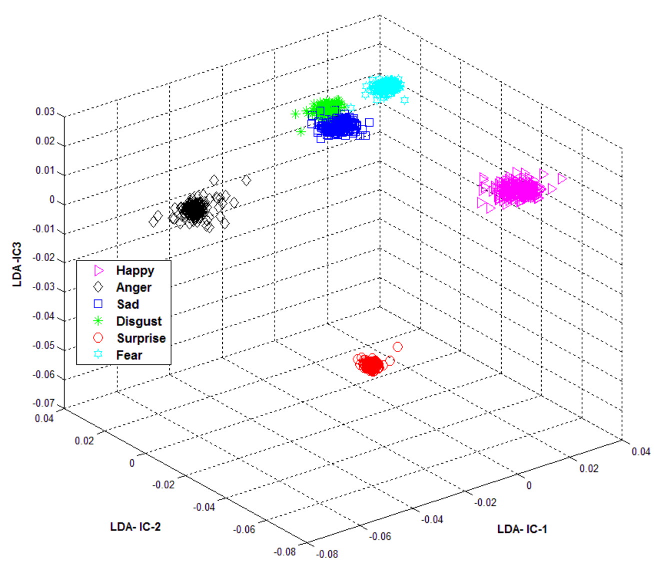


Figure 21 3D-feature plot of the proposed hierarchical recognition scheme for six different types of facial expressions after hierarchical LDA

Once the category of the given expression has been determined, the label for the expression within the recognized category is recognized at the second level by again feeding the features to a combination of LDA and HMM. However, there were three different sets of LDA and HMM at the second level: one for each category. The overall flowchart for the proposed system at the training stage is shown in Figure 9.

3.2.5 UML Diagram

Use case diagram: It communicates with the video camera and different component of activity recognition system are turned on.

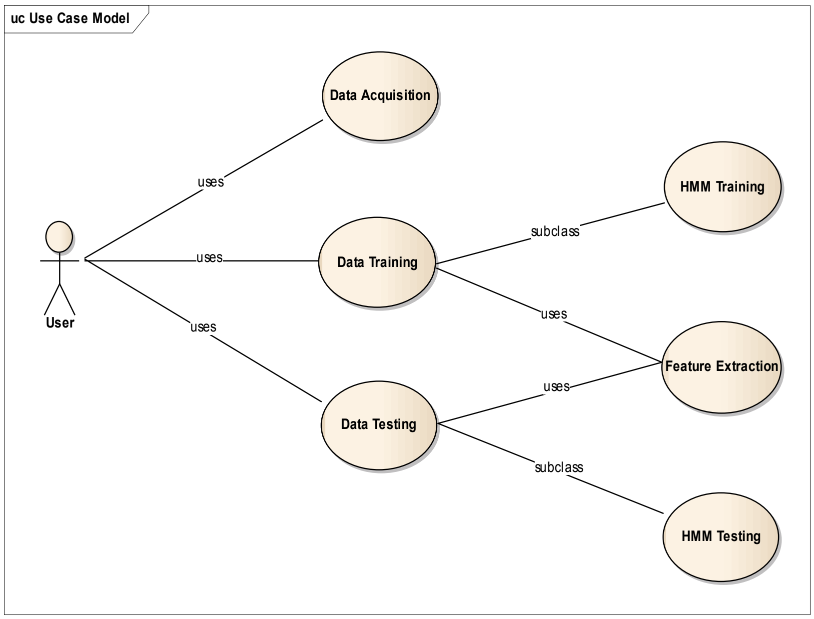


Figure 22 The use case diagram of video*based activity recognition

- As an actor, human communicates with the 2D camera.
- The common supposition is to employ machine learning techniques.
- Processed and cleaned data for training purpose.
- The essential flow should be the incidents of the interaction with human, and there are no errors, no omissions that will be handled to preserve the logs and alerts to the corresponding person.

- **Sequence diagram for training**

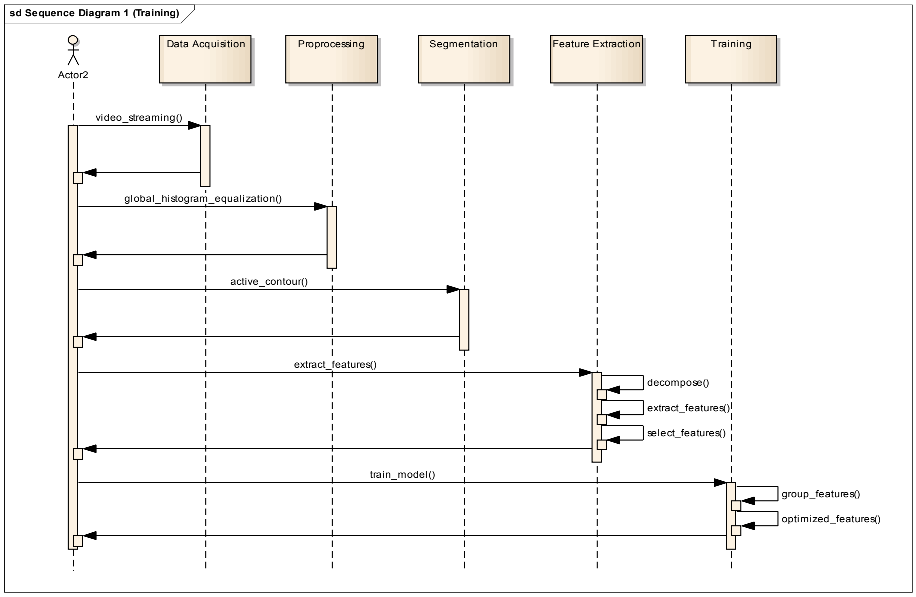


Figure 23 The sequence diagram of human activity recognition for training.

- At the beginning, in the main process the video of the human activity recognition is streamed and cleaned from noise at data acquisition stage.
- Some environmental effects such as lighting effect can be diminished at the preprocessing stage via Global Histogram Equalization (GHE) technique.
- An un-supervised technique such as active contour is employed to segment the human body automatically from the video frame at the segmentation stage.
- A robust technique called wavelet transform is employed to extract features from the segmented body.
- The system will be trained with suitable activity labels.

- **Sequence diagram for testing**

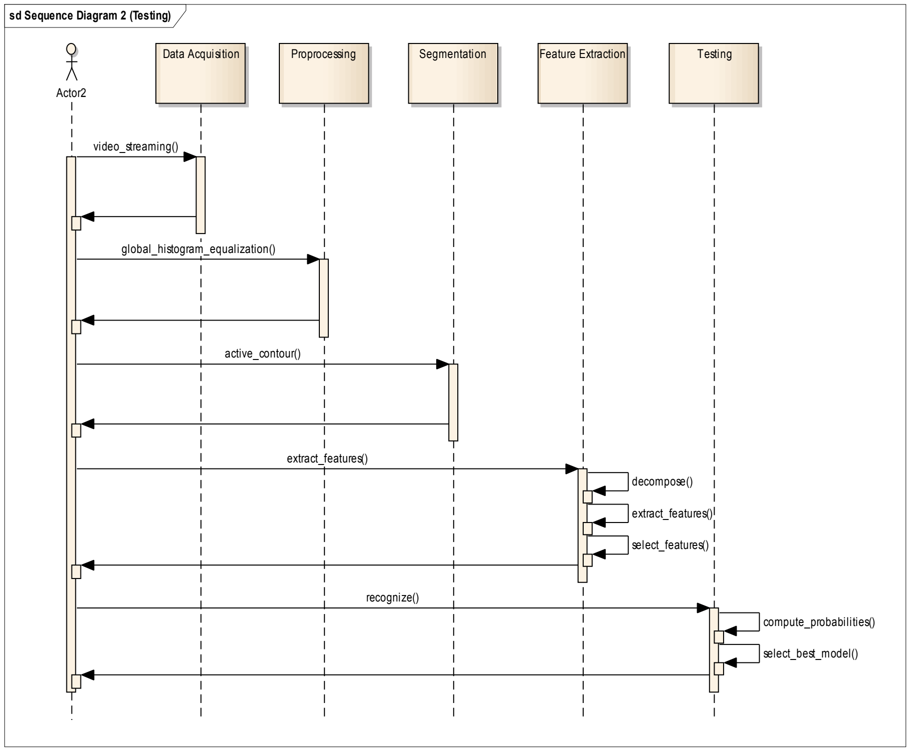


Figure 24 The sequence diagram of human activity recognition system for testing.

- In testing (recognition) phase, the streamed video frames are cleaned from environmental facts and then the human bodies have been segmented from individual activity frame.
- The features has been extracted and selected with the help of wavelet transform.
- The further activities have been recognized according to the trained labels.

- **Class diagram**

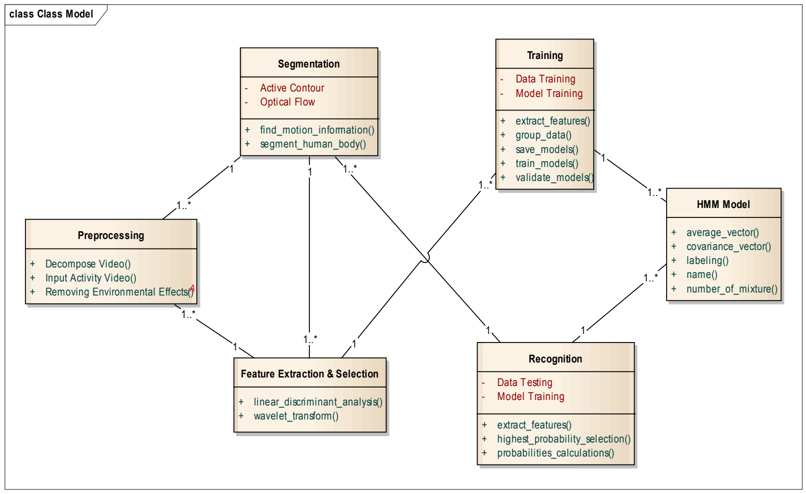


Figure 25 The class diagram for human activity recognition system.

- The class diagram shows how different classes related with each other to provide appropriate decision of activity recognition.
- In preprocessing class, the illumination and lighting effects are diminished to increase the recognition accuracy, using techniques like morphological filters, homomorphic filters, or median filters.
- In segmentation class an unsupervised segmentation technique such as active contour has been exploited for human body segmentation and the motion information between the two consecutive frames has been found by employing optical flow.
- The feature extraction module deals with extracting distinguishable features for each expression and quantizing each of them as a discrete symbol. Therefore, in feature extraction, wavelet transform has been used to extract the useful global and local features. Moreover, for feature selection a well-known statistical approach named linear discriminant analysis has been exploited.
- In recognition class, a classifier is used to train and to generate a label for the human activity recognition contained in the incoming video data. Among all of the classifiers,

hidden Markov model (HMM) can frequently be employed for sequential data such as activity recognition. HMM is trained and tested to recognize incoming activity frames.

- **Component diagram**

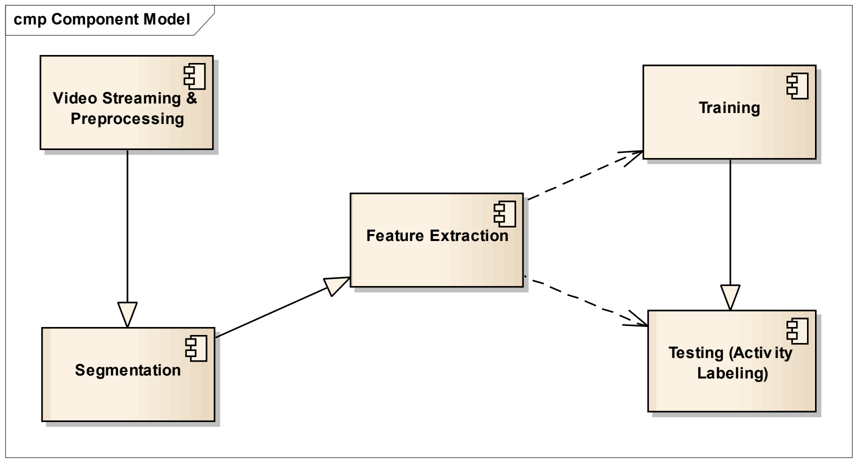


Figure 26 Component diagram of activity recognition system

3.2.6 Contribution and Originality

In preprocessing class, the illumination and lighting effects are diminished to increase the recognition accuracy, using techniques like morphological filters, homomorphic filters, or median filters

- Face contains most of the expression-related information, so, before investigation the expression, face must be detected first. An accurate facial expression recognition system requires automatic face detection which is considered the essential part of the facial expression system. So in face detection class the faces are detected and extracted first.
- The feature extraction module deals with extracting distinguishable features for each expression and quantizing each of them as a discrete symbol. Therefore, in feature extraction and selection some well-known statistical approaches are applied to extract and select informative features.
- In recognition class, a classifier is used to train and to generate a label for the human facial expression contained in the incoming video data. Among all of the classifiers, hidden Markov

model (HMM) can frequently be employed for sequential data such as facial expressions. HMM is trained and tested to recognize incoming expression frames.

3.2.7 Conclusion

Several factors make facial expression recognition (FER) a challenging research problem. These include: varying light conditions in training and test images; need for automatic and accurate face detection before feature extraction; and high similarity among different expressions that makes it difficult to distinguish these expressions with a high accuracy. This work implements a hierarchical FER system to tackle these problems. Unlike the previous systems, the proposed system uses a pre-processing step to eliminate light effects, incorporates a new automatic face detection scheme, employs methods to extract both global and local features, and utilizes a hierarchical recognition scheme to overcome the problem of high similarity among different expressions. Unlike most of the previous works that were evaluated using a single dataset, the performance of the proposed scheme is assessed using three publicly available datasets under three different experimental settings: n-fold cross validation based on subjects for each dataset separately; n-fold cross validation rule based on datasets; and, finally, a last set of experiments to assess the effectiveness of each module of the proposed FER scheme separately.

3.3 Smartphone-based Activity Recognizer

3.3.1 Introduction

Activity recognition recognizes user's activity using accelerometer, video, gps, etc. It is a core technology in the field of IT, and becoming a base element of the megatrend of future technology such as healthcare, ubiquitous, and life log. The research has been undergoing since 1980. Many researches have shown remarkable progress showing high accuracy on various activities.

Especially, using accelerometer is one of the most active research area among activity recognition. The research started from the assumption that when a user performs an activity, there is a distinct change of power. It uses accelerometer to measure features of each activity. Previous researches recognized user's activity by attaching the accelerometer where the values can be gained clearly, and analyzed these data.

Recent emergence of smartphone embedding various sensors has changed the aspect of the research. In previous methods which the accelerometer was fixed became no use that the smartphone is not fixed inside the pocket or a bag. To acquire accuracy independent to smartphone's triaxis accelerometer orientation, many researches tried to gain Signal Vector Magnitude (SVM) from triaxis accelerometer signal and then extract feature from it. It only showed high accuracy when there is a big difference of signal such as walking, running and cycling but not on bus, subway and stay which showed small difference of signal. Therefore, there isn't still a service that recognizes user's movement with accelerometer.

In this research, we propose smartphone based activity recognition to overcome this problem. We recognize walking, jogging, stay, bus and subway independent to smartphone's position and orientation. To do this, we revise accelerometer data with gyroscope data, and acquire fixed signal vector from front and rear, left and right, up and down independent to smartphone's orientation. Then we extract features from this signal to get similar signals which have identical activity. And we acquire data from different positions that we may carry on real life such as in top and bottom cloth, bag, hand, etc.

3.3.2 Related Work

Before the emergence of smartphone, independent sensors were used for research on activity recognition. Bao, Ling, and Stephen S. Intille worked with multiple 2 axis accelerometer. In this research, they attached sensors to forearm, wrist, pelvis, knee, and calf fixed, and recognized walking, jogging, stay, sit, watching TV, cycling, eating, reading, etc. They calculated average, energy, frequency domain entropy, and correlation on each sensors, and classified with C4.5 decision tree, IBL, decision table, and naïve Bayesian distribution. As a result, C4.5 showed the highest accuracy. But some activities which is hard to define the pattern such as stretching, and those which have small differences of signal such as elevator, escalator, and stay showed low accuracy. And if the data collector and experimenter were different, it also showed low accuracy.

There were some experiments using audio to recognize vehicles. Kye-Hwan Lee recognized environmental sound using significant feature vector automatically extracted when 3GPP2 Seletable Mode Vocoder is coded. He used high performance condenser mike, and the recognition ratio was 94.7% high. But this device cannot be used in real life such as smartphone, and did not consider friction sound which affects highly on audio data.

Activity recognition research was still actively undergoing even after the emergence of smartphone. Shuangquan Wang used 3 axis accelerometer of Nokia's N82 mobile phone and recognized 6 activities, such as walking, subway, bus, car, cycling, and stay. To recognize activity independent to smartphone's orientation, he transformed 3 axis accelerometer signal into one using SVM and extracted horizontal and vertical feature from it, and finally used decision tree. This could recognize cycling and walking with high accuracy which shows big differences of signal, but low accuracy in bus, subway, car and stay which shows small differences of signal.

Manhyung Han tried to overcome the limitation of accelerometer based activity recognition, and used audio, gps, wifi, etc. He used accelerometer which has big differences such as walking, running, and stay, and used audio, gps and wifi to recognize bus and subway which has small differences of signal. In this case, it shows low accuracy when gps and wifi does not work properly, and did not consider environmental sound or friction sound when using audio.

3.3.3 Limitations of Existing Work

Existing research using smartphone vector summed 3 axis accelerometer signal into one, and extracted features from this to guarantee the independence from the orientation of the smartphone. It may recognize with high accuracy which has large physical differences such as walking, jogging and stay, but may recognize with low accuracy which has small physical differences such as stay, bus and subway using this method.

To overcome this problem, they used not only accelerometer but also audio or GPS, etc. By using audio, they tried to separate bus and subway from their own sound. But there are many variables to consider, which made it hard to recognize with sound. Those variables include number of passengers, announcement, position of the smartphone, and the friction sound from the mic of the smartphone, etc. GPS is a good method to separate bus and subway if there is a premise that the signal is always well received. But in real-field, reception rate differs considerably according to skyscrapers, location boarding the bus, position of the smartphone from the user, etc. So both audio and GPS have limitations.

3.3.4 Proposed Methodology

Our proposing method uses existing vector sum method which shows high accuracy on recognizing walking and jogging. In addition, we extract unique vibration to recognize other activities. Figure 1 shows the concept how to extract features to recognize five different activities.

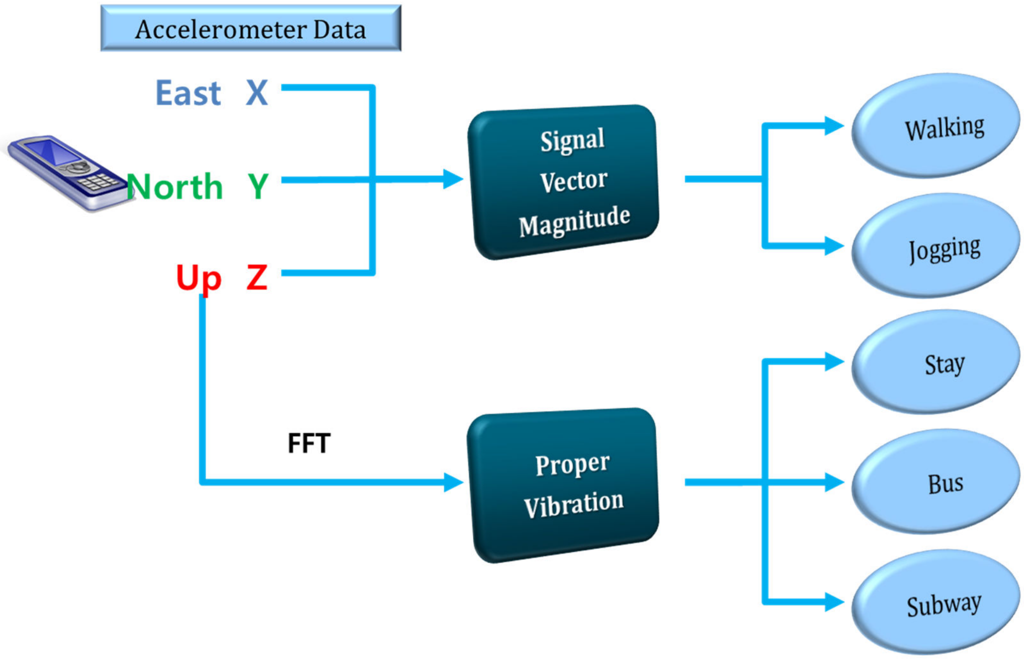


Figure 27 Feature Extractor conceptual diagram for activity recognition

As shown in Figure 26, we extract features from signal processed by Signal Vector Magnitude to recognize walking and jogging. On the other hand, we extract feature from Proper Vibration to recognize Stay, Bus, and Subway, which is difficult to recognize by Signal Vector Magnitude. Figure 12 shows the reason clearly. There are an obvious differences of magnitude of signal and pattern among walking, jogging and stay. But there are weak differences of magnitude of signal and pattern among bus, subway and stay.

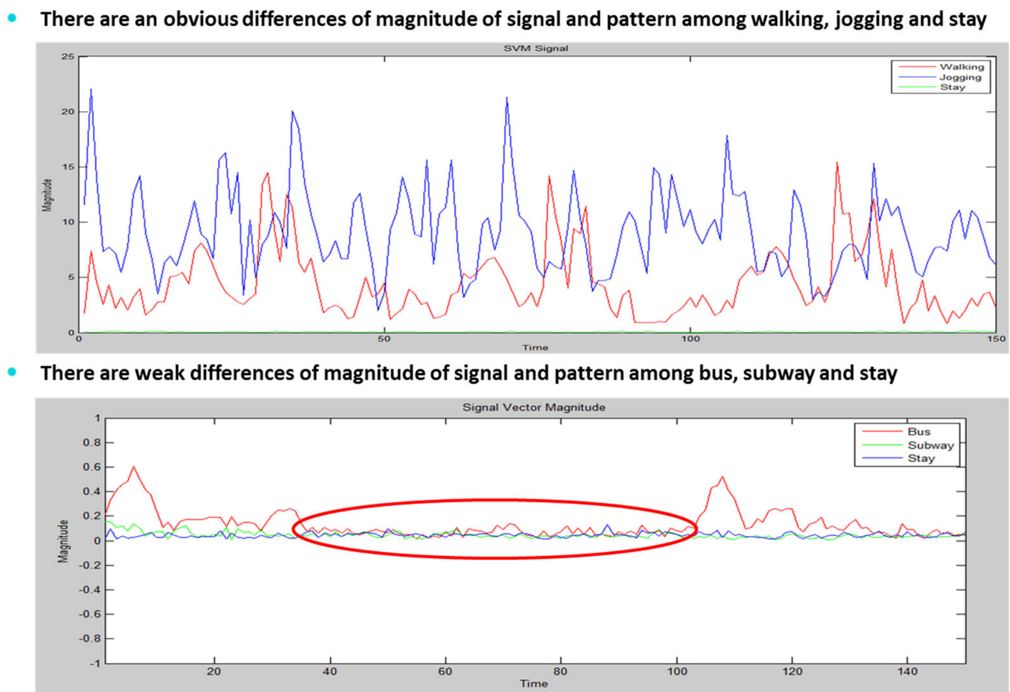


Figure 28 Analysis Signal Magnitude about each activities

So we propose a new method to recognize Stay, Bus, and Subway. The key idea is to use proper vibration of bus and subway. Proper vibration occurs periodically in bus and subway, and not in stay. Using Signal Vector Magnitude is difficult, because there is no way to extract gravity axis signal from it. So the first phase to do is to acquire gravity axis signal independent from smartphone's orientation. This could be done easily by using gyroscope and gain the rotation data. Especially, android basically provides this API. Figure 27 shows the difference of the signal revising the accelerometer signal using gyroscope.

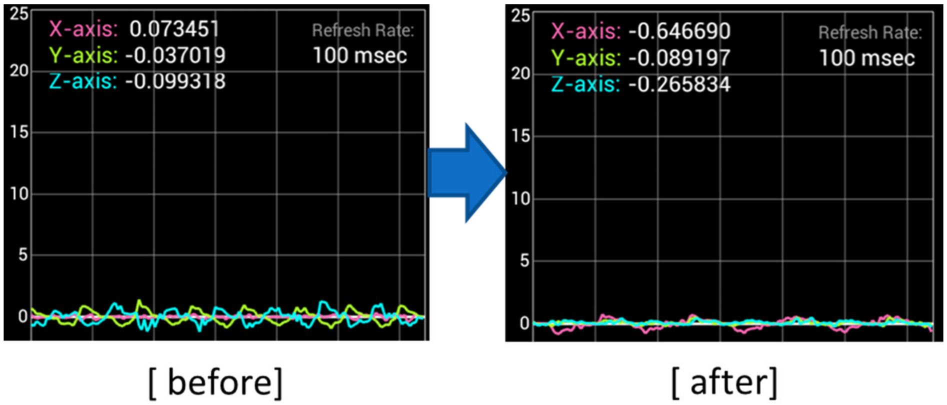


Figure 29 Result of accelerometer signal revision using Gyroscope data

The result on the figure shows when the smartphone is leaned and erected repeatedly. The change of axis is shown clearly before accelerometer signal is revised, but after revising, only the orientation where the phone is facing (east side) changes. Like this, we can get fixed axis signal independent to smartphone if we use gyroscope data. Each of the fixed axis is mapped x to east, y to north, z to up and down, respectively. The main axis which could measure gravity axis is z axis. To measure proper vibration of stay, bus and subway from time domain z axis, it is necessary to apply FFT (Fast Fourier Transform) to change time domain to frequency domain. Figure 14 shows the comparison among stay, bus, and subway signal from frequency domain.

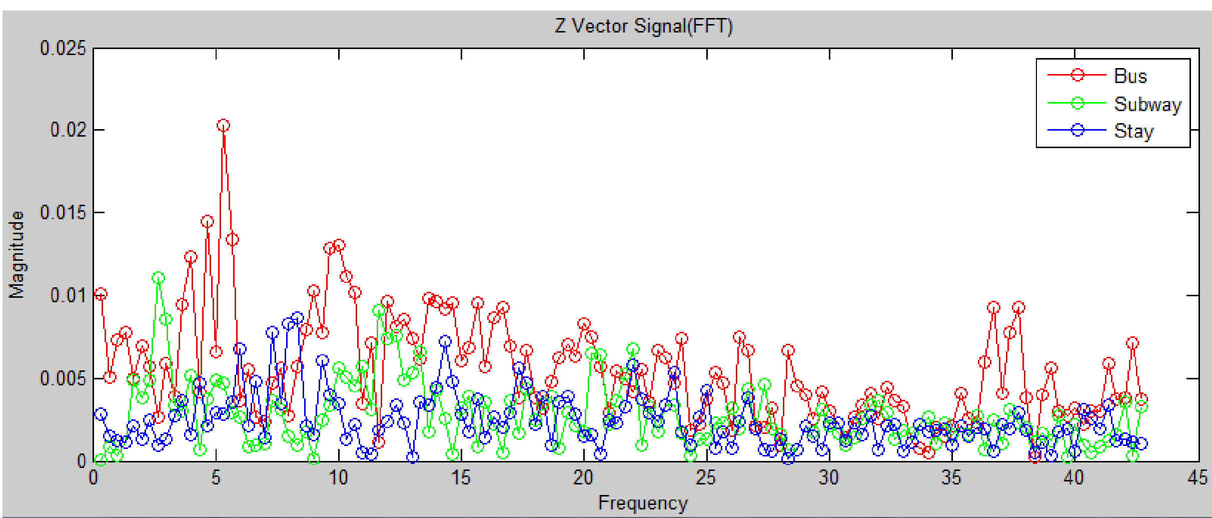


Figure 30 Gravity axis signal of different activities in frequency band

We can see that bus and subway has the maximum value at frequency of 5.3Hz and 2.3Hz, respectively. Especially in bus, the maximum frequency is formed as Gaussian distribution in 3~7hz frequency, and overall size is higher than subway and stay. Subway shows similar to bus, and the Gaussian distribution is formed at 2~4hz frequency. Except these bands, there are no big differences with stay. Stay doesn't show a maximum steady frequency, and Gaussian distribution is not formed.

To classify bus, subway, and stay, we extracted features reflecting vibration. There are total 6 features extracted from Z axis. These are average, standard deviation, ratio of the sum of amplitude in 2~4hz from the whole, ratio of the sum of amplitude in 3~7hz from the whole, maximum amplitude, and frequency with maximum amplitude. Each features reflect the characteristic of bus, subway, and stay.

We classify bus, subway, and stay with the average of whole band of frequency to classify bus and others, which has bigger difference than the others. We use standard deviation to classify stay with others, which has no peak frequency. Ratio of the sum of amplitude is used to classify bus and subway, and maximum amplitude is used to classify bus and subway which Gaussian distribution overlaps at 3~4hz frequency. Frequency with maximum amplitude is the key value which shows proper vibration, and used to classify bus and subway.

We extracted same feature from XY axis assuming that up down left right axis would change similarly if this change happens in Z axis. And used Correlation to apply correlation between two signals. With extracted features, we used GMM (Gaussian Mixture Model) to classify activities. In summary, walking and jogging is recognized by features extracted from SVM signal, and bus, subway, stay is recognized by features extracted from 2 level GMM using vibration of the signal. This process is shown in Figure 29.

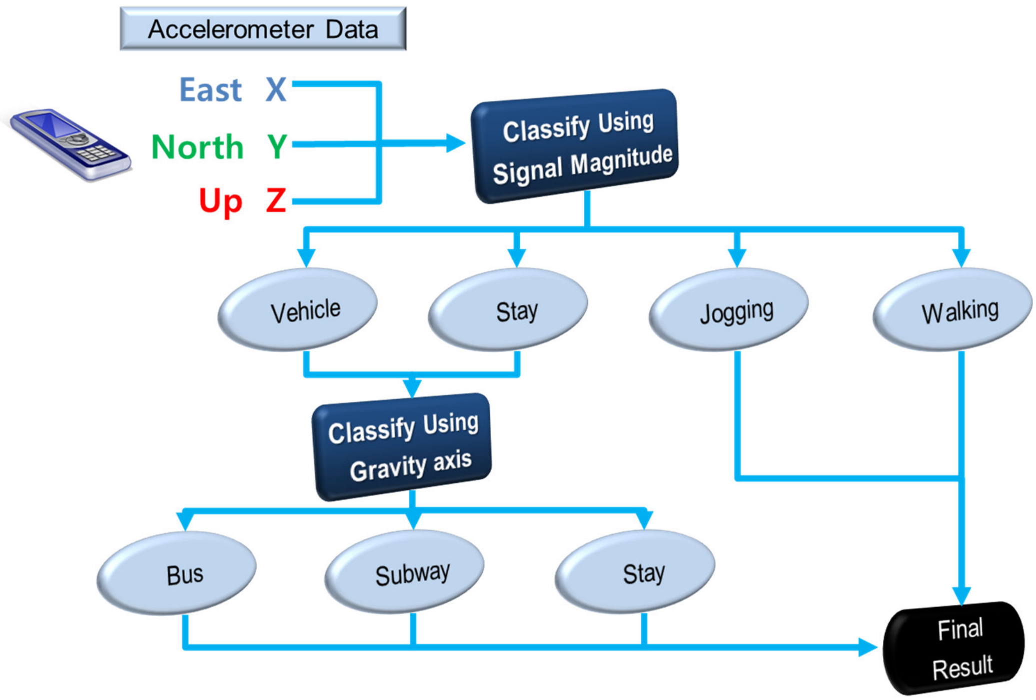


Figure 31 2-Step GMM for Activity Recognition

We could recognize 5 different activities with accelerometer based activity recognition, but there are some variables affecting the accuracy in real-field. Those variables are caused by user difference, position of smartphone, and when user uses smartphone. So we need a revised method to increase the accuracy in real-field.

In this research, we propose revision method by using GPS and logical algorithm. Figure 30 shows the flow of revision algorithm. If GPS signal is received and the speed is high, we classify it with latitude and longitude whether it is a ground subway or not, and then classify if it is a subway or a bus. To prevent the noise affecting activity occurred from accelerometer, it recognizes the activity only if the result shows the same twice. And it continues revision process to properly recognize as a vehicle if stay happens when the bus or the subway stops. Finally, it ends the revision process by revising the misrecognition of stay as a bus or a subway.

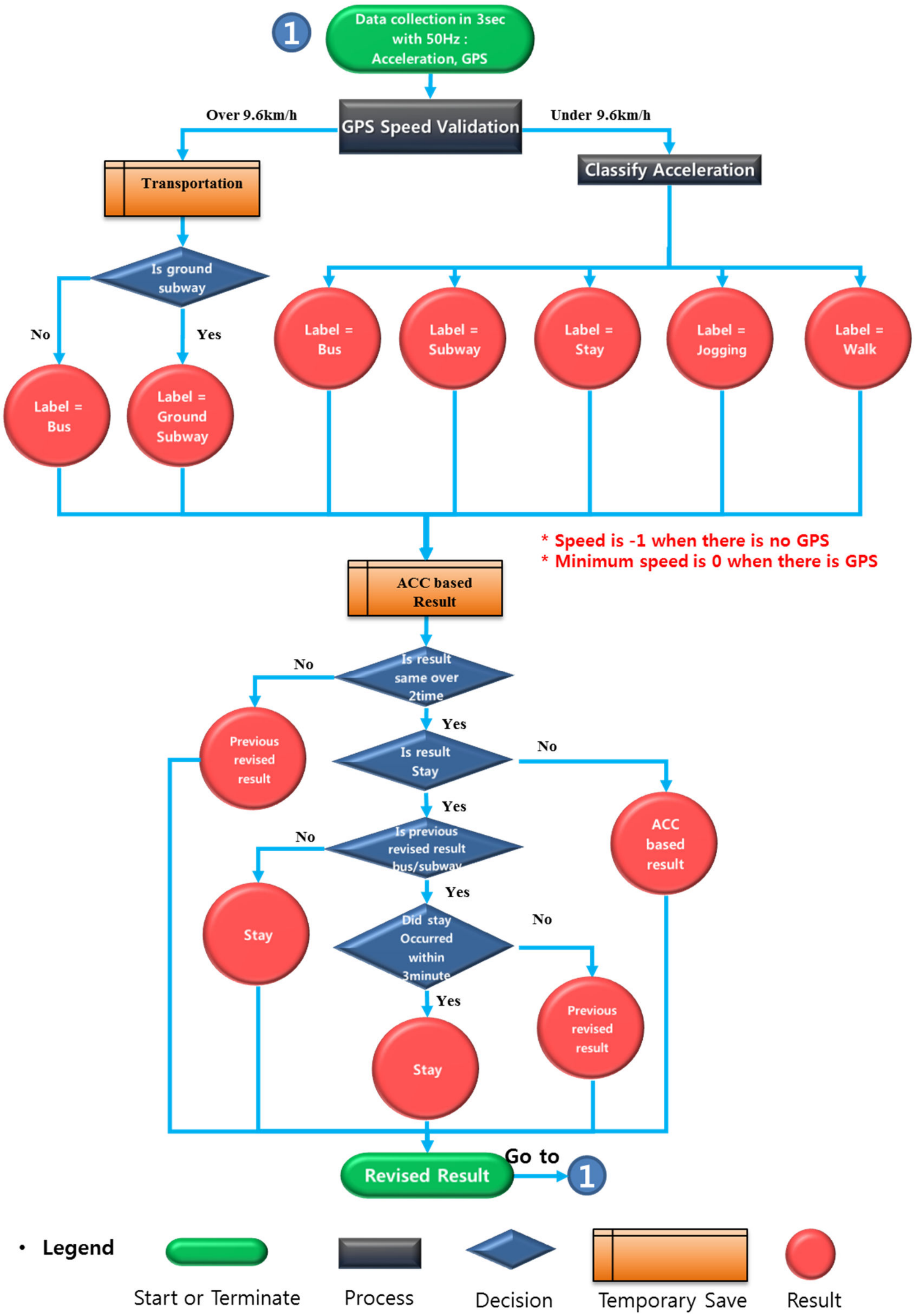


Figure 32 Revise algorithms for high accuracy in real-field

By this revision process, we could get proper stay state occurred while in bus or subway as shown in Figure 17.

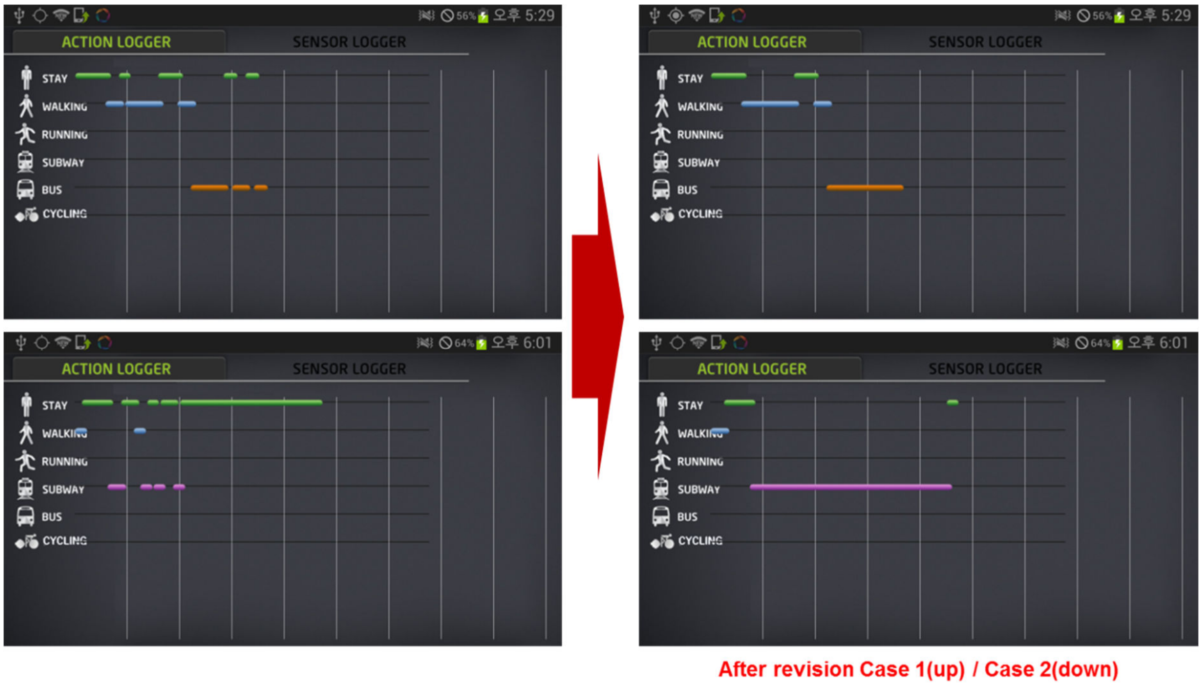


Figure 33 Example of revision algorithm

3.3.5 UML Diagram

- **Use Case Diagram**

  Following figure shows the interaction of the component to construct the Action Logger

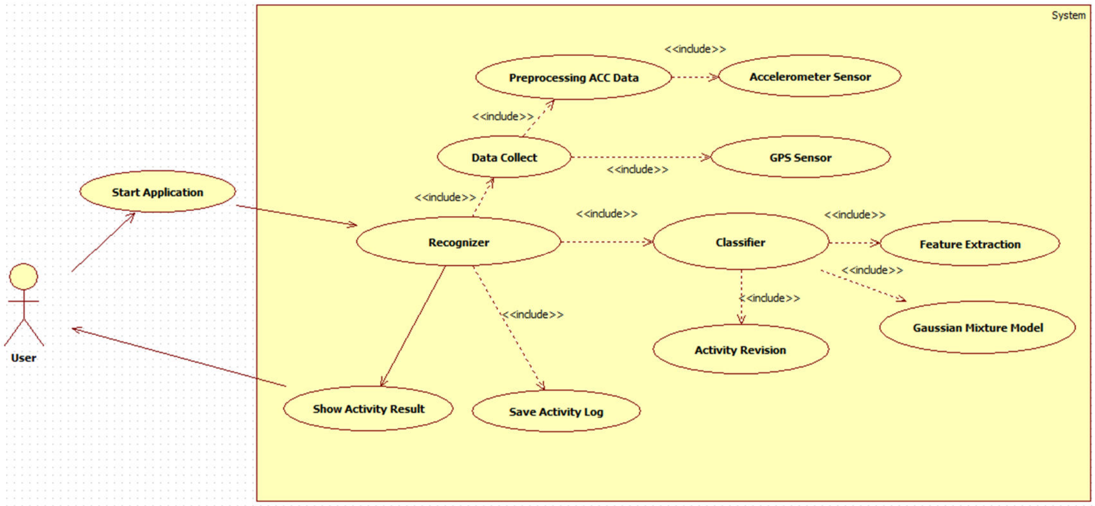


Figure 34 Use case diagram of MSARS

- **Use case Description**
  - **Start Application:** This use case express the starting of application.
  - **Recognizer:** This use case is responsible to recognize action using included cases.
  - **Data Collect:** It is responsible to collect accelerometer and GPS data.
  - **Preprocessing ACC Data:** It process accelerometer data to reduce the gravity and fixing axis formats.
  - **Accelerometer Sensor:** It just gets change of accelerometer signal over the period of time.
  - **GPS Sensor:** It just gets change of GPS signal over the period of time.
  - **Classifier:** This use case is responsible to classify action using included cases.
  - **Feature Extraction:** It extract features from accelerometer data.
  - **Gaussian Mixture Model:** It can classify action through GMM method using features from Feature Extraction case.
  - **Activity Revision:** This use case can make the decision with the recognized action results and GPS data.
  - **Save Activity Log:** This use case save final action result which was obtained from previous step.
  - **Show Activity Result:** This use case responsible to show final results to the user.

- **Sequence Diagram**

Following Action Logger sequence diagrams illustrate the chronological sequence of messages between objects in an interaction:

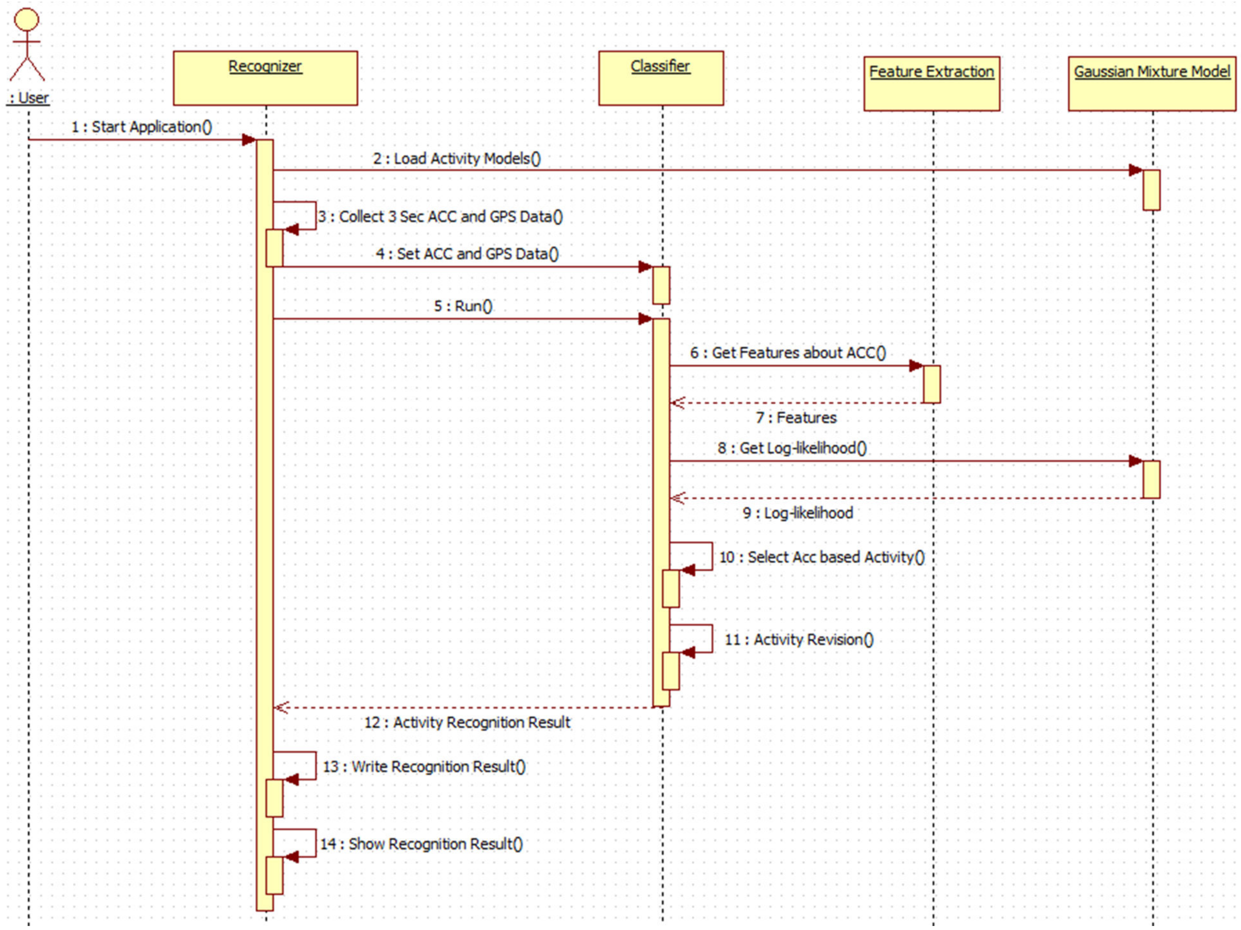


Figure 35 Action Logger sequence diagram of the module

- After application start, Recognizer calls loading activity model method in GMM instance. It collects accelerometer and GPS data for three seconds. The data which gathered from sensors is received to the Classifier and Classifier process it.
- Classifier process sensors data in order to recognize action using Feature Extraction and GMM instances.
- Recognizer save result from previous step and present to the user.

- **Class Diagram**

It consists of the Recorder class that interacts with the internal classes of the component.

- In order to decouple the code we made each module implementation separately and interact with through the proper interfaces.

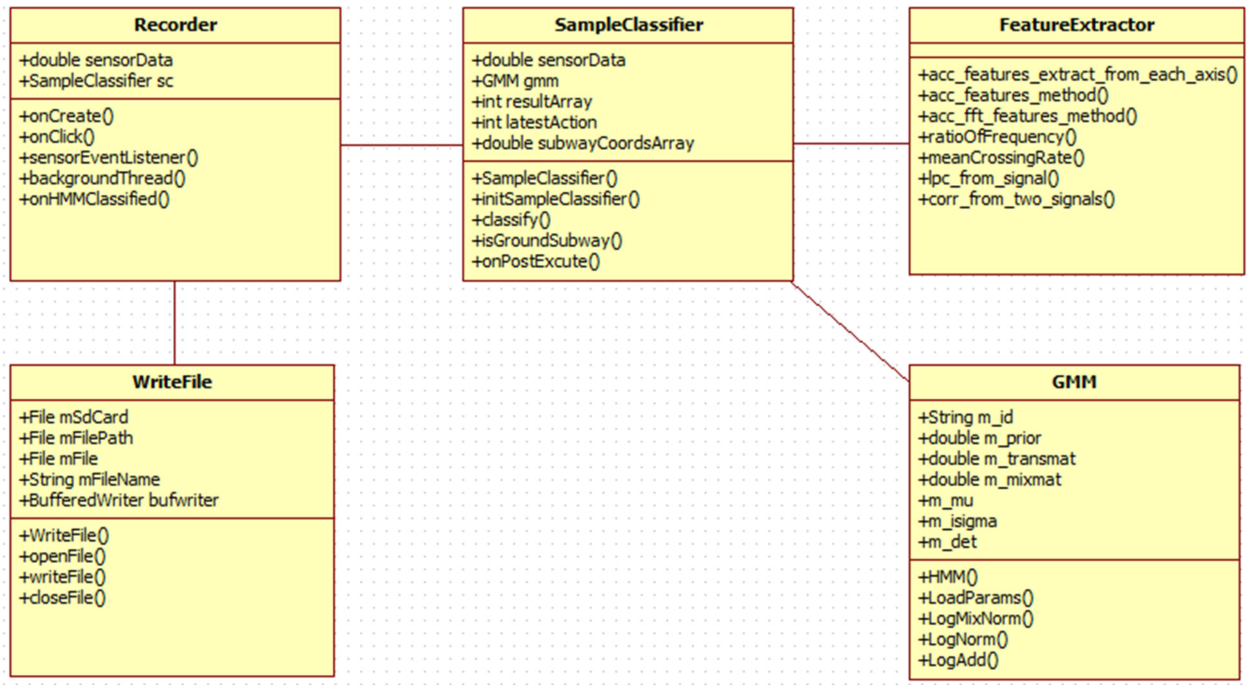


Figure 36 Class diagram of the MSARS

- **Component Diagram**

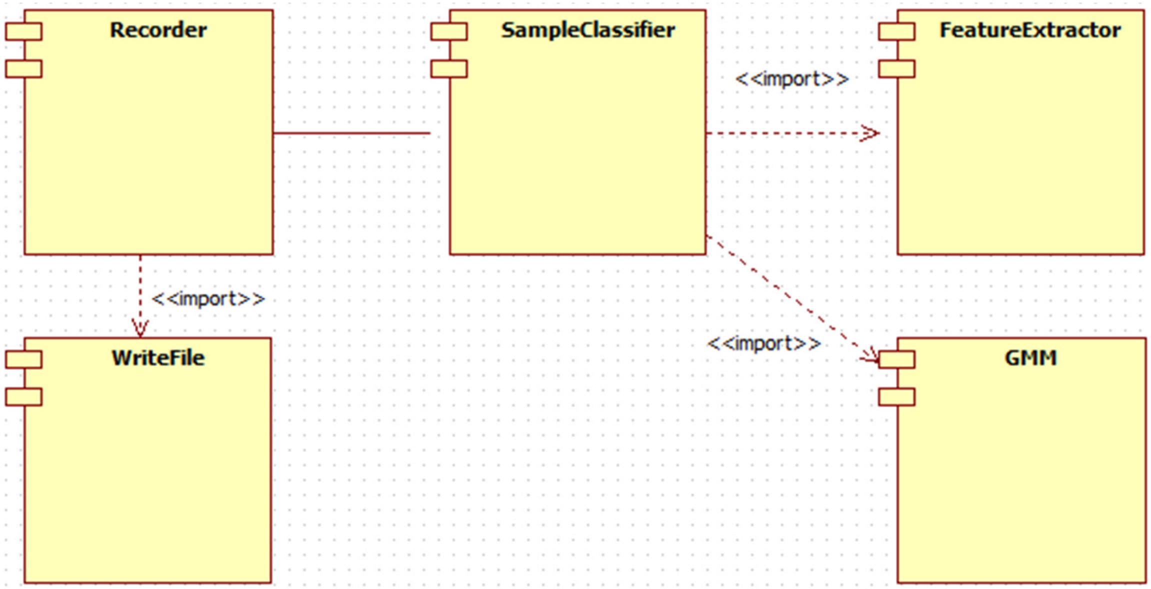


Figure 37 Component diagram of MASRS

- The component diagram shows different components and their relationships with each other. Mainly there are two main components and are explained below.
- Recorder: controller for receiving the sensor data and write log.
- Sample classifier: extracts the features using Feature Extractor instance and classify action using GMM instances.

3.3.6 Contribution and Originality

In our research, we recognized bus, subway, and stay extracting unique vibration from fixed axis signal by accelerometer independent from smartphone's orientation. With this, we could recognize walking, jogging, stay, bus and subway by only using accelerometer with high accuracy. We also proposed a revision algorithm to show high accuracy in real-field, and confirmed it by experiment. Finally, we could minimize the usage of battery by only using accelerometer and GPS among all the other sensors.

3.3.7 Conclusion

In this research, we have recognized 5 different activity which was hard to do in previous research. We have measured the accuracy to evaluate the superiority of our proposed accelerometer based module, and shows in average more than 91% as shown in Figure 37.

	Bus	Subway	Jogging	Stay	Walking	Average Accuracy
Bus	**92.14%**	4.14%	0.01%	3.31%	0.40%	-
Subway	1.92%	**86.19%**	0%	11.67%	0.21%	-
Jogging	0%	0%	**97.13%**	0%	2.87%	-
Stay	4.52%	17.59%	0%	**77.13%**	0.75%	-
Walking	0%	0.04%	0%	5.10%	**94.86%**	-
Average Accuracy	-		-	-	-	**89.54%**

[Existing AR result – Confusion Matrix]

	Bus	Subway	Jogging	Stay	Walking	Average Accuracy
Bus	**89.12%**	1.19%	0%	9.24%	0.45%	-
Subway	1.14%	**81.03%**	0%	17.83%	0%	-
Jogging	0%	0%	**97.13%**	0%	2.87%	-
Stay	1.00%	4.81%	0%	**94.10%**	0.08%	-
Walking	0%	0.04%	0%	5.10%	**94.86%**	-
Average Accuracy	-		-	-	-	**91.24%**

[Proposed AR result – Confusion Matrix]

Figure 38 Test Result of activity recognition engine

In comparison with existing method, our proposed method shows much higher accuracy on stay. In other words, the possibility to misrecognition as bus or subway has reduced while the true activity is stay. On the other hand, our method shows a bit lower accuracy on recognizing bus and subway. But confusion between bus and subway has reduced than existing methods. This could be reduced more by proposing revision algorithm, which means that there would be minimum misrecognition although it my show some delay.

We experimented using revision algorithm making 11 different environments where misrecognition may occur. 229 times out of 234 times showed correct result, proving superiority of our algorithm. Considering the limitation of battery in real life, we will enhance our activity recognition engine to work on low power while still showing high performance in the future work.

3.4 Wearable and Physiological Sensor based Activity Recognizer

3.4.1 Introduction

In this section we explain about our wearable sensor based activity recognition.

3.4.2 Related Work

Existing work in wearable sensor based activity recognition can be classified into 2 main categories

- Segment-wise approach [Bao2004], [Bao2003], [DeVaul2001], [Laerhoven2000], [Intille2005]
- Sequential approach [Lester2005], [Chieu2006], [Suutala2007]

- **Segment-wise approach:**
  - Input signal from sensors will be chopped into equal-length frame by a sliding window (windowing).
  - Each frame is processed separately to produce the predicted label.
  - The general architecture of a segment-wise activity recognition system can be described in Fig. 12.
  - Advantages: Simple to collect training data, light-weight, fast.
  - Disadvantages: Do not take into account the characteristic of activities in practice: the variable duration, the happening order of activities.
  - Taking into account the above mentioned characteristic may help improve much the accuracy of recognition system [Suutala2007].
- **Sequential approach:**
  - Input signal from sensors will be chopped into equal-length frame by a sliding window (windowing).
  - A sequence of frames is processed to produce the activity label
  - Take into account the duration and the happening order of activities: for example “preparing meal” should always happen before “eating”.

3.4.3 Limitation of Existing Work

- The sequential models like HMM or CRF… are suffered from Markov assumption, limiting them to model long-range interdependency
- To overcome the above limitation, a high computational complexity is required [Lester2005].
- To utilize the advantages of a sequential model we propose a novel temporal modeling model, called semiCRF, meanwhile we propose a smart computing algorithm to overcome the complexity problem of the model.

3.4.4 Proposed Solution

Let us first denote the input signal and the input label as X and Y respectively as followings

$$X = \{x_1, x_2, ...x_T\}$$
$$Y = \{y_1, y_2, ...y_T\}$$

- We want to maximized P(Y|X) is maximized. With conventional conditional random fields P(Y|X) is calculated by

$$P(Y \mid X) = \frac{\prod_{t=1}^{T} \Psi(y_{t-1}, y_t, X)}{Z_X}$$

$$\Psi(y_{t-1}, y_t, X) = e^{W^T F(y_{t-1}, y_t, X)}$$

$$Z_X = \sum_{Y'} \prod_{t=1}^{T} \Psi(y'_{t-1}, y'_t, X)$$

where F is a column vector of feature functions (which are often delta functions), W is a column vector of model parameters, and ψ is so-called potential functions. Z_X (normalization factor), is computed by using forward or backward algorithm.

- To overcome the Markovian limitation, we define a new state as $s_i = (y_i, b_i, e_i)$ where s_i is the i^{th} state and y_i, b_i, and e_i in that order are label, begin and end time of the state.
- Unlike the semi Markov model proposed in [Sunita2005], a more general constraint $b_{i+1} > e_i$ is used instead of $b_{i+1} = e_i + 1$ to model long-range transition.
- Now, the likelihood that we want to maximized is defined as

$$P(S \mid X) = \frac{\prod_{i=1}^{P} \Psi(s_{i-1}, s_i, X)}{Z_X},$$

$$Z_X = \sum_{S'} \prod_{i=1}^{P'} \Psi(s'_{i-1}, s'_i, X)$$

With these definitions, potential function is rewritten as

$$\Psi(s_{i-1}, s_i, X) = \begin{pmatrix} e^{Q^{Tr}(s_{i-1}, s_i, X)} \times \\ e^{Q^{D}(s_{i-1}, s_i, X)} \times \\ e^{Q^{O}(s_{i-1}, s_i, X)} \end{pmatrix}$$

Where, $Q^{Tr}(s_{i-1}, s_i, X) = \sum_{y',y} w^{Tr}(y', y)\delta(s_{i-1}.y = y', s_i.y = y)$

is a weighted transition potential function, $w^{Tr}(y',y)$ is the weight of transition from y' to y, and the delta function is defined as

$$\delta(A) = \begin{cases} 1 \text{ if A is true} \\ 0 \text{ if A is false} \end{cases}$$

Next, we define the weighted duration potential function as

$$Q^{D}(s_{i-1}, s_i, X) = \sum_{y,d} G^{D}(y, d)\delta(s_i.y = y, d = s_i.e - s_i.b + 1)$$

$$= \sum_{y,d} w^{D}(y) \frac{(d - m_y)^2}{2\sigma_y^2} \delta(s_i.y = y, d = s_i.e - s_i.b + 1)$$

Where $w^D(y)$ is the weight of duration of label y, m_y and σ_y^2 are the mean and variance of label y's duration respectively, which are extracted from training data.

$$Q^{O}(s_{i-1}, s_i, X) = \sum_{y,t_1,t_2} \begin{pmatrix} G_y(y, t_1, t_2) \times \\ \delta(s_i.y = y, s_i.b = t_1, s_i.e = t_2) + \\ G_{IA}(IA, t_1, t_2) \times \\ \delta(s_{i-1}.e + 1 = t_1, s_i.b - 1 = t_2) \end{pmatrix}$$

is a weighted observation potential function, with

$$G_y(y, t_1, t_2) = \sum_{t=t_1}^{t_2} \sum_{o} w^{O}(y, o)\delta(x_t = o) \text{ and } G_{IA}(IA, t_1, t_2) = \sum_{t=t_1}^{t_2} \sum_{o} w^{O}(IA, o)\delta(x_t = o)$$

where $w^o(y,o)$ and $w^o(IA,o)$ in that order are the weights of the observation given that input symbol o is observed in state with label y (label of expected activity, which is the activity that we want to recognize) and IA (label of unexpected activity, which is the activity that we do not intend to detect).

- Making use of semi-Markov conditional random fields, we present here a block diagram of our recognition system as in following Figure 38.

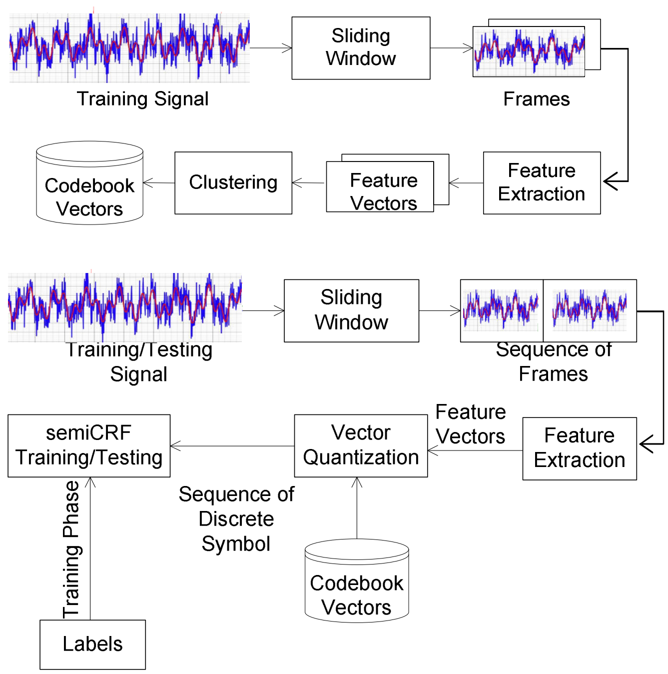


Figure 39 Block diagram of Training/Testing phase

3.4.5 UML Diagram

- **Class Diagram**

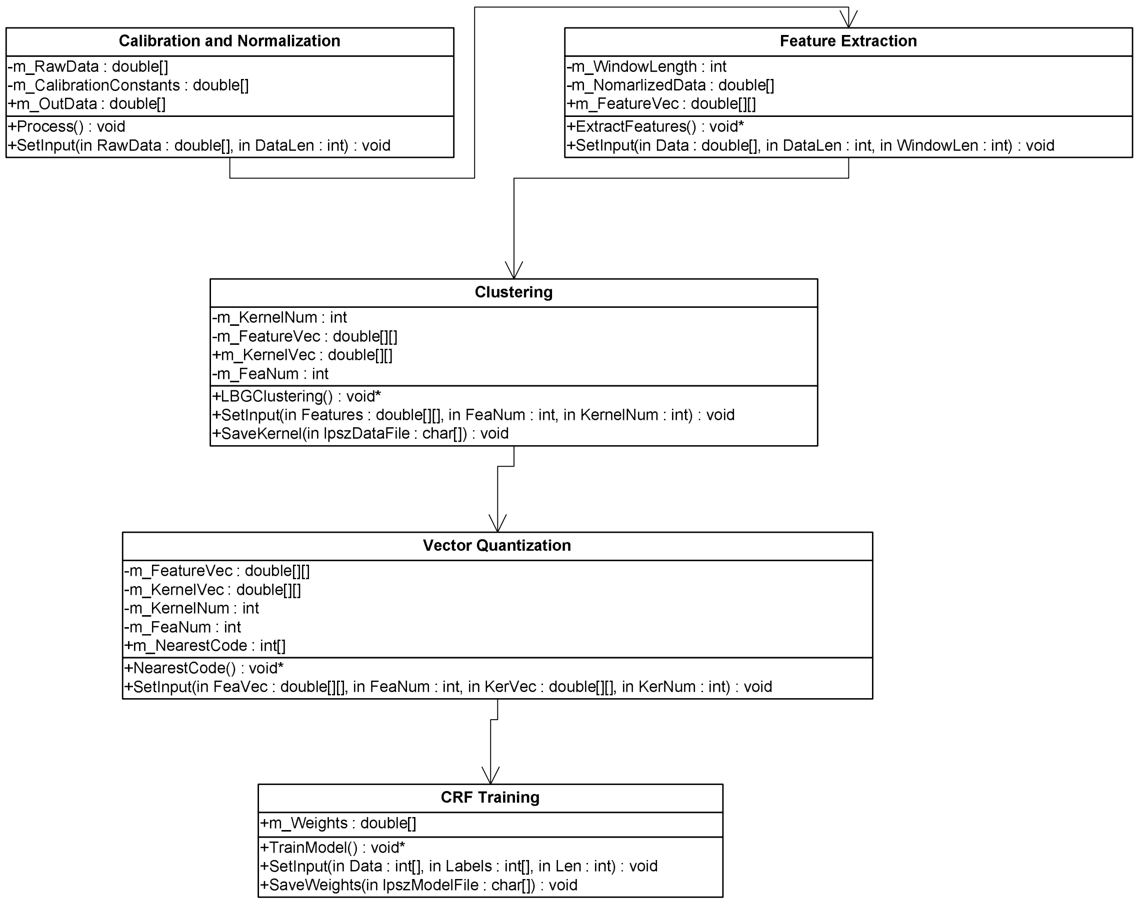


Figure 40 Class Diagram of Wearable Sensor-based AR

- **Sequence Diagram**

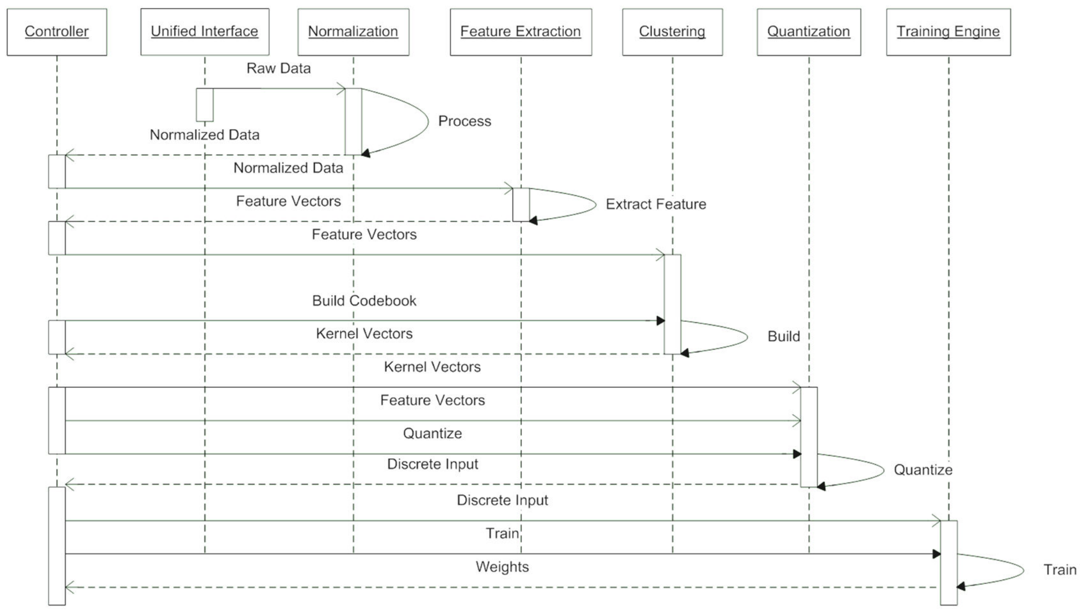


Figure 41 Training Sequence Diagram of Wearable Sensor based AR

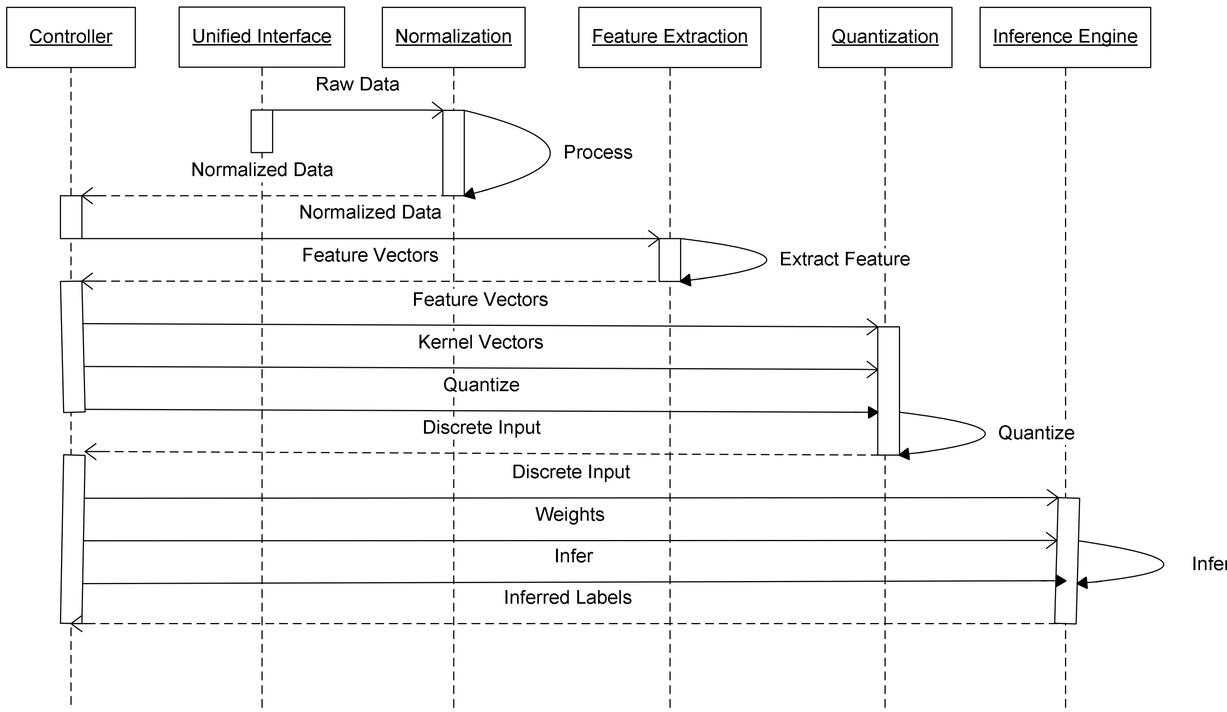


Figure 42 Inference Sequence Diagram of Wearable Sensor based AR

3.4.6 Uniqueness and Contribution

Propose a novel model to take into account

- Activity duration information and
- Interdependency among activities.

We have made following contributions:

- Activity Duration model helps to eliminate incorrect short-length segments.
- Interdependency helps to increase the likelihood of correct labels and decrease the likelihood of the incorrect labels.
- Propose novel algorithms, which help reduce the computation complexity of the model.

3.4.7 Conclusion

- We proposed a new conditional random field approach for wearable sensor-based AR including accelerometer and gyroscope to recognize daily live activities.
- To develop a robust sequential model which is capable of handling long-range transitions

among states.

- To develop a smart computing algorithm to reduce the computational complexity of the model and evaluate and compare our algorithm with existing algorithms to prove our improvement.

3.5 Social Media Interactor

In this module, we aim to improve the users' health by utilizing his social interaction in order to suggest them appropriate lifestyle patterns. For instance, after observing a user's daily routines, our proposed Social Media Interactor (SMI) is able to finds some complications with his lifestyle. He/she usually sleeps late; does not exercise regularly; does not take eats on time; eats too much. Obviously, these lifestyles are not good for healthy living. The proposed (SMI) is integrated through lifelog in the behavioral analysis module which is under development at UC Lab. The lifelog will take the information and integrate it with patient demographic to facilitate the behavioral analysis and suggest changes in unhealthy life patterns through better way.

To achieve above goals, we design (SMI) with several novel ideas. Firstly, tweet analysis extracts user interest, health conditions and sentiment from user tweets. Secondly, trajectory in terms of outdoor movement of the patient is tracked using GPS enabled location aware mobile devices, such as smart phones. Finally, email interaction analyzes the users' actions to identify significant behavior and life threatening complications in daily routines to gain knowledge about their habits and preferences. The detail of each component is described in the subsequent sections.

3.5.1 Tweet Analysis

3.5.1.1 Introduction

- By monitoring person's social activities, interest and emotions can be extracted, help to provide personalized services to person.
- System monitors user stream from Twitter and process tweets to extracts user interest and sentiments from tweets.
- Our proposed system integrates as a plug-in application, while extracting user related information including profile information, person interests and emotions.

Analyzing the interest, behavior and lifestyle of person provides assistance in better decision making and personalized services

3.5.1.2 Related Work

Lacking of social aspects in healthcare decision creates thirst for behavioral knowledge regarding patient's lifestyle. Much research work has been done to analyze the tweets, trajectory, interaction and other social media resources for different application domains [Abel2011-3] [Juyoung2010] [Christopher2003]. Chen et al. [Chen2010] analyzed URL recommendations on Twitter using data stream technique. System working is based on content sources, topic interest models and social voting to design URL recommender. They analyzed user modeling on Twitter for personalized news recommendation and enrich news with tweets to improve the semantic of Twitter activities. Celik et al. [Celik2011] studied semantic relationship between entities in Twitter to provide a medium where users can easily access relevant content for what they are interested in. It shows that Twitter is a suitable source as it allows for discovering trending topics with higher accuracy and with lower delay in time than traditional news media.

3.5.1.3 Limitations of Existing Work

- Twitter data must be collected to use it for research purpose. Different analysis tools are available to collect twitter public data. Archivist is one of the tool to collect tweets.
- Grabeeter is another tool to get individual personal and public tweets and store them for future use. Twitter data is available for mining unstructured data and analyzing hidden patterns in it. J. Chen et al [Chen2010] introduced a system for URL recommendations on Twitter using data stream technique.
- The system was based on content sources, topic interest models, and social voting to design URL recommender and compare different recommender techniques.
- Fabian Abel et al. [Abel2011-1] [Abel2011-2] [Abel2011-3] analyzed user modeling on Twitter for personalized news recommendation and enrich news with tweets to improve the semantic of Twitter activities. The work used methods including topic, entity, and hashtag based to analyze the user modeling.
- It also focused on temporal pattern extraction in user profile. Ilknur Celik et al. [Celik2011]

studied semantic relationship between entities in Twitter toprovide a medium where users can easily access relevant content for what they are interested in.

- Eleanor Clark et al. [Clark2011] introduced a system to apply text normalization for Twitter. System categorized errors and irregular languages used in casual English of social media into different groups and then applied natural language processing techniques to correct common phonetic and slang mistakes in tweets.
- Tetsuya Nasukawa et al. [Nasukawa2003] used natural language processing techniques to identify sentiment related to particular subject in a document.
- They used Markov-modal based tagger for recognizing part of speech and then applied statistics based techniques to identify sentiments related to subject in speech.
- Jeonghee Yi et al. [Yi2003] presented a model to extract sentiments about particular subject rather than extracting sentiment of whole document collectively.
- This model proceeded by extracting topics, then sentiments and then mixture model to detect relation of topics with sentiments. Whereas Namrata Godbole et al. [Godbole2007] introduced a sentiment analysis system for news and blog entities.
- This system determined the public sentiment on each of the entities in posts and measured how this sentiment varies with time. They used synonyms and antonyms to find path between positive and negative polarity to increase the seed list.
- Andranik Tumasjan et al. [Tumasjan2010] analyzed Twitter as a source of predicting elections. They used the context of the German federal election to investigate whether Twitter is used as a forum for political deliberation. They used LIWC2007 [Liwc2012], a text analysis software developed to assess emotional, cognitive, and structural components of text samples using a psychometrically validated internal dictionary.
- They focused on 12 dimensions in order to profile political sentiment: Future orientation, past orientation, positive emotions, negative emotions, sadness, anxiety, anger, tentativeness, certainty, work, achievement, and money.
- Bernard J et al. [Jansen2009] performed analysis of Twitter as electronic word of mouth in the product marketing domain. They analyzed filtered tweets for frequency, range, timing and

content.

- They found that 19% of a random sample of tweets contained mentions of a brand or product and that an automated classification was able to extract statistically significant differences of customer sentiment.
- Similarly Archivist [Archivist2012]is a service that uses the Twitter Search API to find and archive tweets. It helps to have a look at trends such as frequency of Tweets over time, top users and words and many more. It also helps user to get real time trend information on Twitter.
- Jeff Clark used Venn diagram to show illustrating pattern in twitter data [Clark2008]. By using venn diagram he explore overlap of different topics with each other in tweets. Collecting tweets alone and analyzing them for sentiments just on the available keyword is not enough to understand the real semantics of tweets.

There is a need to precisely parse and process the tweet for the contained knowledge.

3.5.1.4 Proposed Methodology

The proposed system architecture consists of four main components. Data Manager, Knowledge Generator, architecture of whole system is shown in Figure 42. Knowledge Enhancer, and Filter Engine. These components are elaborated as follows.

- **Data Manager**
    - Data Manager is our plugable application that interacts with Twitter. It consists of the following subcomponents.
    - **Data Fetcher**: Data Fetcher sends request to Twitter for stream of user. The fetched data is in JSON format [Archivist2012] that is a lightweight data-interchange format.
    - **Data Processor**: Fetched data requires some pre-processing before analyzing. Data Processor converts data in required useable format. It also removes user slangs from tweets.

- **Knowledge Generator**
    - Our purpose is to extract valuable information hidden in tweets and build user

profile. Twitter data collected by our system is given to Alchemy API.

- It accepts unstructured text, processes it using natural language processing and machine learning techniques, and returns keywords and sentiments of users about keywords. We extract participating keywords and sentiments associated with those keywords.
- After extraction of knowledge, all tweets, participating keywords, and associated sentiments are stored in the repository for further processing as discussed below. However, the information extracted by knowledge generator is of low precision.
- So, it needs further processing to better identify user interest and analyze sentiments of domain specific interest.

- **Knowledge Enhancer**
  - Knowledge enhancer module add additional knowledge which was not extracted as keyword by Alchemy API.
  - The proposed system uses part of speech tagging and entity extraction on tweets and then adds additional data in the knowledge, extracted by Alchemy API.
  - Entity extraction by using Alchemy API helps by extracting entities, not extracted as keyword.
  - The proposed system have been tested with addition of subjects, verbs, objects, and entities in knowledge; however, just addition of verb and entities increases information collected from tweets.
- **Filter Engine**

  For classifying tweets into different categories on the basis of knowledge extracted from tweets, the proposed system applies filtering on the extracted data. The filtering process is domain specific.

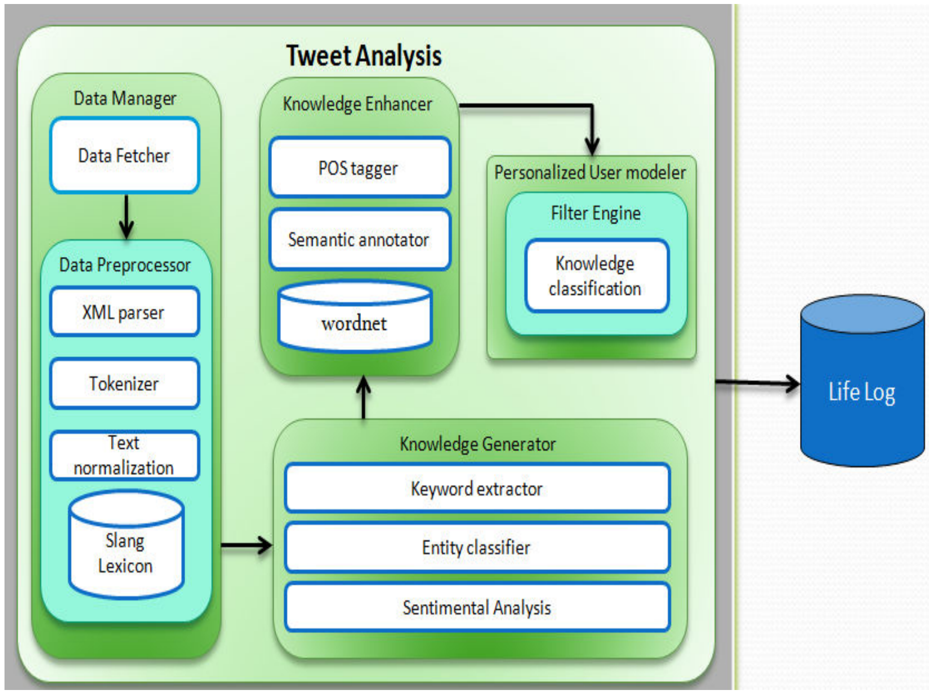


Figure 43 Overall Flow of Tweet Analysis

3.5.1.5 UML Diagram

- **Use Case Diagram**

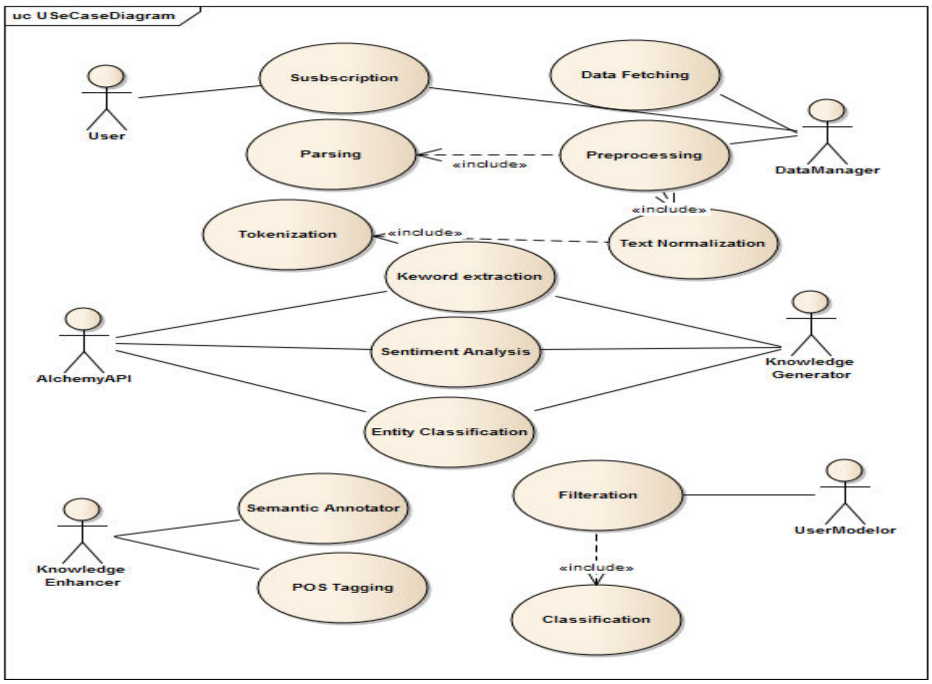


Figure 44 Use case diagram of tweet analysis

- **Actors**

  Alchemy API: Third party component use to extract knowledge from tweets.

  Knowledge Enhancer: Application component used to enhance knowledge of the system

  User Modeler: Responsible to generate personalized profile on the basis of information extracted from tweets.

  Data Manager: Handles data access from twitter and system's data store.

- **Brief Descriptions of Use Cases**

Subscription: Responsible for register user with the application. Application send request to user and user verify application to access his tweets.

Data Fetching: This use case is responsible to fetch user tweets from Twitter to generate user profile.

Preprocessing: Data preprocessor handle with data parsing and slang removal from tweets.
Parsing: Parser use XML parser to convert XML data from twitter to standardized individual objects.

Tokenization: Tokenization converts sentences into separate word to lookup on each word individually.

Text Normalization: This use case process tweets and search for slangs in tweets to map slangs with their respective original word.

Keyword extraction: To extract meaningful information from huge text Keyword extraction process extracts important keywords. It accepts tweets and return known keywords present in those tweets.

Entity classification: This use case is responsible for recognizing individual entities from text and classifies those entities into different groups.

Sentiment analysis: Aim of this use case is to determine the attitude of a speaker or a writer with respect to entities and keywords. This helps to know user behavior towards specific entities.

Semantic annotator: It is about attaching synonyms and definitions, to keywords and entities. It provides additional information about an existing piece of data.

POS tagging: It is the process of marking up a word in a text as corresponding to a particular part of speech, i.e. relationship with adjacent and related words in a phrase sentences nouns, adjectives, adverbs, etc.

Classification: Tweets may be classified into different domain specific categories on the basis of entities and keywords extracted from tweets.

Filtration: A data filtration is a process that allows domain specific data to pass for personalized modeler and ignore other information.

- **Sequence Diagram**

The objective of Interaction model of a system is to depict the process scenario of how different objects interact with each other. Life span and sequencing of objects are the prime components of any interaction diagram. Sequence diagrams are described in following section.

- **Stream Collection:** Data Fetcher sends request to twitter to collect tweets. After tweet collection from Twitter it passes data to preprocessor.

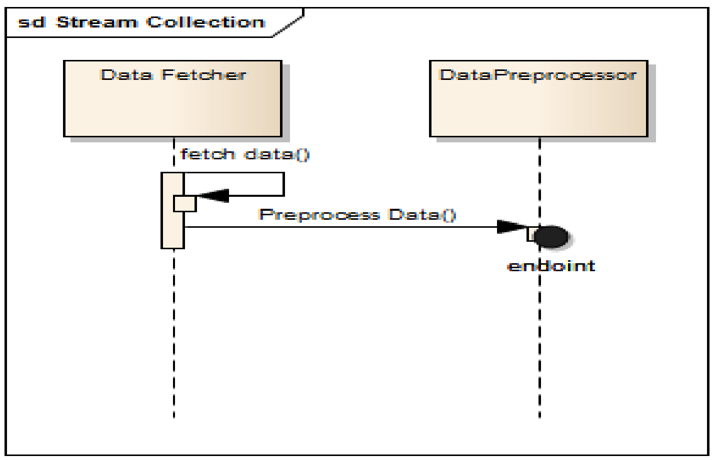


Figure 45 Sequence diagram of Tweets analysis

- ## Preprocessing

Data preprocessor component processes to identify presence of any short hand notation and normalizes them to meaningful words. It passes data to XML parser. XML parser parses data using DOM parser and return parsed data. Preprocess then pass data to text normalizer. Text normalizes call tokenizer and passes data to apply tokenization on data. Tokenizer returns tokenized data to text normalize. Text normalizes replace slangs with original words.

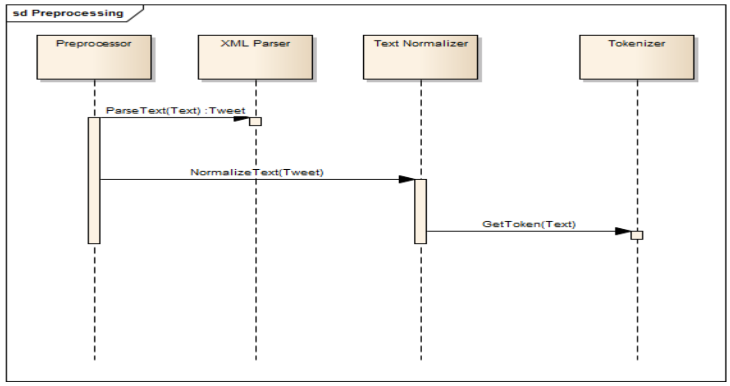


Figure 46 Preprocessing sequence diagram of tweets

- **Knowledge generation**

Knowledge generator pass tweets to keyword extractor which extracts known key phrases from tweets. Knowledge generator then pass tweet to entity classifier which identify different entities from tweets and return entities and their type. Sentiment analysis returns user sentiments towards those entities and keywords.

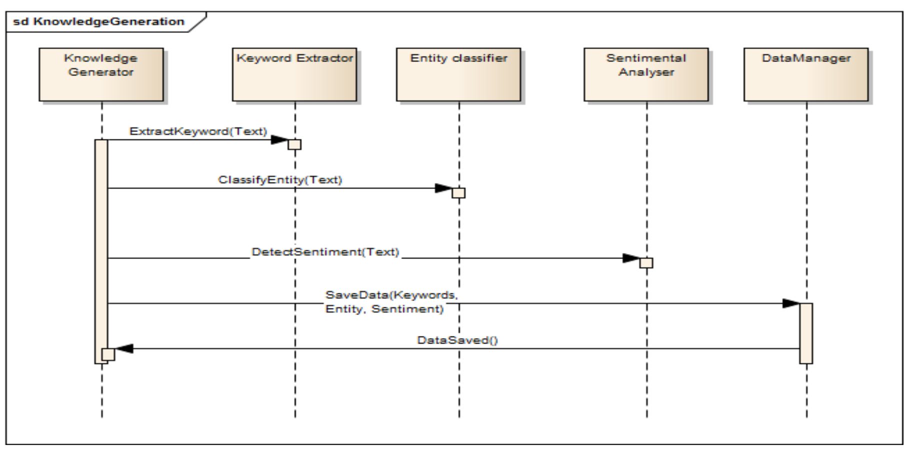


Figure 47 Knowledge generation of Tweets

- **Knowledge Enhancer**

  Knowledge enhancer module passes tweet to part of speech tagger which split text into noun, verb, object, subject etc. Then knowledge enhancer pass keywords and entities to semantic annotator which use wordnet to increase knowledge by adding synonyms and definition.

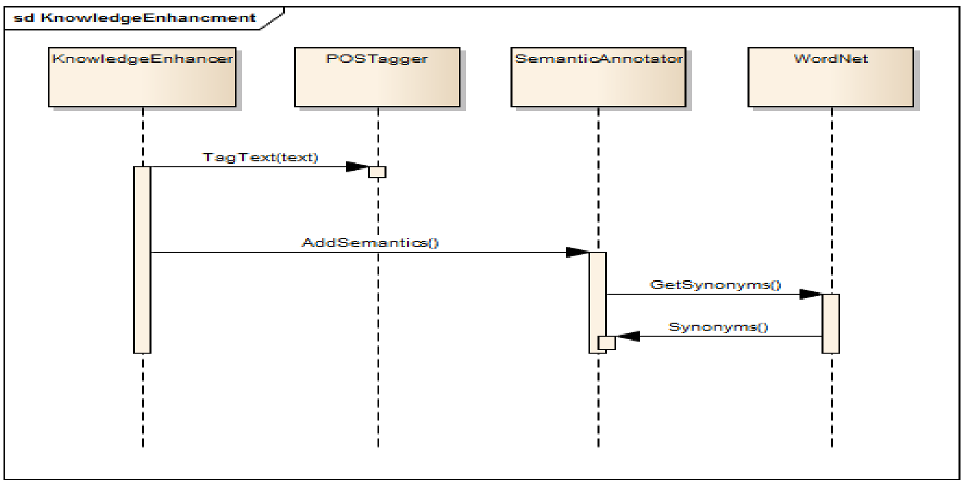


Figure 48 Knowledge enhancement of tweets

- **User modeling**

User modeler passes data to filter which filters data to make it domain specific like for health care it only passes information which is related to health care and ignore other information. Then information is passed to data manager which maintains user profile for future use.

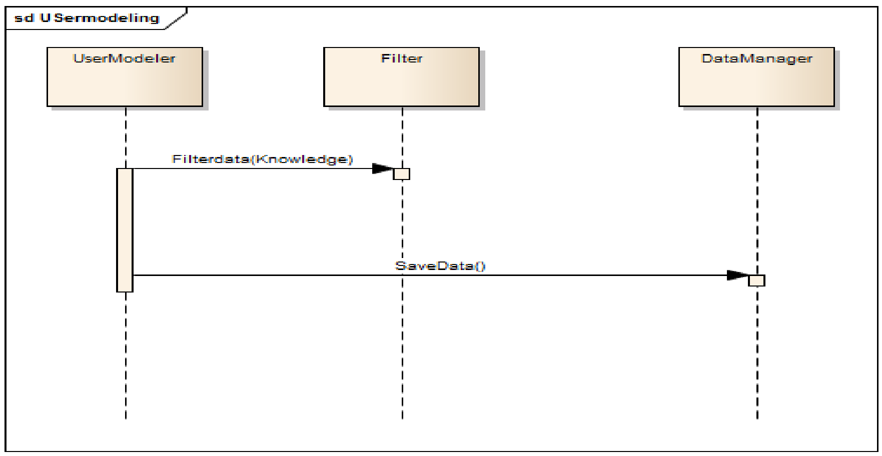


Figure 49 User modeling of tweets

- ## Class Diagram

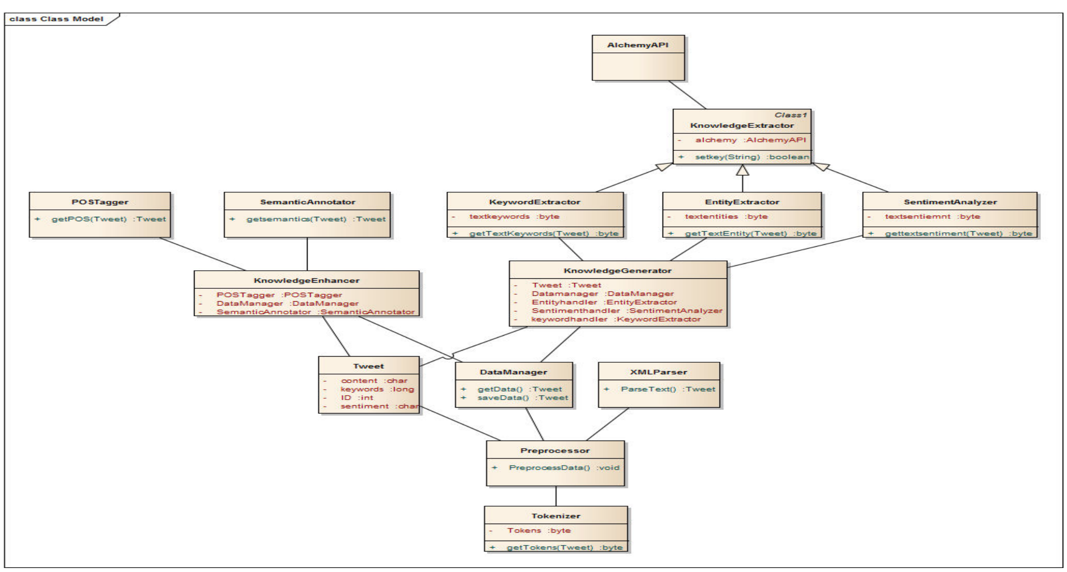


Figure 50 Class diagram of Tweets

Component Diagram

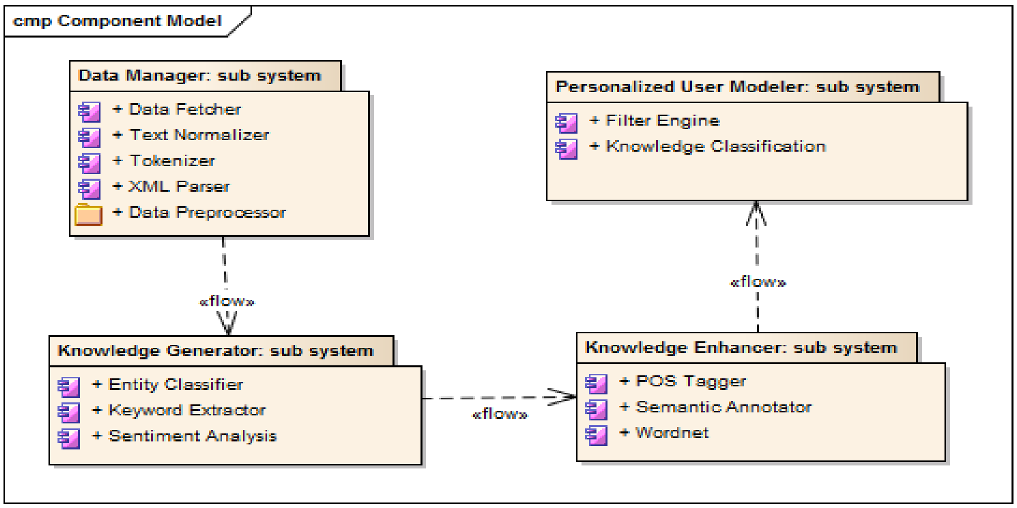


Figure 51 Component diagram of Tweets

- **Data Manager**

This sub system is responsible for fetching data from social media and processing the fetched data. It has two parts.

Data Fetcher: Data Fetcher sends request to social media for stream of user. The fetched data is in different format for each media.

Data Processor: Fetched data requires some preprocessing before analyzing.

XML Parser: XML parser uses Dom parser to convert XML data into required usable format and store data into different fields.

Text Normalizer: Users use abbreviations to save time and space. Such kind of noise in data effects knowledge extracted from tweets. Therefore to remove such kind of noise, Text normalization removes slang and abbreviated word using slang lexicon

Tokenizer: It split sentence into text based on the defined delimiter. Tokens are then used by text normalize to remove slang.

- **Knowledge Generator**

Knowledge Generator extracts user's interest by using Alchemy API. It obtains knowledge by exposing the semantic richness hidden in post.

Knowledge Enhancer: Knowledge enhancer enhances knowledge of system using semantic annotator and part of speech tagging to make system context aware.

POS Tagging: To know about relation of user with entity and to add more knowledge system extract part of speech and then add verb into information already extracted by knowledge generator. It also adds knowledge about relation of subject or object with user.

Semantic Annotator: Use of word net makes it possible to add semantic of individual keywords and entities by addition of synonyms and definition of each entity and keyword.

Personalized user modeler: Better services delivery requires maintenance of history of individual's interest and behaviors. Personalized User Modeler maintains user's data in Personalized Profile.

Classification: To provide domain specific service based on user temporal patterns system classify data into different domains and store them into profile.

Filter Engine: Filter engine activated and filter domain specific knowledge to provide better personalized services.

3.5.1.6 Contribution and Originality

- Semantically processing of Natural language from Twitter to extract user interest and sentiments to build user profile. This profile would be used to provide personalized services.
- Classification of user interest into different categorizes to enhance system efficacy in providing domain specific services.

3.5.1.7 Conclusion

Tweet analysis extracts user interest, health conditions and sentiment from user's tweets. Twitter allows users to post a short text upto 140 characters into one tweet, so due to space limitation people use abbreviations, slangs and URL's. Our proposed approach process this information using natural language processing techniques with machine learning algorithms and returns entities, sentiments of the user about specific health condition to be used as knowledge for clinicians

3.5.2 Trajectory Analysis

3.5.2.1 Introduction

- GPS is a commendable technology to find location related activities. Presently a huge number of devices are enabled with this technology and getting more common with rapid speed. Currently more of these technologies are used for advancement of overall society and mankind. Like how to control traffic in a better way, finding peak and low rush hours and movement behavior of people of a particular area.

- Our proposed system is incorporating trajectory mining techniques to a person's direct life and particularly its usage in healthcare domain is targeted. A GPS based real time activity monitoring system is developed which is used for tracking daily life routine of a user. Further these patterns are compared with the patterns prescribed by physicians and also recommendations for the better carrying out of prescribed schedule are presented to the user.

3.5.2.2 Related Work

For trajectory analysis, mostly work is done for finding effective and efficient path tracking based on movement patterns. Yang et al. [Yang2009] used GPS for finding people preferences regarding attractive areas and movement patterns, which can lead to instructive insight to transport management, urban planning, and Location-Based Services (LBS). Zhu et al. [Zhu2011] proposed Automatic Identification System (AIS) that uses trajectory mining techniques for finding the ship movement paths. Its purpose is self-navigation and collision avoidance. Braga et al. [Braga2011] designed a trajectory based tracking system named 'Captain'. This system is designed for tracking of short, yacht trajectories. The focus of this system is to record the movement path of the person by using the parameters of the pictures, temperature, and coordinates of the locations. In interaction analysis, the focus of existing work is on analysis of email network to identify importance of individuals on the basis of their communication patterns in network.

3.5.2.3 Limitations of Existing Work

- A recent study used trajectory information of people for finding people attractive areas and their related movement patterns, which can lead to instructive insight to transport management, urban planning and location-based services (LBS).
- They considered taxi as an important mode of transport and acquired road traffic condition, travel patterns, average speed estimation and attractive places where people often visit [yue 2009].
- In [Coll2011] the trajectory mining is used for mining ship spatial trajectory and an Automatically Identification System (AIS) is developed as a result of this study in which GPS enabled technology is used for finding the paths of ships [Coll2011].
- The basic purpose of this study was self-navigation and collision avoidance but it can be extended for better marine traffic management and distribution. But both of these studies cannot be applied to human life because of the limitations and restriction involved like the most appropriate device for tracking and recording all of this information is mobile phone, which has very limited computation power and storage space.
- Correspondingly all of these parameters are not required when we discuss about human life as we only are interested in daily routine activities and its positions so we have modified our

approach accordingly.

3.5.2.4 Proposed Methodology

The proposed method is a healthcare service which monitors user's routine activities and assists to follow prescribed schedule. Detailed architecture of the proposed system is shown in Figure 51. As shown in the figure that architecture is divided into 3 main processing module, Data Preprocessor, Schedule Manager and Activity Manager. Each of these modules are discussed below in detail.

- **Data Preprocessor**
  - GPS coordinates of the user's position are fetched by using a GPS receiver, after a minimum time interval T_{min}. After that each of these coordinates are sent to Data preprocessor. The main module of data processor, imperative location finder confirms the significance of the position. Two main parameters of time and distance are used for conformance of imperative location. Position and corresponding activity is only treated as imperative if both of these thresholds are satisfied.
  - Then these coordinates of imperative location are sent to Geo tag transformer where Google API is used to convert it to Geo tags. Semantic tag of the imperative location is also fetched from the user for the acquiring contextual information about the location.

- **Schedule Manager**
  - After preprocessing of data, all of the information is sent to to the schedule manager for further processing. First of all semantic tag mappers plays its role of mapping all of the corresponding information and sent it to the repository for the storage. Followed schedule of the user is stored it followed patterns.
  - Prescribed schedule of physician is stored in prescribed patterns and detail of each of activity in prescribed schedule is stored in the recommendations. Activity analysis is the main part of our proposed system with the purpose of comparing both followed and prescribed schedule. Inconsistencies of these schedules are shown to the user and physician as well for further improvement of the daily routine.

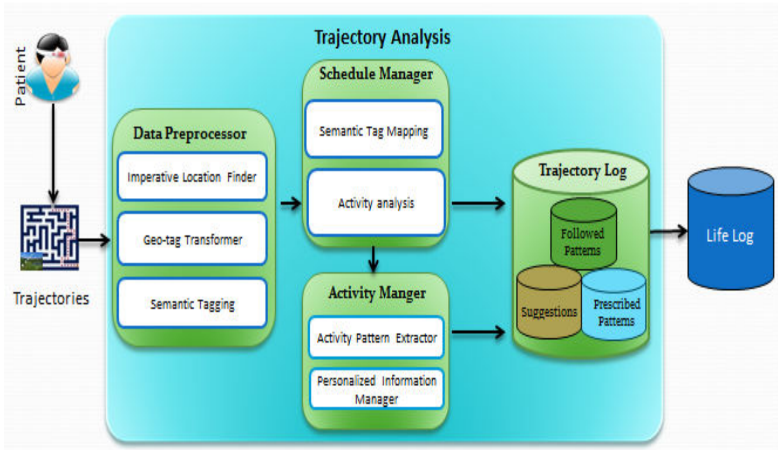


Figure 52 Architecture of Trajectory Analysis

3.5.2.5 UML Diagram

- **Use Case Description**

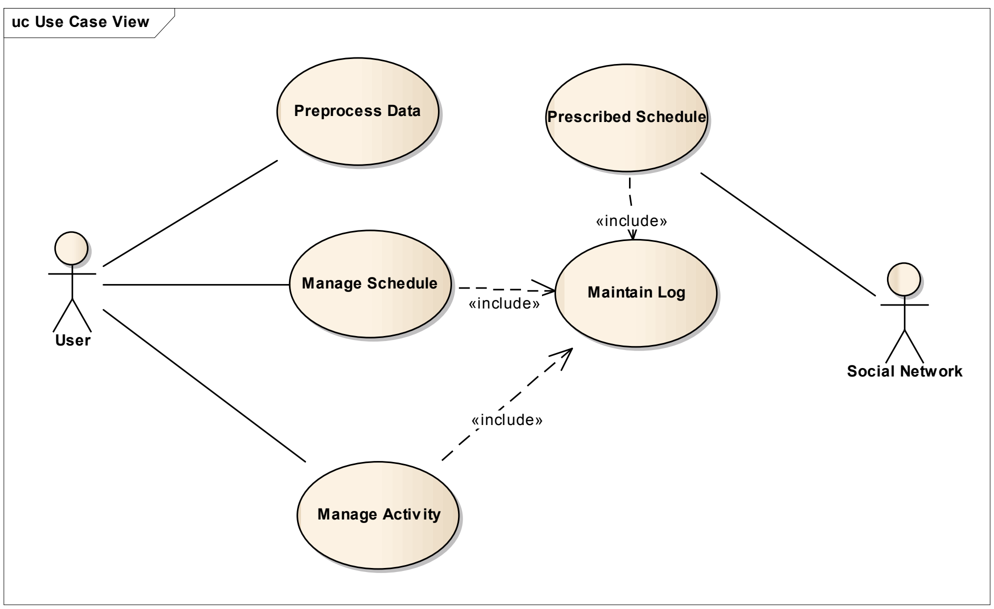


Figure 53 Use case diagram of Trajectory analysis

- **Brief Descriptions of Use Cases**

Manage Activity: Manage Activity is main use case responsible for fetching the details of particular activity. As user changes its current activity location, system starts tracking the triggering of new frequent activity. Conversion of GPS coordinates, which are recorded by GPS enabled smart device of user into Geo tag is also a part of this use case.

Manage Schedule: In Manage schedule user adds his preferred schedule if he/she want to add some recommended schedule. Schedule includes activities name, duration and number of occurrences in a defined period.

Preprocess Data: Role of Preprocess data is to analyze the performed activities of user as compared to prescribed patterns by trendsetter or user recommended patterns. All the inconsistencies in performed activities are fetched and shown to the user in the form of a report.

Add prescribed Schedule: Practitioner is required to add suggestions for a particular activity and also the complete schedule for the user. This prescribed schedule is taken as a reference and all the performed activities of user are evaluated against this schedule. This schedule is stored in repository using maintain log module.

Interaction Model: The objective of Interaction model of a system is to depict the process scenario of how different objects interact with each other. Life span and sequencing of objects are the prime components of any interaction diagram. Sequence diagrams are described in following section.

Analyze performed schedule: Purpose of this interaction model is to track, monitor and evaluate user's schedule. On the change of activity location, movementTracker, fetches the required information of new activity using movementInformation(). GPS coordinates information is passed from movementTracker and corresponding semantic tags of the location are acquired by the user. All the data are mapped with semantic tag and stored in the trajectoryRepositiory by the stroreActivity(). Activity Analyzer is the main function to analyze and compare the activity schedule. It fetches the performed activities of user of a particular period and compares it with the prescribed schedule of practitioner. Results of this module are sent to the network adopter.

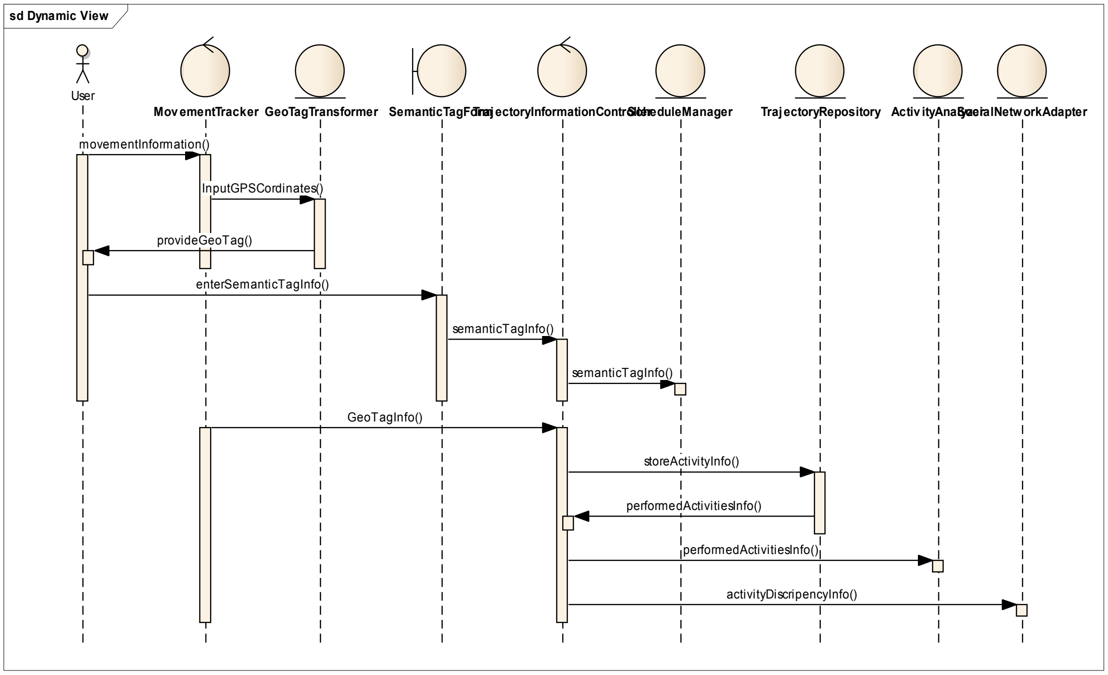


Figure 54 Sequence diagram of Trajectory analysis

Evaluate performed Schedule: Trendsetter module acquires the schedule from well-known personalities and also suggestions roe ah of activity is fetched. All of this information is stored in Trajectory Repository. Activity analyzer fetches this information and after comparing it with performed schedule of patient send it to social network adopter.

- **Class Diagram**

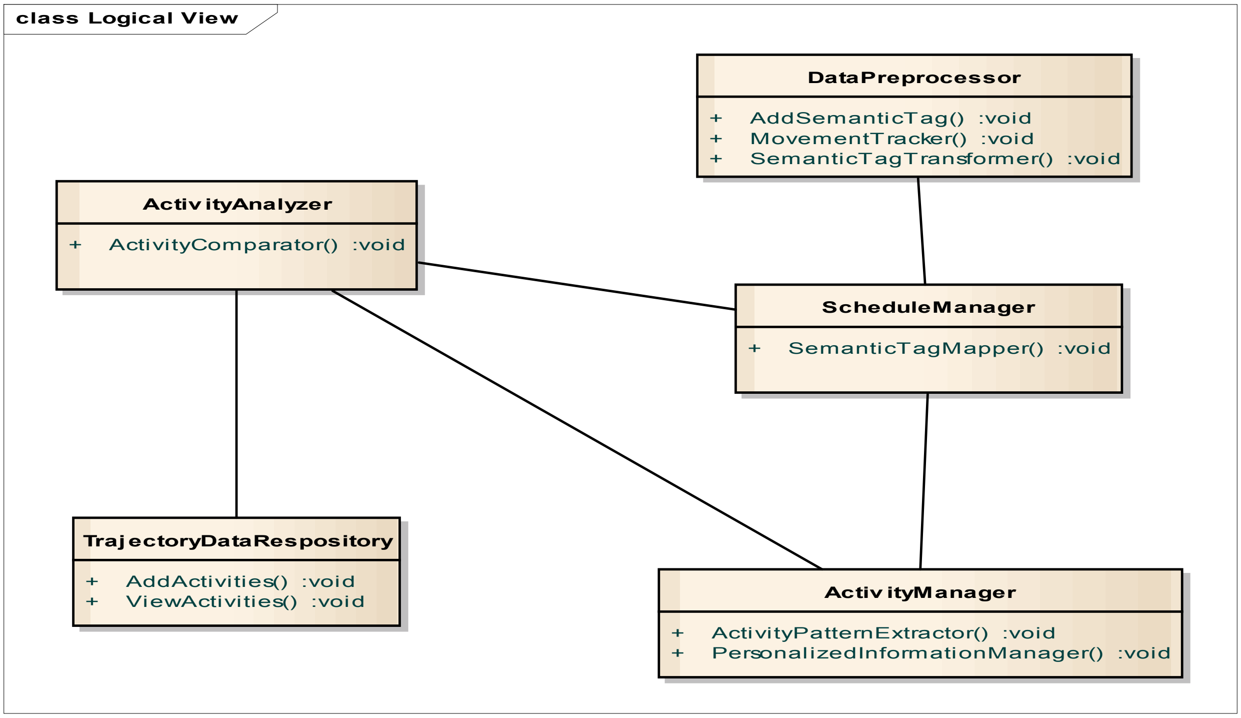


Figure 55 Class diagram of Trajectory analysis

Detailed Description of Components

A Component is a software package, or a module, that encapsulates a set of related functions. All system processes are placed into separate components so that all of the data and functions inside each component are semantically related (just as with the contents of classes). Because of this principle, it is often said that components are modular and cohesive. By keeping above definition of software component, we divided our work into different components as shown in Figure below.

- Data Preprocessor
- Schedule Manager
- Activity Manager
- Trajectory Repository

Data Preprocessor: Purpose of Data Preprocessor is to fetch all the data from the movement patterns of the patient. It further includes three parts. The imperative location finder is to detect that either particular location satisfy all the parameters of frequent patterns. Semantic tag acquires the context information of the particular activity location and task of Geo tag transformer is to convert GPS coordinates into Geo tag by using Google API.

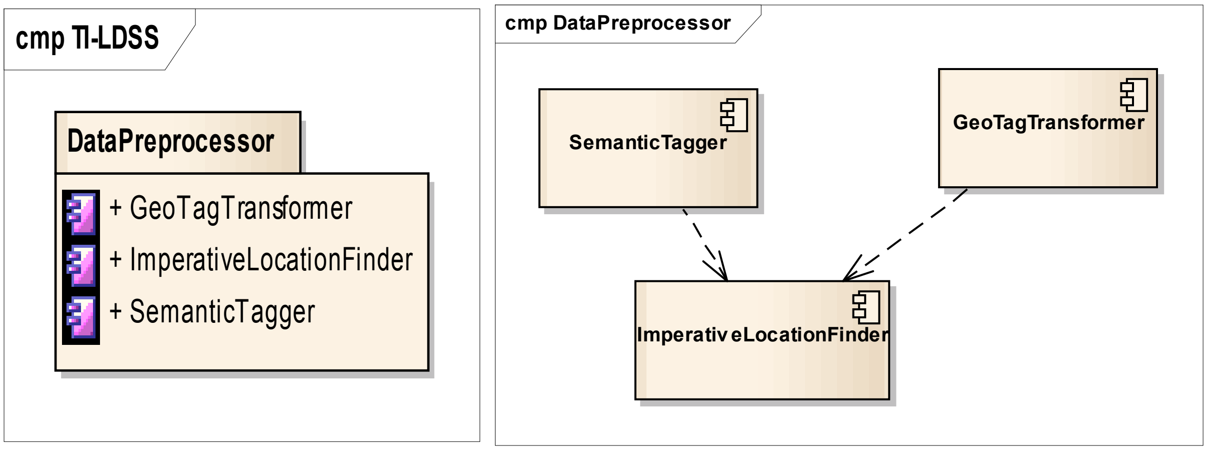


Figure 56 Component diagram of Trajectory analysis

Schedule Manager: Schedule manager prepares and processes the data to find inconsistencies. It includes Semantic tag Mapper which links the semantic tag of location and other required information and pass it to Activity Manager and then to the trajectory repository. Purpose of second subpart, Activity analyzer is to compare the trendsetter schedule and user's performed schedule. Following is the component diagram of the schedule Manager.

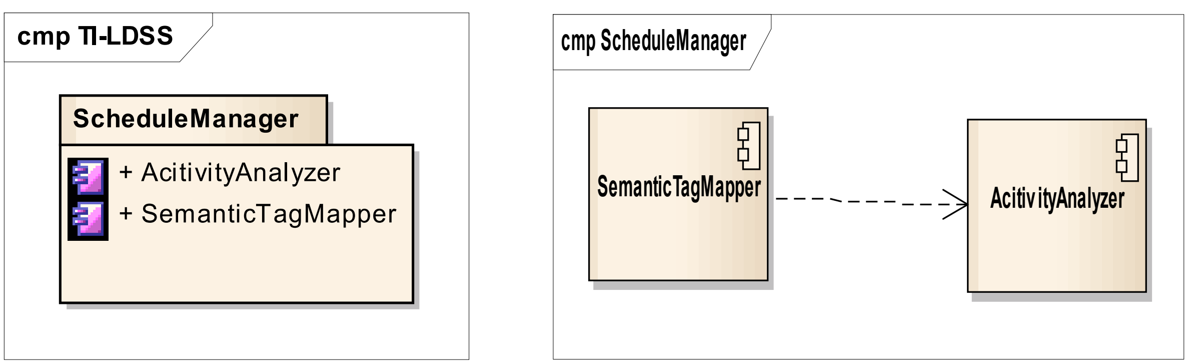


Figure 57 Schedule manage component diagram

Activity Manager:

Activity Manager is responsible for extracting the personalized information from the daily performed patterns of the user. For this first particular patterns are extracted from the activities and then passed into Personalized Information Manager.

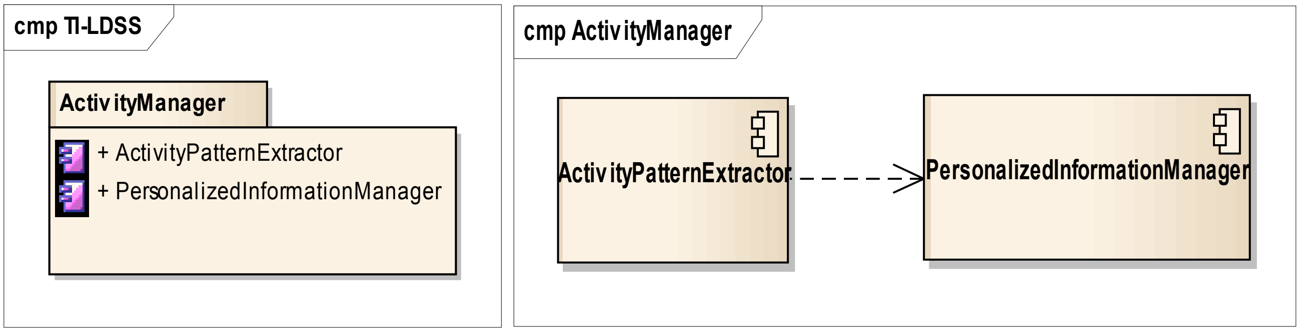


Figure 58 Activity manager component diagram

Trajectory Repository: All the three kind of data, 1) Performed patterns, the activities which are performed in daily life by user. 2) Prescribed patterns, the schedule which is added by trendsetter and 3) Suggestions, the recommendations for each of activity in prescribed schedule are stored in Trajectory Repository.

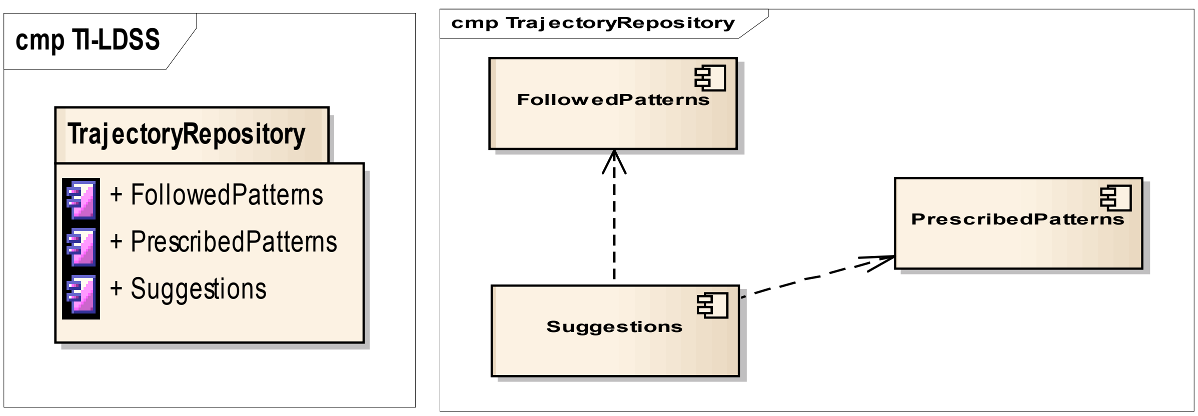


Figure 59 Trajectory Repository component diagram

3.5.2.6 Contribution and Originality

We processed the GPS enabled smart phone data with the availability of internet at each imperative location and fetch all the required information. Furthermore, we process this data over the Google API for conversion of GPS coordinates to Geo tags and further processing.

3.5.2.7 Conclusion

Trajectory analysis in terms of outdoor movement of the patient is tracked using GPS enabled location aware devices, such as smart phones. Usually a patient is prescribed to follow a particular schedule from practitioner based on ailment e.g., it may contain suggestions of daily exercise, avoidance of alcohol, and timely medication. Trajectory analysis identifies the focused activities after considering imperative location and semantic tags.

3.5.3 Interaction Analysis

3.5.3.1 Introduction

- In this module, we aim to improve the users' health by utilizing his social interaction in order to suggest them appropriate lifestyle patterns. For instance, after observing a user's daily routines, our proposed interaction analysis is able to finds some complications with his lifestyle. He/she usually sleeps late; does not exercise regularly; does not take eats on time. Obviously, these lifestyles are not good for healthy living.
- The proposed method is integrated through lifelog in the behavioral analysis module which is under development at UC Lab.
- The lifelog will take the information and integrate it with patient demographic to facilitate the behavioral analysis and suggest changes in unhealthy life patterns through better way.

3.5.3.2 Related Work

In interaction analysis, the focus of existing work is on analysis of email network to identify importance of individuals on the basis of their communication patterns in network. The interaction analysis is also used to analyze the huge amount of data such as e-mail habits [Lahiri2010], mobile phone usage patterns [Amit2006], and dominance behavior [Hayley2011]. Christopher et al. [Christopher2003] analyzed the email contents to discover experts on particular topic. They proposed two approaches (a) content based approach consider emails text and (b) graph based approach that consider both text and communication network. They find answers to questions by following people with specific knowledge, skill, or experience. Yingjie et al. [Yingjie2010] examined email data by applying value patterns to cluster a social network. They applied statistical analyses, including hierarchical clustering, overlapping clustering, and correspondence analysis, to identify the value profiles of the employees. Paweł et al. [Pawel2012] studied the email network to discover the importance of individuals according to their communication capacity. They scrutinized the delays in answering emails. They find implicit ranking about the importance of users and by measuring the procrastination in answering of messages.

3.5.3.3 Limitations of Existing Work

- The main motivation of our work is that time varying interaction data is collected in very diverse settings which need social network analysis to identify the meaningful information.
- The network analysis has been used in a variety of fields to analyze the huge amount of data such as the Internet [Faloutsos1999], animal behavior [Fischhoff2007] [Sundaresan2007], e-mail habits [Chapanond2005][Diesner2005][Lahiri2010], mobile phone usage patterns [Nanavati2006], co-authorship patterns in research publications [Barabási2001][Newman2001], Dominance behavior and social association patterns of the animals [Juang2002].
- In this module we analyzed the email interaction data with intensions to extract information that can facilitate the LDSS system in taking the more meaningful decisions.
- We analyzed the recurring patterns correspond to seasonal and other recurrent association patterns. The similar work is done for analyzing the human behavior with location-aware cellphones [Eagle2006].
- We applied it on email interaction of the from daily living of users. We are interested to identify the typical periodicities and specific interaction patterns that may affect the patients' health.

3.5.3.4 Proposed Methodology

- We propose a two-phase strategy to identify the hidden structures shared across different dimensions in dynamic networks such as type of interaction, time of interaction, interaction intervals and interaction response based on priorities.
- We extract structural features from each dimension of the email network via periodic and frequent interaction mining, and then integrate them to find out robust patterns about patients as shown in Figure 59.
- Furthermore, with the right formal definition of what constitutes periodic behavior, the aggregate periodicities of an entire set of mined interaction patterns can assist LDSS in better decision making.
- Therefore, learning patients' common behaviors becomes an important step towards

allowing LDSS to provide personalized services more accurately and effectively.

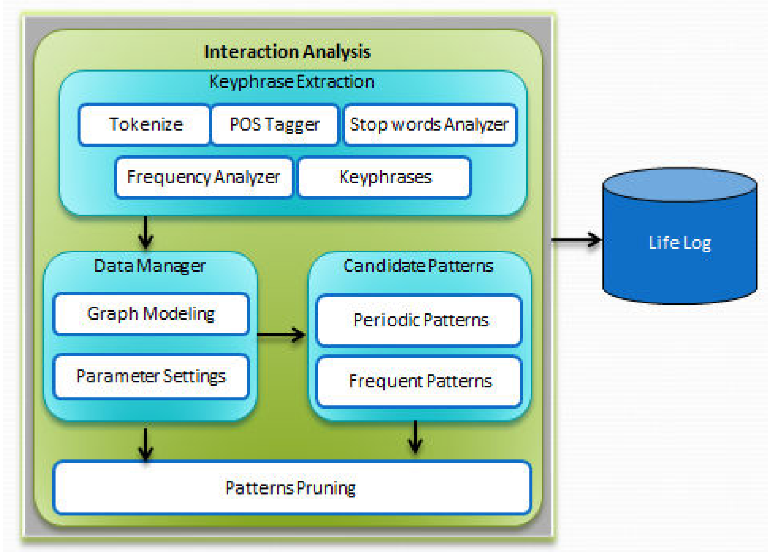


Figure 60 Overall Architecture for Interaction Analysis

- **Keyphrase Extraction**
  - The keypharses are extracted from the contents of the email by using the Algorithm shown in Figure 55.
  - Extraction of the semantic keyphrases is the essential requirement of the accurate data modeling with the user interaction. First of all parameters of the extraction algorithm KEA++ [KEA] are set with respect to keyphrases' length in the taxonomy and length of the documents. Secondly train KEA++ on the set of Emails using taxonomy.
  - Then apply KEA++ on actual Emails (data). First email contents are tokenized by using POS tagger and stop words analyzer. The frequency of each word is counted in the email and then KEA++ return the relevant keypharses.
  - The keyphrases returned by KEA++ is processed to get its level label in the taxonomy. Identify level labels is required before applying the refinement rules because they represent the hierarchical order of the keyphrases.
  - If the KEA++ result has training level keyphrases then these training level keyphrases are retained in the result.
  - Lower level keyphrases are stemmed to their training level keyphrases and kept in the result set if they are associated with the general category at the lower level in taxonomy.

Otherwise lower level keyphrases are discarded.

- Upper level keyphrases are discarded after identifying and preserving their equivalent keyphrases from taxonomy which belong to the same level of training level keyphrases.
- If the initial result does not contain any training level keyphrases then lower level keyphrases of the result are preserved and added in the final refined result.
- Upper level keyphrases are discarded after identifying and preserving their equivalent keyphrases from taxonomy which belong to the same level of training level keyphrases.
- Finally redundant keyphrases are removed from the final refined set of keyphrases.

- **Data Manager**
    - This module helps in data modeling and parameter settings before applying the mining algorithm.
    - It extracts a population of interest from messy email interaction data by removing noise.
    - The extracted information is modeled in graphs based on user defined interactions intervals and extracted keyphrases.
    - In each graph nodes are the individuals with keypharses as node label and directed edge represents the interaction between them.
    - Parameters set the thresholds of frequency and periodicity to identify the patterns of interest. For that, it is necessary to define a demanded minimum level (minimum confidence), so that all those sets of actions that have higher confidence level than the minimum confidence are considered as basic frequent periodic patterns.

- **Candidate Patterns**
    - This module identifies a set of frequent and periodic patterns from email interaction graphs.
    - Frequent patterns emphasize the significance of patterns and periodic patterns consider the regularity between them. Frequents patterns are mined by using the FP tree based approach while periodic patterns are mined using PSEMiner with integration optimization.

- The objective is to identify the sets of actions that frequently and periodically occur together.
- Once basic frequent periodic patterns have been discovered, an aspect to consider is if there is any action which is not frequent taking into accounts all the periods, so that it is not discovered in the previous task, but it is frequent enough in those periods where the basic frequent periodic patterns occur.

- **Patterns Pruning**

  - This module applies one mining process to identify frequent and periodic patterns under the given parameter settings.
  - Patterns pruning reflects the common characteristics of a typical email interaction with some unusual association between patterns. For that, the starting point will be the candidate patterns are transformed into integrated set in order to make it useful comprehensively.
  - Briefly explained, it infers meaningful actions from the data collected by email data and then it splits the string of actions into periodic sequences based on some frequent support.
  - Combining these two concepts allows us to define periodic patterns in a way that avoids any redundant information.

3.5.3.5 UML Diagram

- **Use Case Diagram**

The use case diagram of interaction analysis and its description is given below

User: The individual, whose emails are monitored and analyzed to find regular, frequent behavior.
Keyphrases Extraction: Application component used to extract keyphrases from the contents of interaction
Data Manager: Responsible to model graph on the basis of interaction between users with relevant keyphrases. Data Manager is also responsible to set the parameters for significance of the identified patterns

Patterns identification: Identify the candidate frequent and regular patterns and prune then according to the user defined parameters.

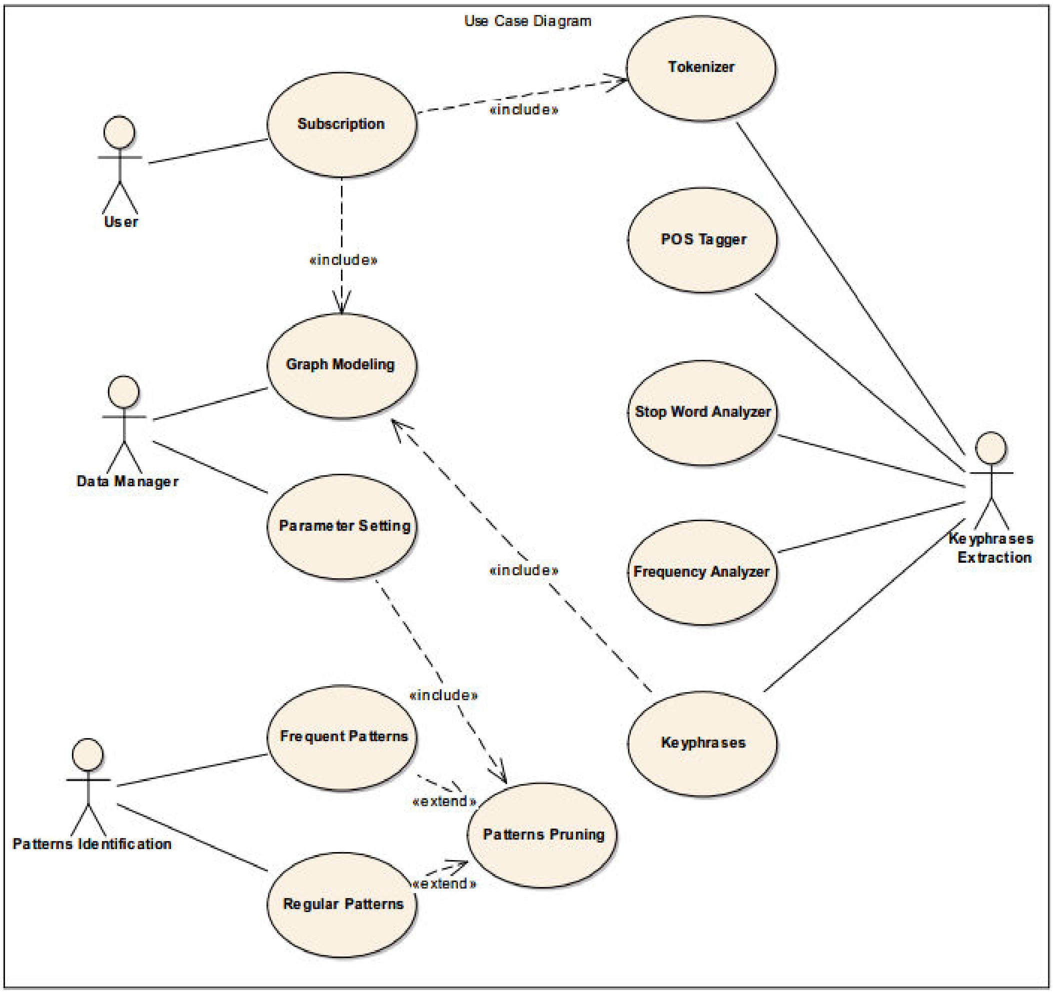


Figure 61 Use case diagram of Interaction Analysis

- **Brief Descriptions of Use Cases**

Subscription: Responsible for register user with the application. Application send request to user and user verify application to access his emails.

Tokenization: Tokenization converts sentences into separate word to lookup on each word individually.

POS tagger: It is the process of marking up a word in a text as corresponding to a particular part of speech, i.e. relationship with adjacent and related words in a phrase or sentence as nouns, verbs, adjectives, adverbs, etc.

Stop Word Analyzer: This use case process email contents and search for stops words after tagging into different parts. It removes the stop words from the contents of interaction.

Frequency Analyzer: To identify the repetition of a particular word in the text, this use case calculates frequency of words which are semantically similar.

Keyphrases: This use case collects the final keyphrases extracted at the end of NLP processing.

Graph Modeling: Role of graph modeling is to model the graph from the user interaction on the basis of time and attach the relevant extracted keyphrases on each node which gives the semantic of interaction at a particular time.

Parameter Setting: Aim of this use case is to set the threshold parameters for the identification of regular and frequent patterns.

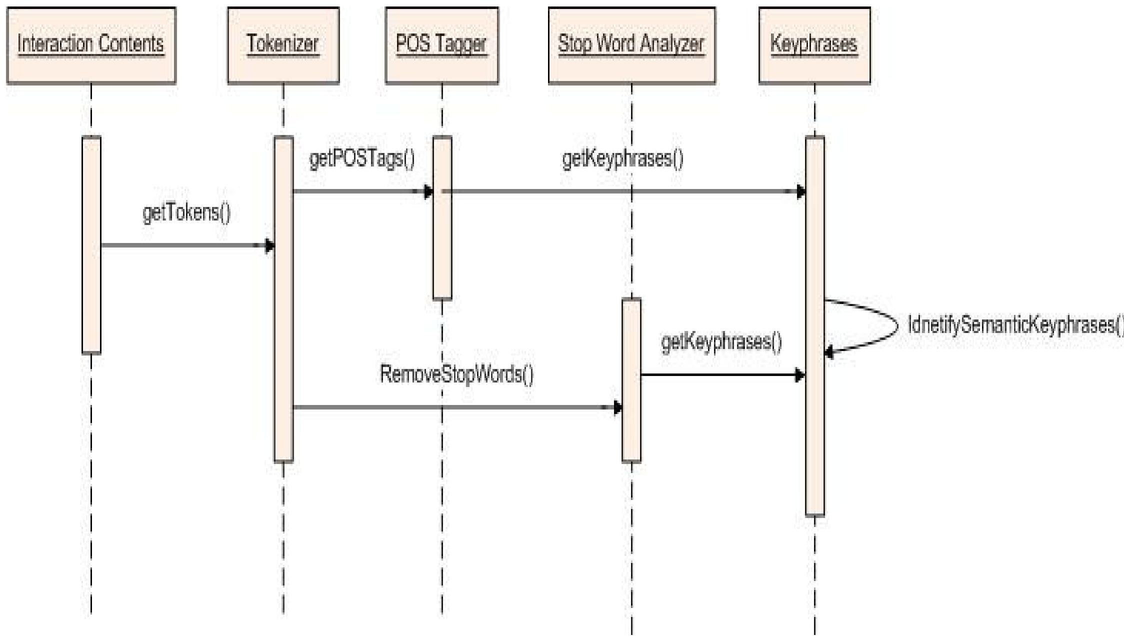
Frequent Patterns: This use case is responsible for mine the frequent patterns from the graph model of interactions.

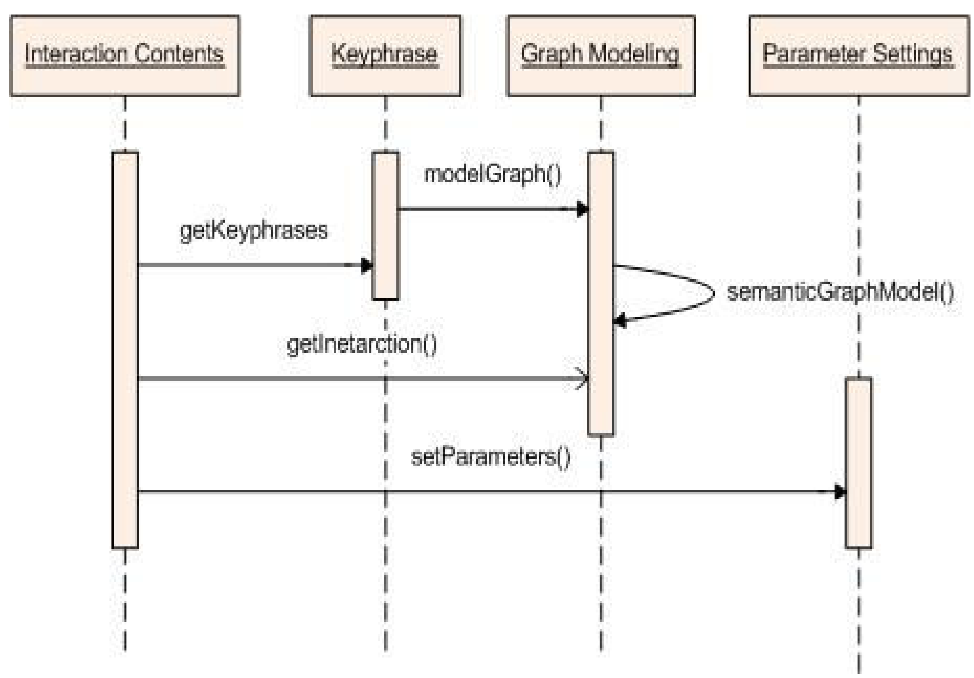
Regular Patterns: This use case is responsible for mine the regular patterns from the graph model of interactions.

Patterns Pruning: It identifies the patterns of interest from the set of frequent and regular patterns after looking into the parameter settings of threshold.

- ## Sequence Diagram

The objective of Interaction model of a system is to depict the process scenario of how different objects interact with each other. Life span and sequencing of objects are the prime components of any interaction diagram. Sequence diagrams are described in following section.


Interaction Contents
Tokenizer
POS Tagger
Stop Word Analyzer
Keyphrases
getPOSTags()
getKeyphrases()
getTokens()
IdnetifySemanticKeyphrases()
getKeyphrases()
RemoveStopWords()


Interaction Contents
Keyphrase
Graph Modeling
Parameter Settings
modelGraph()
getKeyphrases
semanticGraphModel()
getInetarction()
setParameters()

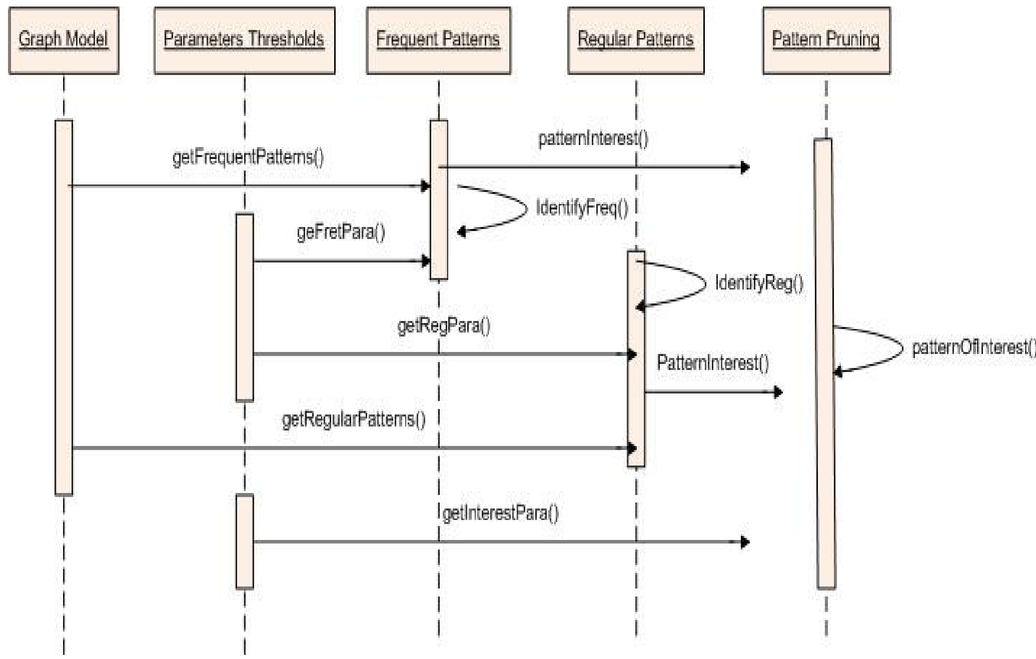


Figure 62 Sequence diagram of interaction analysis

- ## Class Diagram

Task assigned to the class keyphrases is to extract keyphrases from the contents of interaction after applying the NLP techniques like POS tagging and stop words analyzer. GraphModel maps the interaction and semantic keyphrases into the graphical format. FrequentPatterns and PeriodicPattens identify the candidate patterns while PatternsPruning identifies the patterns of interest after taking into account the parameter thresholds.

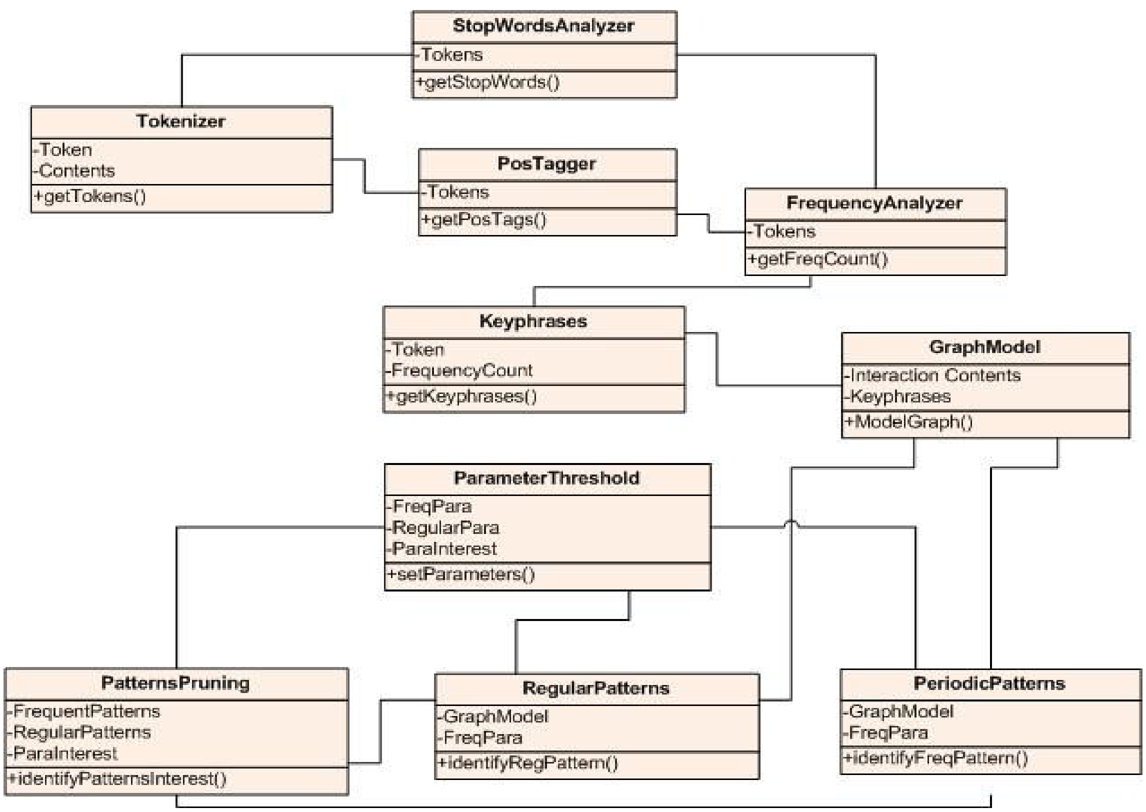


Figure 63 Class diagram of interaction analysis

- **Component Diagram**

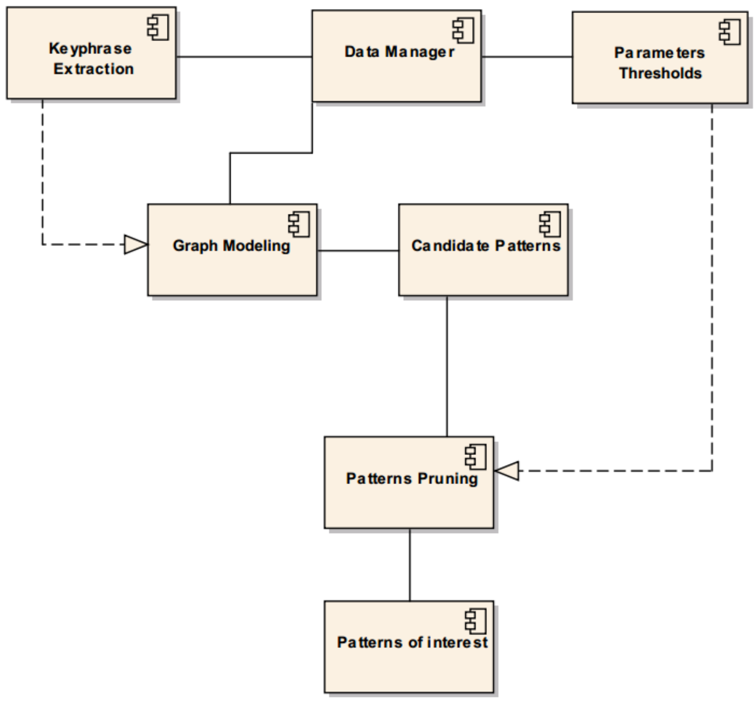


Figure 64 Component diagram of interaction analysis

3.5.3.6 Contribution and Originality

In this module we mine the patients' frequent and periodic interaction patterns that change over time. The purpose is to gain knowledge about the preferences, needs and habits of the user. Users can act in two different roles: senders and receivers. These two roles are not interchangeable while mining the patterns of interest from his daily interaction routine.

3.5.3.7 Conclusion

Email interaction analyzes the patient's actions to identify significant behavior and communication trends in daily routines. It mines the frequent and periodic interaction patterns that change over time to gain knowledge about their habits and preferences.

3.6 Context-aware Recognizer

3.6.1 Introduction

As the human lifespan increases, people are becoming more interested in living a healthy life, which results in high-cost healthcare systems and services. Maintaining good quality and widely available healthcare services at a minimal cost is challenging [Khattak2010]. Home healthcare systems are becoming a more important form of healthcare service delivery. The management, maintenance, and coordination of healthcare services, educating users, and empowerment of individuals to manage their own health are the main focus. To support this, a powerful, flexible, and cost-effective infrastructure is required for healthcare services that can fulfill the vision of *ubiquitous healthcare (u-healthcare)*. Cloud Computing can potentially provide a huge cost savings, flexiblility, high-throughput, and ease of use for different services [Buyya2009] as well as for healthcare services. For this reason, we have developed an architecture, called Secured Wireless Sensor Network (WSN)-integrated Cloud Computing for u-LifeCare (SC^3) [Hung2010]. Different wireless sensors are deployed that collect real-time data that is transmitted to a Cloud Server through a Cloud Gateway. Based on this real-time data collected by different sensors, SC^3 provides real-time home care and safety monitoring services, an information sharing and exchange facility, emergency connection services, and patient monitoring and care services.

One of the main components of SC^3 is the Human Activity Recognition Engine (HARE) *[Khattak2010]*. This engine is necessary to provide improved daily medical care and real-time reaction to medical emergencies, and identifying patient activities (i.e., Activity Recognition (AR)) is a prerequisite. Low level activities are defined as simple motions or actions detected by the sensing device that are very general and unclear in meaning such as hand movement. High level activities are the linkage of low level activities in a sequence with reference to context to make it more understandable. For example, in the process of making tea, picking up the cup, boiling water, using sugar, and using a spoon are all low level activities and are unclear when interpreted separately. However, when these activities are sequenced together and are used in context with the kitchen location, then they comprise “making tea” as a high level activity.

Our focus is on CAME [6] as a component of our proposed HARE [Khattak2010] that is beyond the limits of traditional systems. We propose the integration of all the activities detected using different types of sensors together along with context and profile information of the subject.

We model the activities in domain ontology within the explicit context of the activity and execution pattern. In addition, we apply semantic reasoning to infer high level activities (user intention for performed activity) and use it for decision making. This will help in enhancing capabilities of healthcare systems to facilitate more personalized recommendations and decision making, and it has tremendous value for intelligent/efficient service provisioning.

For the CAME implementation, we use different sources of information to avoid the possibility of missing information or imperfect context information [Henricksen2004]. For context representation and profile information, we use an ontology and have developed a semantic structure for information representation. Ontology is formally defined as *an explicit and formal specification of a shared conceptualization* [Gruber1993].

Sensors are deployed to collect real-time data about a person's activities and environmental information. Then with the use of an ontology (containing expert knowledge of the medical domain and user profile information) these detected activities are intelligently manipulated to infer higher level activities and also to make a situational analysis. The experimental results of the match-making process of CAME yielded good results. Rule-based filtering for situation analysis and decision making has verified our claims, and the results of activity recognition and manipulation are very encouraging in terms of accuracy. CAME uses both A-Box (instance level) and T-Box (structure level) inference techniques that confer better accuracy. A filter is also implemented in CAME to filter out an "unknown activity" during the match making phase. This not only improves the accuracy of the CAME, but also results in better system response time.

3.6.2 Related Work

Numerous developments in industry and academia have already begun or are being used currenlty to facilitate better healthcare. In July 2008, the Ministry for Health, Welfare, and Family Affairs, Korea released u-Care System for a Solitary Senior Citizen (SSC). SSC monitors human health at home and provides limited services such as 24 hours×365 days safety monitoring services for a SSC, emergency-connection services, and information sharing services. Microsoft and Google are two pioneers who have brought Cloud healthcare platforms to reality for healthcare applications and services with low cost and increased performance.

Microsoft developed a platform to store and maintain health and fitness information, called Health Vault [MS]. It is a Cloud service that helps people collect, store, and share their personal health information. Google provides a personal health information centralization service known as Google Health [Google]. The service allows Google users to volunteer their health records into the Google Health system. Volunteered information can include health conditions, medications, allergies, and lab results. Google Health uses the information to provide the user with a merged health record, information on conditions, and possible interactions between drugs, conditions, and allergies. The Unified Cloud Interface (UCI) standardization [UCIS] or Cloud broker serves as a common interface for interaction with remote platforms, systems, networks, data, identity, applications, and services. UCI is composed of a semantic specification and ontology. The ontology provides the actual model descriptions, while the specification defines the details for integration with other management models.

Various wireless technologies are currently being used in healthcare. CodeBlue [Gao2008] is one of the technologies developed by Harvard Sensor Network Lab. CodeBlue is based on a publish/subscribe model for its different services. CodeBlue mainly supports physicians and nurses that monitor patients; however, some of the focus is shifting toward research on providing reminders for the elderly to perform daily life activities [Pollack2003]. These are mostly plan-based approaches to decide when and how to prompt subjects effectively, and are thus centered around time-based activities. To overcome the limitations of this system, a location-based reminder system was introduced [Sohn2005], where a key element for reminders in this system is the subject's location. But in fact, context for reminders is more important than simple location or time and context includes both location and time as subsets. ComMotion [Marmasse2000] is an example of a context-aware system that supports reminder applications that use only one sensor and are mainly based on time. It addresses how and when to prompt the subjects. HYCARE [Du2008] is the most recent reminder system that takes context into consideration, and it develops a novel scheduling mechanism that can coordinate with different reminder services and remedy possible conflicts.

The idea in [Boger2006] is based on the Markov process for decision making (a decision model capable of taking into account the uncertain effects of an action with the tradeoffs of both short-term and long-term objectives). The system is designed to monitor elderly dementia patients and provide them autonomous guidance to complete their activities of daily life. The authors of that study focused on facilitating hand washing activity using a video camera. A conceptual model/space is developed for hand washing and then used by the system when the activity is being performed by patients, and it provides reminders for different steps from the conceptual model/space. The system in [Wang2009] is a more realistic system that not only uses ontology to incorporate context in intelligent processing of the collected information, but also focuses on the information collected from sensors such as a smoke detector, GPRS modem, infrared control and X10 appliances that actually facilitate more in-home care for the person than person healthcare. This system is based on the Event-Condition-Action (ECA) model; however, for support in healthcare, the system needs to collect data on the activities performed by humans in addition to environmental information.

3.6.3 Limitations of Existing Work

The systems discussed above do not use real-time activities or only use a single type of real-time activity performed by the subject and then generate reminders or even make decisions based on that information. They only consider the context to the level of time and location, which results in inflexible system behavior. These systems can mostly be categorized as reminder systems or homecare systems, but the important thing is to facilitate healthcare where these systems fail to perform. The existing Cloud-based Healthcare system does not integrate wireless sensor networks, which is necessary to obtain real-time information on patients and/or the environment in order to monitor and analyze emergency situations.

The existing systems are based on a simple condition and action model [Wang2009], not using context information including time, location, and user profile. In some cases, the existing systems use imperfect low level context information [Henricksen2004], which makes the system results unpredictable. Their focus is more on environmental sensors (e.g., smoke detector, infrared control, and GPRS modem) rather than on real-time human activity. Traditional systems are moving from location or time based reminder systems toward context-aware activity recognition. However, humans rely on several modalities including the five classical senses and other senses such as thermoception (temperature) and equilibrioception (balance and acceleration) together with context information such as location, and time for everyday tasks. Currently, to the best of our knowledge, there is no systematic way to integrate multi-modalities such as profile information, vision with motion, environment, location, and time to infer human intentions, whereas the traditional systems are based on simple activity with a condition and action model.

3.6.4 Proposed Methodology

CAME is the process of inferring high level activities from low level activities recognized by different sensors. The component based framework architecture diagram of CAME and the information flow is given in Figure 64, while the detail description of all the components are given in their corresponding sections. For instance, the Activity Extractor component extract activity related information from XML and Text files, then with the help of context information available in Knowledgebase and customized rules we infer high level/actual activity performed by human body. Based on the activities performed, CAME also gives suggestions and makes decisions in different environment with the help of context information available. For example; we have all the context/profile information (i.e. professor name, designation, current courses, class room no, and class timings) about a professor in the knowledgebase (ontology). Now if Professor enters a class room on his class time, then the body, motion, location and video sensors will recognize that Professor has entered the class room at a specified time. Then CAME using these information from the sensors and information available in the Knowledgebase infers that its lecture time of Professor. So the system starts issuing commands for turning off class room lights, turn on computer and turn on plus scroll down multimedia (projector) in class room.

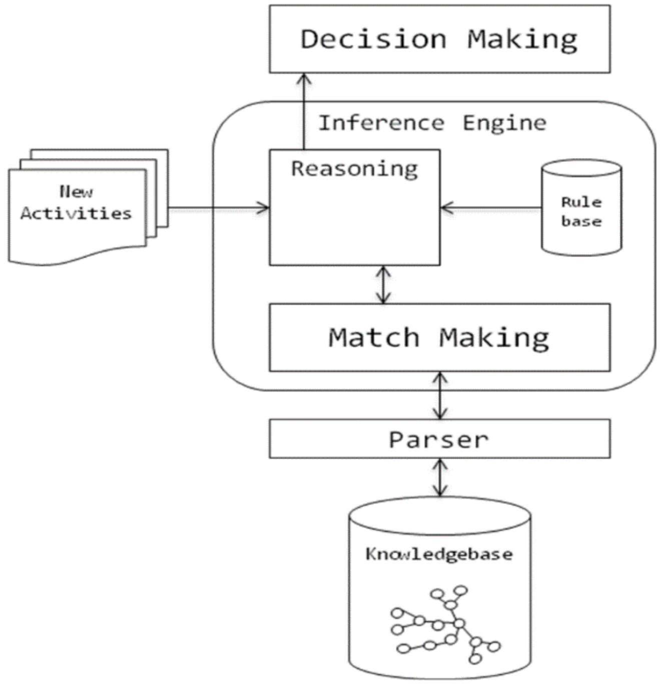


Figure 65 Context-aware Activity Manipulation Engine (CAME)

a. Activity Extractor

Activity Extractor is a component that is responsible for recognizing data inputs from diverse sources. Video-based, sensor-based, motion-based, and location-based activity recognition engines will provide output in different formats like XML and simple text. So there is need of extractor in the engine to properly parse all type of output produced by these different AR engines. Then it can extract the data from the file and provide these to the next module i.e. Activity Representation.

XML output produced by motion sensor containing activity information


```xml
<?xml version="1.0" encoding="UTF-8"?>
<activities>
<activity type="Motion">
<detectedBy>Motion Sensor</detectedBy>
<hasName>Prof. SY Lee</hasName>
<activityName>Entering Class</activityName>
<id>345</id>
```

<time>2009:06:14:14:00:13</time>
</activity>
</activities>

b. Activity Representation

As the extracted activity from the xml or text file will be stored in Knowledgebase and will also be used in Inference Engine to deduce higher level activity, so the activity needs to be formally represented in predefined semantic structure [ShE08]. For this reason, the Activity Representation component formally represent the activities that are extracted in the previous module, while the representation (see Figure 65) is provided by the Knowledgebase (explained later).

OWL representation (using N3 notation) of Activity (Person entering in a class)

```
activityOnto:Activity_Instance_20090614140013345
a       activityOnto:Activity ;
activityOnto:hasConsequentAction  activityOnto:Action_Instance_145413546;
activityOnto:hasID                345;
activityOnto:hasName              "Entering Class";
activityOnto:hasType              "Motion";
activityOnto:isA                  activityOnto:Room_Instance_Class;
activityOnto:performedAtTime      2009:06:14:14:00:13;
activityOnto:performedBy          activityOnto:Person_Instance_345.
```

The process of formal representation of activities is also important in a sense as we will have to check the activity for its consistency against the Knowledgebase and also it will be dump in the Knowledgebase for later use.

c. Knowledgebase

Knowledgebase (KB) serves as the back bone of CAME. It is responsible for proper communication of information among all the components of CAME. It stores all the possible types of activities that a human body can perform in different context/situation, with the information of different activities priority for different users and group of users.

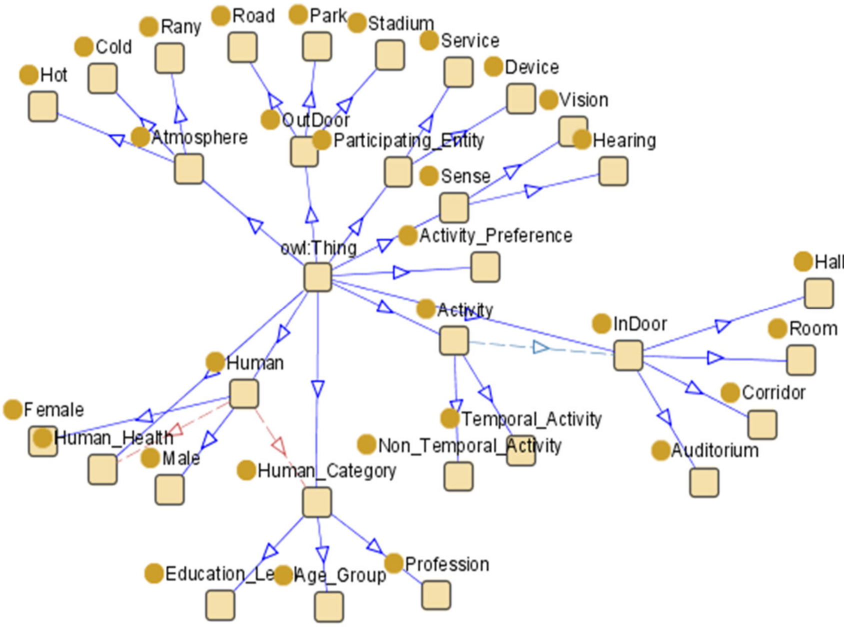


Figure 66 Knowledgebase (Human Activities Ontology)

The proper engineering of the KB is most important activity in the development of CAME. To engineer the KB (see Figure 24) we have to look at the same problem from different directions, for example; if a building has caught fire then no one is allowed to enter that building, but firemen are allowed to perform their work and even enter the building. So we need to introduce some type of priority for different actions that a particular group of human can perform in a given context while the other cannot.

When an activity is recognized by the sensors then this knowledgebase is parsed and if required in different situations then inferenceing is done for decisions against activities. So it is actually the ontology, where all the activities are semantically modeled and available for analysis and decision making.

d. Activity Verification

Activity Verifying is important for two reasons:

- Check for the consistency of the newly recognized activity against the knowledgebase developed for the activities. In consistency verification, the activity represented in Activity Representation component is verified against the KB for its structure and the information contained in it. So basically the verification is made to check that weather the activity fulfill all the requirements or not. So if consistency verification is positive the other modules work on that activity.

- Secondly after consistency verification, the existence verification is done for the activity that is this activity already present in the knowledgebase or not? If not present then it is given to Knowledgebase Population module to store this in the Knowledgebase.

e. Knowledgebase Population

Knowledgebase (ontology) evolution is of two types i.e. ontology enrichments and ontology population [FPG06, CFH06].

- **Ontology Population:** When we get new instances of concept(s) already present in the ontology. Then this concept(s) is not inserted for the second time. Here only the new instance(s) of this concept(s) is introduced and the ontology is populated.
- **Ontology Enrichment:** When we get new concept(s), which is totally new for our ontology or it does have some sort of changes from its counter concept(s) in the ontology. Then we enrich our ontology to accommodate the new changes and also populate our ontology for its instance.

Here our focus is on ontology population where new instances are introduced in the Knowledgebase against the already present concepts. Knowledgebase Population module is responsible to store all the newly recognized activities in the KB for later use, where this logging of activities in the Knowledgebase is achieved with the help of Parser.

f. Parser

For any type of information manipulation from the Knowledgebase, Parser is responsible to properly handle all the operation regarding that matter. The Parser normally communicates with Activity Representation component to properly represent the activity, it also parse the Knowledgebase for the Inference Engine for verity of different reasons like verification of activity and decision making, To populate the KB for newly recognized activity, the Parser is also used in that case.

g. Inference Engine

To understanding the context of an activity and to extract high level (abstract) activities from low level activities recognized by sensors, we need to have an Inference Engine for analysis of these activities and to make proper decisions on behalf of human users. So the Inference Engine is very important component of CAME. It uses the activities information with respect to their context information and infers high level activities. The decisions or suggestions of Inference Engine are very much dependent on the domain and user intensions. So for this reason we also introduced the user defined customized rules in the inferenceing process. E.g., if a person is falling from a building in a stadium then its context maybe that there is a jumping competition, but if a person if falling from a building and that building is of some educational institute then its context is that there is an emergency situation over there. So we need to have domain specific customized rules.

h. Rule base

Every organization have their own customized rules; E.g., in Kyung Hee University (KHU), Korea, one course can only once be studied in a program. Now for example if a person *Tea Ho* is taking the Data Mining course for the second time and he has got B+ or above grade previously, so according to KHU rules it is not possible to take this course again in the same program.

So for these sorts of situations and actions, we need to define customized rules for different activities.

i. Decision Making

After the process of inferenceing, the system can take decisions or give suggestion against different activities. So this module is responsible for performing some actions against the suggestions made by the Inference Engine. This module also visualizes the activities and the Knowledgebase for proper understanding of the activities.

3.6.5 UML Diagrams

- **Use Case Diagram**

The use case diagram description is given below.

Actors

Admin:User is the main user of the system that is using CAME for activity analysis and decision making.

ActivityRecognitionEngine: Is the main source of input to CAME. The activity information coming in into CAME is manipulated and decision is propagated to the consumers.

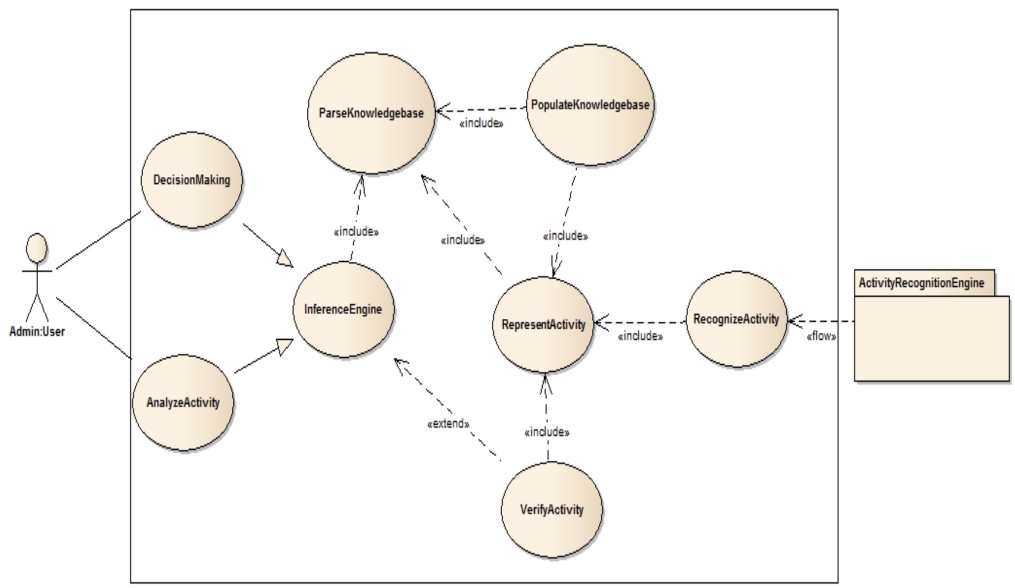


Figure 67 Use case diagram of CAME

Use case Description

- **Recognize Activity:** This use case receives the incoming activities from the sensors and identifies its format.
- **Represent Activity:** This use case is responsible for representing the incoming activity from Activity Recognizer in ontological structure while take help from VerifyActivity for verification of activity.

- **Verify Activity:** This use case is used to verify the incoming activity against the Knowledgebase for its consistency and existence.
- **Populate Knowledgebase:** It is responsible for logging the verified activity in the knowledgebase.
- **Parse Knowledgebase:** The responsibility of this use case is to parse the knowledgebase for inference engine and its processing.
- **Inference Engine:** Inference engine involves the reasoning that include MatchMaking and flitering
- **Analyze Activity:** This use case analyze the activity based on the reasoning and recognize the situation of user.
- **Decision Making:** This use case makes the decisions based on the reasoning which is performed in Inference Engine.

- ## Sequence Diagram

Sequence diagrams for CAME are described below that shows the interaction between different objects of the system for the achievement of objectives.

Activity Representation

When the activity is received in CAME then for its usage in Inference Engine and storage in Knowledgebase needs to be in Knowledgebase representational structure.

- It calls the ActivityRecognizer using getActivityContents() and receive the activity.
- It gets the representational structure from Knowledgebase by calling getRepresentation().
- Which is executed by Parser and Knowledgebase is parsed for that. Then the activity is represented using representActivity().

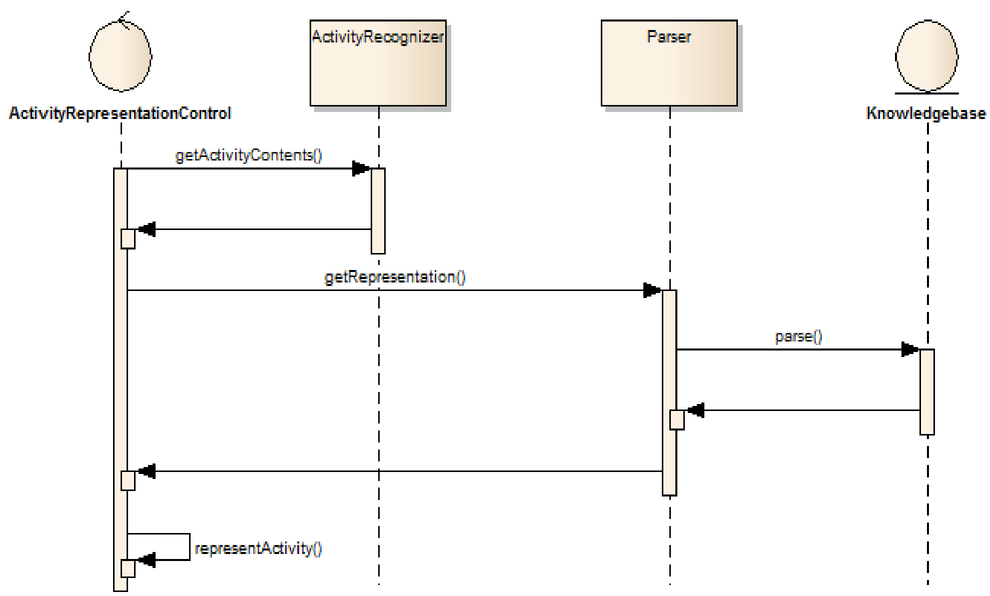


Figure 68 Sequence diagram of CAME Activity Representation

- **Analyze Activity**

The activity is first extracted using extractActivity() from Knowledgebase and then forwarded to Inferencer using analyzeActivity().

Inferencer performs matchmaking and then apply rule using applyRules() extracted from Rules

Then the result is displayed using displayResult().

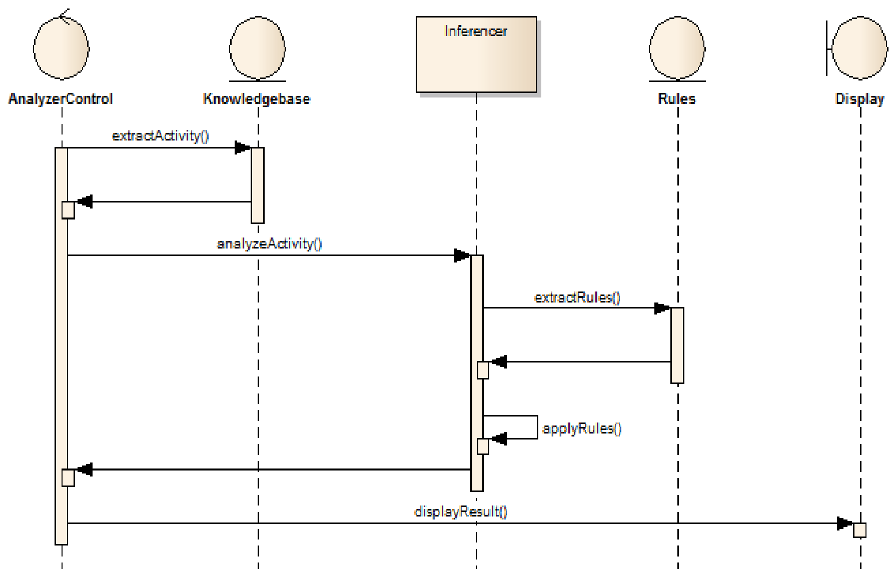


Figure 69 Sequence diagram of CAME Analyze Activity

Decision Making

- The detected activity is first represented in the Knowledgebase representational structure and then the DecisionControl is activated.
- The DecisionControl extract the relevant activities form Knowledgebase using matchmaking process.
- Then the DecisionControl apply the rules extracted from Rules using applyRules().

The activity is then identified and decision is made. The decision is then displayed or propagated to DisplayDecision.

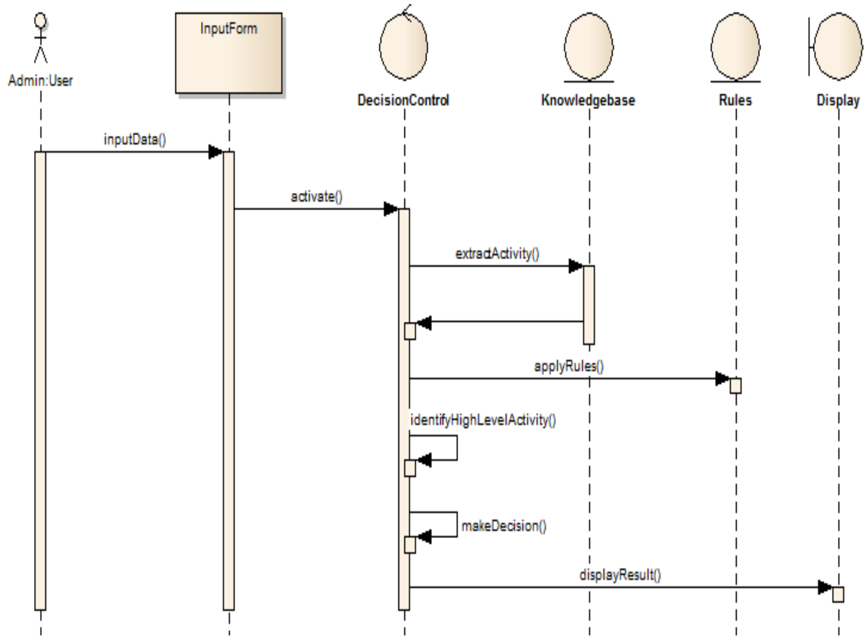


Figure 70 Sequence diagram of CAME Decision Making

- ## Class Diagram

  - Class diagram of CAME shows the different classes and their relationships with each other.
  - Initially the ActivityRecognizer and ActivityRepresentation are loaded which work together for incoming activities.
  - Then the activity is Verification class is called for activity verification. The verified activity is then logged using PopulateKnowledgebase that uses Parser class for the job.
  - Inferencer class initiates the matchmaking and filtering for the new activity and makes the situation analysis. This is also responsible for decision making.

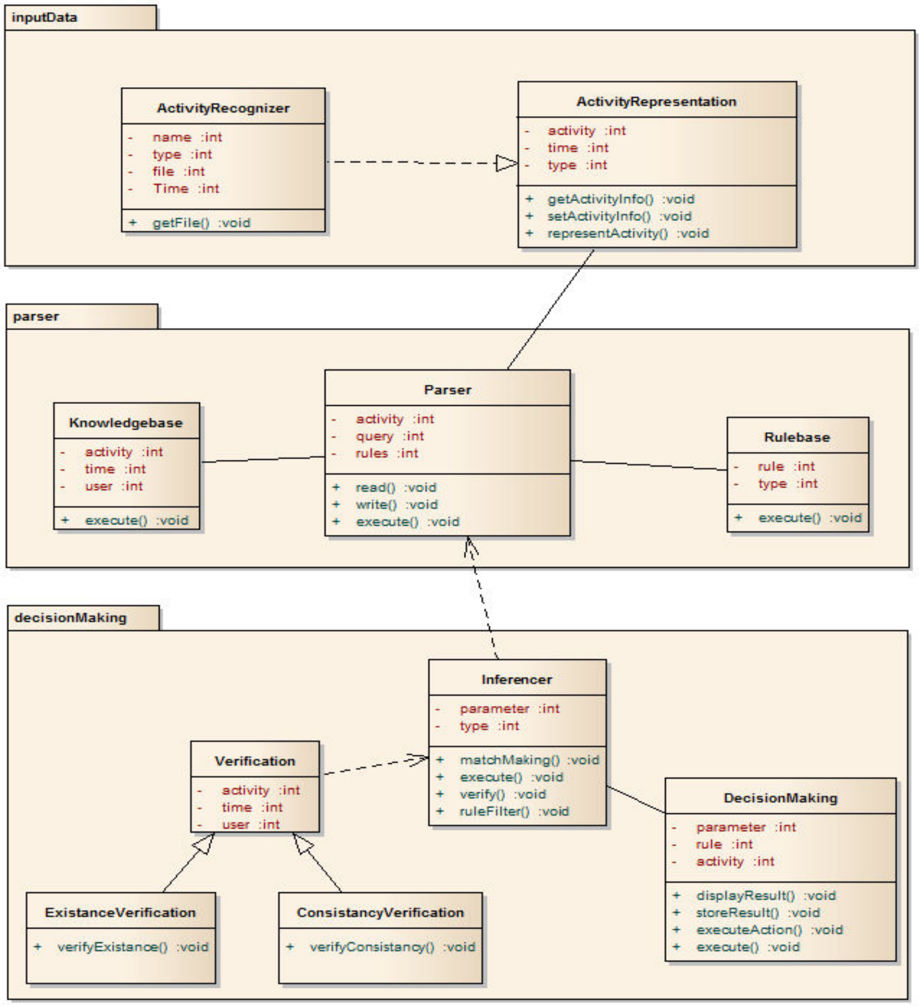


Figure 71 Class diagram of CAME

- ## Component Diagram

The component diagram of CAME shows different components and their relationships with each other. Also it shows the subcomponents interaction, purpose, and their relationships with each other. Mainly there are four main components and are explained below.

Activity Recognizer Component: It is the main component of CAME that is responsible for collecting the activity information coming from different sources.

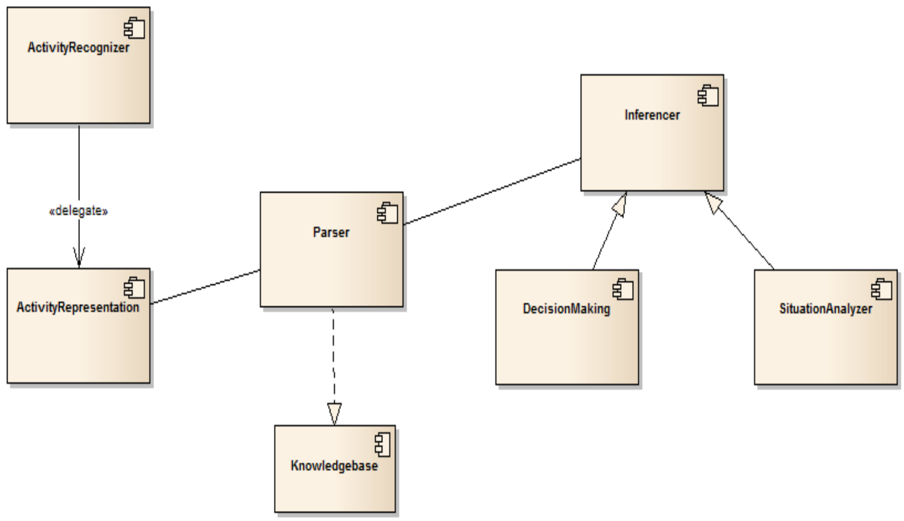


Figure 72 Component diagram of CAME

- **Activity Representation Component:** It represents the incoming activities information in the ontological structure. It also uses the help of verification for verifying the activities consistency.
- **Parser Component:** It is responsible for CAME components interaction with Knowledgebase for activity logging and extraction. It is the main component that is always connected with the Knowledgebase and fulfills the jobs coming for knowledgebase.
- **Inference Component:** Inference contains the brain of CAME. It is the main component that performs the matchmaking and filtering. It uses the services of DecisionMaking and SituationAnalyzer for analysis and decisions.

3.6.6 Contribution and Originality

Based on the unified approach of CAME for detecting high-level activities and situation analysis, the proposed system has incorporated following innovative contributions:

- Using ontology for modeling the context, user profile information, and representation of information.
- Knowledge driven approach using ontology is used to make decisions after detail context analysis.
- Using ontology to infer higher level activities using forward chaining for detection of human behavior.

- Using profile information (Life style) of a person for making personalize decision.
- Two phase filtering procedure is used to make proper decisions and to minimize error rate.
- Match making using H-Match and Falcon. Description Logic Rules based on expert (Doctors) knowledge for decision making.

3.6.7 Conclusion

The Context-aware Activity Manipulation Engine (CAME) has been presented using a knowledge-driven approach to recognize Activities of Daily Livings (ADLs). The objective of this system is to infer high-level activities from low level real-time ADLs detected by sensors and to facilitate the provision of better healthcare services. The nature and characteristics of ADLs were analyzed. Based on the analyses, ontology was used to model the ADLs (including activity, location, time, profile, and environmental information), domain knowledge, and expert knowledge. Using ontology with the knowledge engineering practice, a context model for personalized service provisioning and intelligent healthcare facilities has been developed. Ontological modeling of the context and using it for recommendation is the compelling feature of the proposed system. An integrated framework architecture has been developed in addition to the modeled knowledge in order to use the sensed activity information for generating reminders, alerts, and emergency situation analysis for decision making. To achieve better results and provide caregivers an interface for rich interaction, description logic rules have been incorporated. The description logic rules filter out the unnecessary information during decision making. The proposed system was more accurate and had shorter response time for a given situation. To view the detailed operation of the proposed system, please see the video demonstration.

We are planning to test the system on more activities with an extensive set of rules in future studies. We are also planning to work on and provide more services for different kinds of diseases such as stroke and Parkinson’s disease. The system in its current state produces some conflicting results when there is more than one subject in the environment. We are trying to overcome this issue as there are some cases in which the appropriate system response is unclear. For example, two subjects are in same room and one is reading a book while the other wants to watch TV. We are developing different heuristics, rules, and scheduling to overcome these issues. Currently planned solutions are: 1) set priorities and levels for different subjects; 2) a subject who initiated activity first will be served in cases of conflict; 3) the location of the conflict will be considered for resolution, i.e., if its subject A's room then the system will respond in favor of subject A; and 4) the subject's schedule will play an important role in handling conflicts, i.e., if a subject's planned activity is relaxing or entertainment then that subject will be served in a common room location.

3.7 Physical Activity-based Behavior Analyzer

3.7.1 Introduction

- Physical activities are performed by inhabitants in a sequential manner characterized by preceding and following activities to identify their influence on each other [Rashidi2010]. For example, taking medicine is very likely followed by eating, and brushing teeth is usually preceded the face washing activity.
- Therefore, the activity log in terms of performed activities can be effectively analyzed to discover the sequential behavior patterns.
- The identified patterns provide the significant list of action that mostly occurs together in daily routine to support the health maintenance and functional capability of individuals.
- In a particular scenario, the daily routine of inhabitant Mr. Ben, if the significant sequential behavioral pattern is: (wakeup, exercise, bathing, breakfast, medication), reflects that Mr. Ben's activities includes daily exercise before breakfast and he is on constant medication.
- In this case, the care givers can easily identify the missing exercise and medication routines after analyzing his lifestyle based on frequently performed activities. Furthermore, assuming that human beings perform behaviors based on habits, it could be inferred that patterns describing past and present behaviors will define the future actions as well.

3.7.2 Related Work

Now we state other techniques which have methods and tools along with some extensions and variations for analyzing the human behavior. Nugent *et al.* [Nugent2007] analyzed the user's interaction with technology and environment in order to provide useful information relating to lifestyle trends and how the environment can be adapted to improve the user's experience. They proposed homeML, an XML based cross-system standard, to support information exchange between intra- and inter-institutional levels. Their proposed XML-based schema improved the accessibility and analysis of the collected data for meaningful analysis of person's life within smart home environments. Rashidi *et al.* [Rashidi2011] applied data mining techniques to solve the problem of sensor selection for activity recognition along with classifier selection in smart homes. They examined the issue of selecting and placing sensors effectively in order to maximize activity recognition accuracy. Chikhaoui *et al.* [Chikhaoui2010] applied sequential pattern mining for person identification in a multiuser environment. Their proposed approach is utilized for audiovisual and image files collected from heterogeneous sensors in smart homes. Fusion techniques play an important role to achieve high accuracy as compared to single classifiers and successfully produced more accurate results in different application domains such as image processing [Wang2004], and gene functional classification [Chen2010]. In the context of activity recognition, [Hong2009] addressed the fusion process of contextual information derived from the sensor data. They analyzed the Dempster-Shafer theory and merged with a weighted sum to recognize the activities of daily living. Research in [Xu2008]] proposed classifier fusion as a learning paradigm where many classifiers are jointly used to solve the prediction problem. They used seven wearable sensors including five accelerometers and two hydrophones. Their used classifiers are Linear Discriminant Classifier (LDC), Quadratic Discriminant Classifier, k-Nearest Neighbor (k-NN) and Classification and Regression Trees (CART).

So far, most of the applications where a learning process is involved have treated it as an action to map the overall situation instead of relating the actions among themselves. They process independent pieces of information instead of complete and comprehensive representation of user behavior. However, some of the research groups started to create methods to relate user actions. Fernández et al. [Fernández2009] applied the workflow mining technique to infer human behaviors. Their approach involved an expert user who can identify the changes in behavior of dementia patients. They validated their approach on synthetic data to identify the deviation from normal behavior. Aztiria et al. [Aztiria2010] focused on automatic discovery of user behavior as a sequence of actions. Their developed approach is based on discovery of frequent sets, identification of topology and temporal relations of performed activities with other constraints. Doctor et al.[Doctor2005] focused on developing an application based on set of fuzzy rules to represent the users" patterns. They recorded changes caused by users in the smart environment and generated the membership functions that mapped the data into fuzzy rules. A survey of all these works can be found in [Liming2012]. The focus of all the above mentioned research is to discover the behavior patterns; however a step towards predicting the future actions from a set of performed activities is still need to be explored for better analysis of human lifestyle and intended services. Our objective is to overcome the limitation of existing methods by introducing a unified framework for behavior analysis of inhabitants that ranges from activity log to action prediction in order to support the smart home inhabitants in performing their daily tasks and providing personalized services adapted to their needs.

3.7.3 Limitations of Existing Work

- In individual activities, learning of user behavior by means of a sequence of actions is highly desirable and is not yet available.
- The prediction about future actions allows caregivers to take proactive actions for the wellbeing of inhabitants after analyzing their healthy or unhealthy routines.
- Thus, according to the routine of Mr. Be, after his exercise activity the most likely activity is of having a breakfast and the framework can remind him to measure his blood pressure and heart rate just before breakfast, if required.
- However, there is a shortage of formal, systematic and unified behavior modeling and analysis methodologies based on daily life activities.
- So far, most of the existing applications (as mentioned in related work) relate an action to the set of sensor values instead of relating the actions among themselves.
- In conclusion dependability of physical environment can be avoaided while analyzing the human behavior along with the propagation of multiple types of information instead of single information.

3.7.4 Proposed Methodology

In the proposed approach, an activity is defined as set of active sensors at a particular time that perform a certain task in a smart home environment. The proposed framework consists of two major modules, as shown in Figure 72 (1) Behavior pattern discovery: to identify the sequential behavior patterns from the activity log. (2)Behavior Prediction: to predict the future actions by utilizing the significant behavior of inhabitants' daily life. The details of each module are described in the following sections.

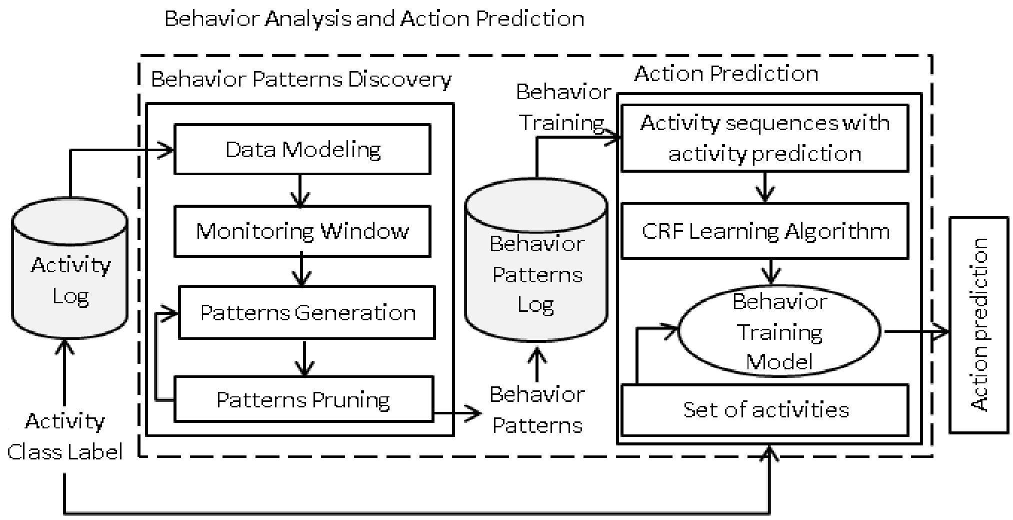


Figure 73 The Architecture of the Proposed Framework

3.7.5 Behavior Pattern Discovery

Representing the inhabitants' actions by means of ordered sequence of activities facilitates our understanding of the significant behavior patterns in daily lifestyles. Sequential pattern mining is a process to identify statistically relevant patterns between data examples where the values are delivered in a sequence. A activity log of sequences stores a number of records with some ordered events, with or without concrete notions of time. A typical example of sequence activity log is collection of store items a person performed every week for one month. Thus, records in a sequence activity log can be of different lengths, and each event in a sequence can have one or more activities in its set. A sequential pattern-mining algorithm mines the activity log for repeating patterns which can be later used by domain experts to find association between different instances of activities for purposes such as healthcare, recommender systems and prediction and planning.

Therefore, the objective of this module is to identify the set of actions that frequently occur together. One intuitive way for behavior pattern generation is to apply a sequential pattern mining technique. For this purpose, a repository of activity log "*Al*" is given where activities are stored in sequential order with respect to activity time. Let $D = \{a_1, a_2, \ldots, a_m\}$ is a set of m activities performed in a particular day in a temporal manner T. Let each sequence in the "*Al*" be $S = \{D_1, D_2, \ldots, D_n\}$, where D_i is a set of performed sequences of activities on different days. For instance a set of sequential activities is defined as an individual who comes to the bedroom to sleep is likely to read or watch TV before the sleep activity. The sample activity log is shown in Table 1. In our proposed data modeling, the monitoring window is a list of activities performed in three days ordered by activity time.

Table 1. Representative Repository of an Activity Log.

Sequence ID	Days	Activities
S1	1	Read, Sleep
	2	Kitchen, Master Bedroom , Read
	3	Kitchen, Master Bedroom , Watch TV
S2	4	Read, Sleep, Chores
	5	Master Bedroom , Read, Sleep
	6	Kitchen, Master Bedroom, Watch TV, Master Bathroom
S3	7	Master Bedroom , Read, Watch TV, Kitchen
	8	Read, Sleep, Master Bathroom, Sleep
	9	Watch TV, Master Bathroom, Sleep

Here, the problem is to discover all sequential patterns with a specified minimum support, where the support of a pattern is the number of data-sequences that contain the pattern as shown in Equation (8). Therefore, a sequence pattern is a non-empty set of "*Al*" and a day D_i is said to contain pattern P if $P \subseteq D_i$:

$$Supp(P) = \frac{the\ number\ of\ instances\ containing\ P\ in\ Al}{the\ number\ of\ instances\ in\ Al} \tag{8}$$

Algorithm 1: Frequent Sequential Behavior Patterns

Input: *Al*: Activity log
∝: Support threshold
Output: *Bp*: Behavior patterns

```
Begin
S_1 = fGenCanSet(Al)
k=2
While (S_k-1 != Null)
    CS = fGenActivitySequence(S_k)
    for j= 1:length (CS)
        if (Supp. (CS (j)) > ∝)
            Count (CS (j)) = Count (CS (j)) +1
            S_k=CS(j)
            k = k+1
        end
    end
    Bp = Union(S_k)
end
End
```

The pseudocode for the frequent sequential behavior patterns is shown in Algorithm 1 for activity log *Al* and support threshold ∝. Here, S_k is the candidate set for level *k,* genrated by *fGenCanSet*(*Al*) method and *fGenActivitySequence* (S_k) method is assumed to generate the candidate sets *CS* from the large activities of the preceding level. The downward closure *count* (CS) accesses a field of the data structure that represents candidate set *CS*, which is initially assumed to be zero. Therefore, all the activities in an element of a sequential pattern necessarily present in a single day activities for the data-sequence to support the pattern. A pattern is regarded as persistent if it has the highest support.

This demonstrates the most significant behavior of inhabitant due to its high continued or repeated ratio as compared to other identified patterns under same support threshold. The analysis of frequent user behaviors *Bp* reveals the significant habits of inhabitants from their daily routines and provides the basis for behavior learning to predict their future actions.

3.7.6 Action Prediction

The objective of this module is to predict the next action from the set of activities that occur together. For the learning process of action prediction, required data is extracted from the behavior pattern log. Let"s consider activities shown in Table 2 are occurring together in different sets of actions and the same set of activities with their relationships among them is presented in Figure 73. It is obvious that the occurrence of each activity depends on the set of previous actions. For example, "Meditate" comes after "Sleep" or "Chores", whereas, "Sleep" comes after "Watch TV" or "Master Bathroom" and there could be the repetitive actions in the same sequence. Therefore, a decision about the next activity depends on the transition of previous actions. For instance, "Kitchen" activity follows by "Meditate" or "Sleep" represents breakfast while "Kitchen" activity after "Enter Home" represents dinner. So it is clear that a set of previous actions provide remarkable evidence to identify the meaningful behavior in terms of forthcoming action. In our proposed approach, sequences of 8 to 10 activities are considered to predict the next action.

Table 2. Representative Sequences from Behavioral Patterns.

Sequence	Prev. Activity 3	Prev. Activity 2	Prev. Activity 1	Next Activity
1	Kitchen	MasterBedroom	WatchTV	Sleep
2	—	WatchTV	MasterBathroom	Sleep
3	WatchTV	MasterBathroom	Sleep	Chores
4	—	Sleep	Chores	Meditate
5	MasterBathroom	Sleep	Meditate	Kitchen

Once the sequences of activities are selected, then these activities can be used for the learning process of action prediction. In the proposed framework, CRF is designed as a learning classifier for predicting the future actions. It is a discriminative and generative probabilistic model for labeling the sequences under the conditional probability $p(y|x)$.

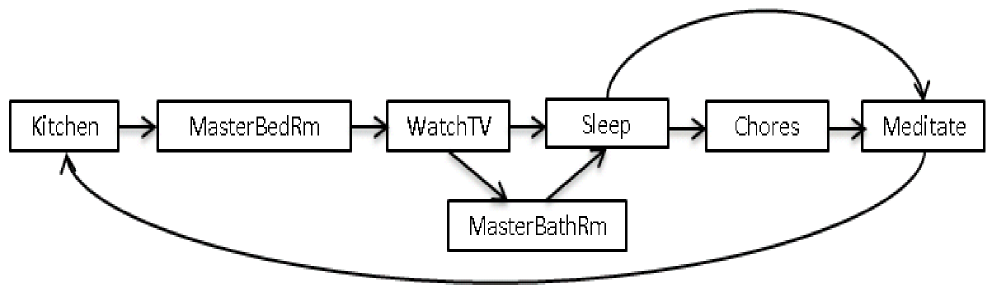


Figure 74 Set of Sequences with Activity Relationships.

It is modeled as undirected acyclic graph that allows arbitrary, non-independent relationships among the observation sequences. A CRF flexibly capture the relation between a pair of observations and label sequences that do not explicitly model the marginal probability of observations. It uses a potential function instead of a joint probability. Suppose there are finite label sequences $Y = (y_1, y_2, \ldots, y_{T-1}, y_T)$ and observations $X = (x_1, x_2, \ldots, x_T)$. In Figure 74 a design of CRF is shown for the activity sequences presented in Table 2.

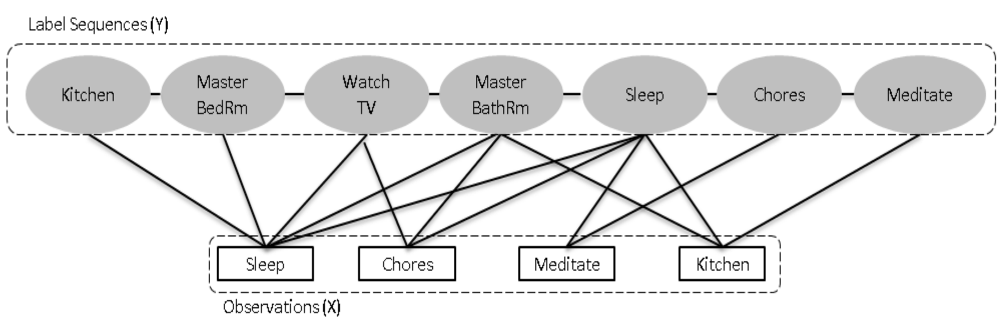


Figure 75 The Design of CRF for Activity Sequences

It is a discriminative probabilistic graph model for labeling and segmenting structured data, such as sequences, trees and lattices [Krose2008].

In the CRF model, the conditional probabilities of next action with respect to previous activity observations are calculated as follows:

$$p(y_{1:T}|x_{1:T}) = \frac{1}{Z(x_{1:T}, w)} exp\left\{\sum_{j=1}^{N_f} w_j F_j(x_{1:T}, Y_{1:T})\right\} \quad (2)$$

In Equation (9), Z denotes normalized factor and $F_{\mathrm{j}}(x_{1:\mathrm{T}}, Y_{1:\mathrm{T}})$ is a feature function that is computed as:

$$F_j(x_{1:T}|y_{1:T}) = \sum_{t=1}^{T} f_{j\,(y_{t-1}, y_t, x_{1:T}, t)} \tag{3}$$

In Equation (5.3), the feature function depends on known observations $x_{1:T}$ and is determined by any combination of input values instead of considering all arguments. To make the inference in the model, the most likely activity sequence is computed as follows:

$$y^*_{1:T} = \operatorname{argmax}_{\mathrm{y}'_{1:\mathrm{T}}} \mathrm{p}(\mathrm{y}'_{1:\mathrm{T}}|x_{1:T}, w) \tag{4}$$

Hence, the learning capability of CRF in terms of sequences of actions is able to capture long-range transition among activities collected from behavior patterns log for future action prediction.

3.7.7 UML Diagram

Use Case Diagram

The use case diagram of interaction analysis and its description is given below

User: The individual, whose daily life activities are collected in activity to find significant sequential behavior and action prediction.

Patterns identification: Identify the candidate frequent and sequential patterns and prune then according to the user defined parameters.

Action Prediction: Responsible to train the model of CRF based the identified patterns sequential patterns and then predict the action.

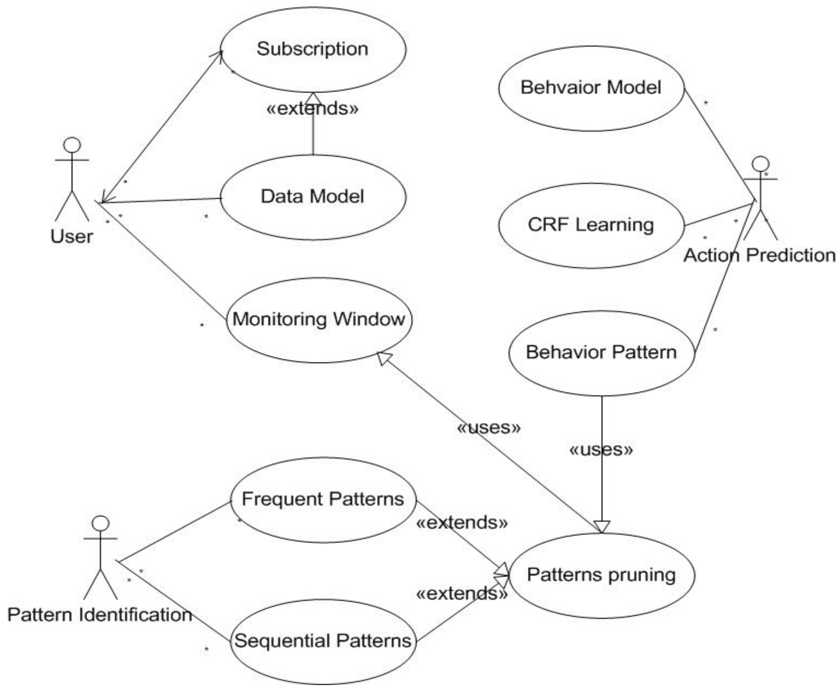


Figure 76 Use case diagram of Physical Activity Based Behavior Analysis

- **Brief Descriptions of Use Cases**

Subscription: Responsible for register user with the application. Application send request to user and user verify application to access his emails.

Data Model: Role of data model is to model the daily life activities in machine understandable format.

Monitoring Window: It is the process of segmenting the data based on the user specified intend. One sequence may contain a list of activities from a list of days so monitoring window divides the data into set of sequences.

Frequent Patterns: This use case is responsible for mine the frequent patterns from the data model of activities.

Regular Patterns: This use case is responsible for mine the sequential patterns from the data model of activities.

Patterns Pruning: It identifies the patterns of interest from the set of frequent and sequential patterns after looking into the parameter settings of threshold.

Behavior Pattern: This use case processes the significant sequential patterns as a significant behavior in daily life of an individual.

CRF Learning: To identify the future action, this use case learn the behaviors from user's lifelog

Behavior Model: This use case models the complete behavior after the learning of CRF model. It helps in predicting the future actions based on past learning.

- ## Sequence Diagram

The objective of Interaction model of a system is to depict the process scenario of how different objects interact with each other. Life span and sequencing of objects are the prime components of any interaction diagram. Sequence diagrams are described in following section.

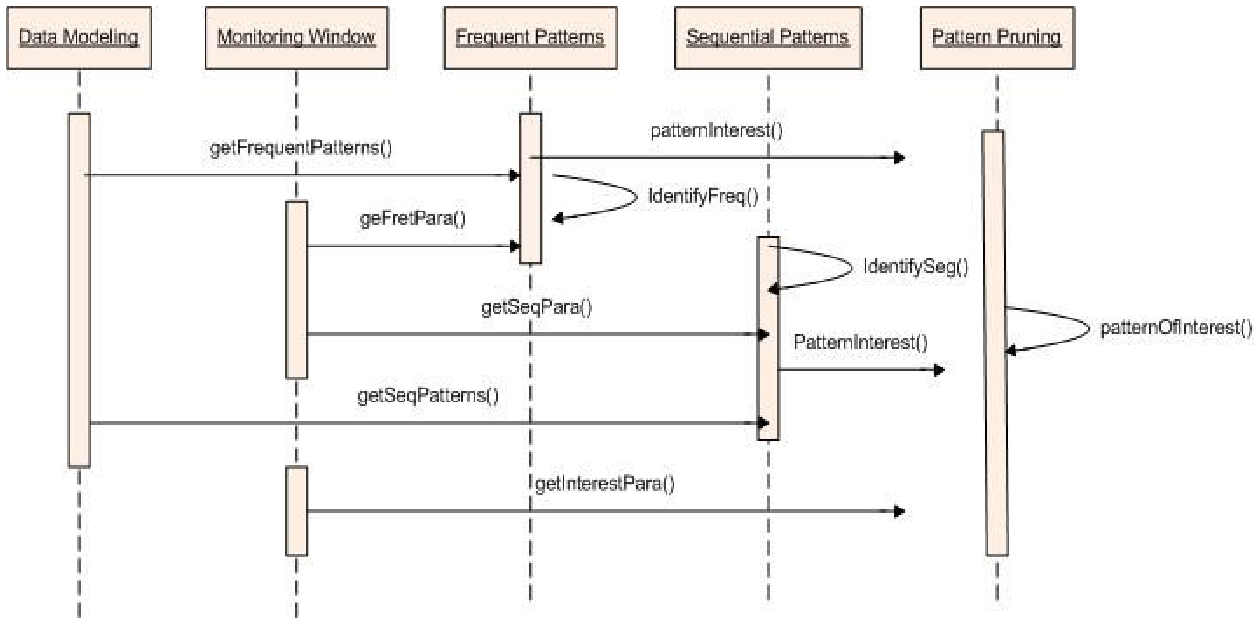


Figure 77 Sequence diagram of Physical Activity Based Behavior Analysis.

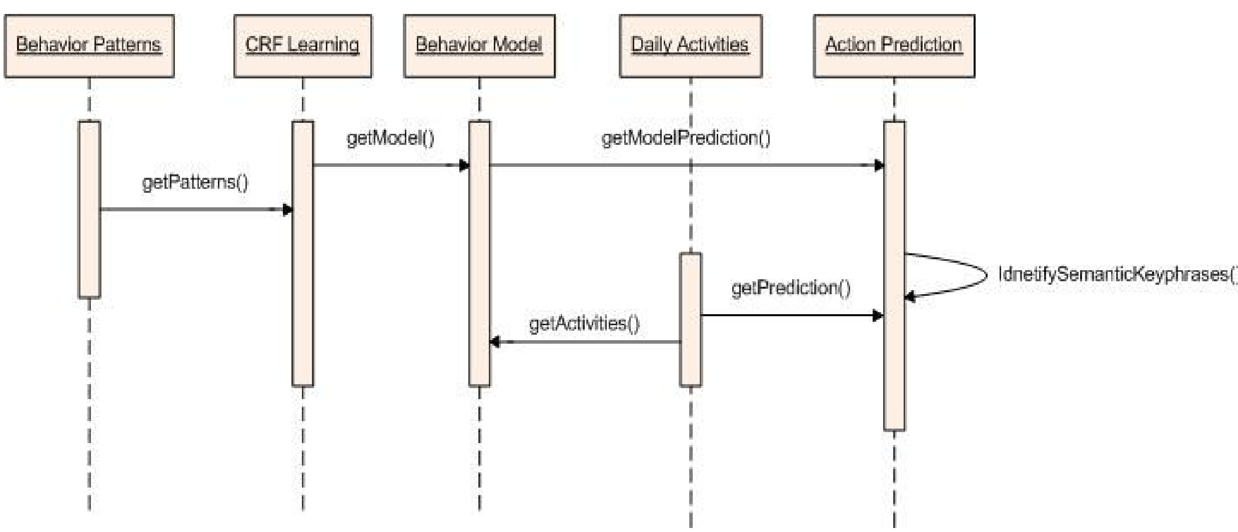


Figure 78 Sequence diagram of Physical Activity Based Behavior Analysis.

3.7.8 Contribution and Originality

- In order to analyze the human behavior based on their physical activities. First, the behavioral patterns are extracted from the day to day performed activities in a sequential manner with the help of data mining techniques.
- The sequential pattern mining algorithm is applied by modifying it according to the requirements of behavior modeling from the activity log.
- In our proposed framework, each sequence is a set of activities performed in a temporal order of three days for consistent sequence prediction.
- Finally, the sequential activity trace is utilized for behavior learning to predict the future actions.
- A Conditional Random Fields (CRF) algorithm is designed for ongoing activities as labeled sequences and future actions as observations.
- Therefore, the analysis of the history information transmitted by users' activities helps in discovering the routine behavior patterns and future actions of inhabitants in a home environment.

3.7.9 Conclusion

For analysis of physical activities personalized service providers need to know the common behaviors and preferences of the inhabitants in leveraging the use of technology for different application domains. In this research, a unified framework for behavior analysis and action prediction is proposed. This informs the service provider about inhabitants' significant behavior in order to perform meaningful interventions. The proposed model is based on data mining based reasoning. First the data mining techniques is applied to identify the significant behavior and then these behaviors are used for the learning of machine learning module to predict the future actions. In the proposed framework, the recognized activity log is utilized for behavioral pattern discovery with the help of frequent sequential mining technique on a set of activities that are performed in a temporal sequence of three days. Finally, CRF is investigated for the actions that occur together in order to predict the next activity from a current situation. Our study found that identification of behavior patterns and prediction of forthcoming action with high precision signifies the possibility of helping people by analyzing the long-term data of one's behavior to fulfill his needs in the current circumstances and in future.

Chapter 4: System Integration and Deployment

4.1 Motivation

ATHENA is dependent on internal heterogeneous engines to process the activities, emotions and social interactions data. These engines processed information independently and pass to inference engine for making the group consensus and deliver the recommendations and services to the users, caregivers and family members. This integration is performed using a centralized integration framework called System for Integration and Management Services (SIMS) framework. It behaves as a bus for communication between different external engines.

4.2 Goals

- SIMS framework behaves as a bus for communication of ATHENA with PARE, KAL, MER, CAME, and SMIE.
- Controls the overall flow of information and also provides load balancing services. It handles the non-blocking communication of different engines to processing heterogeneous sources.
- Provisioning of integration services for seamless communication through respective interfaces.

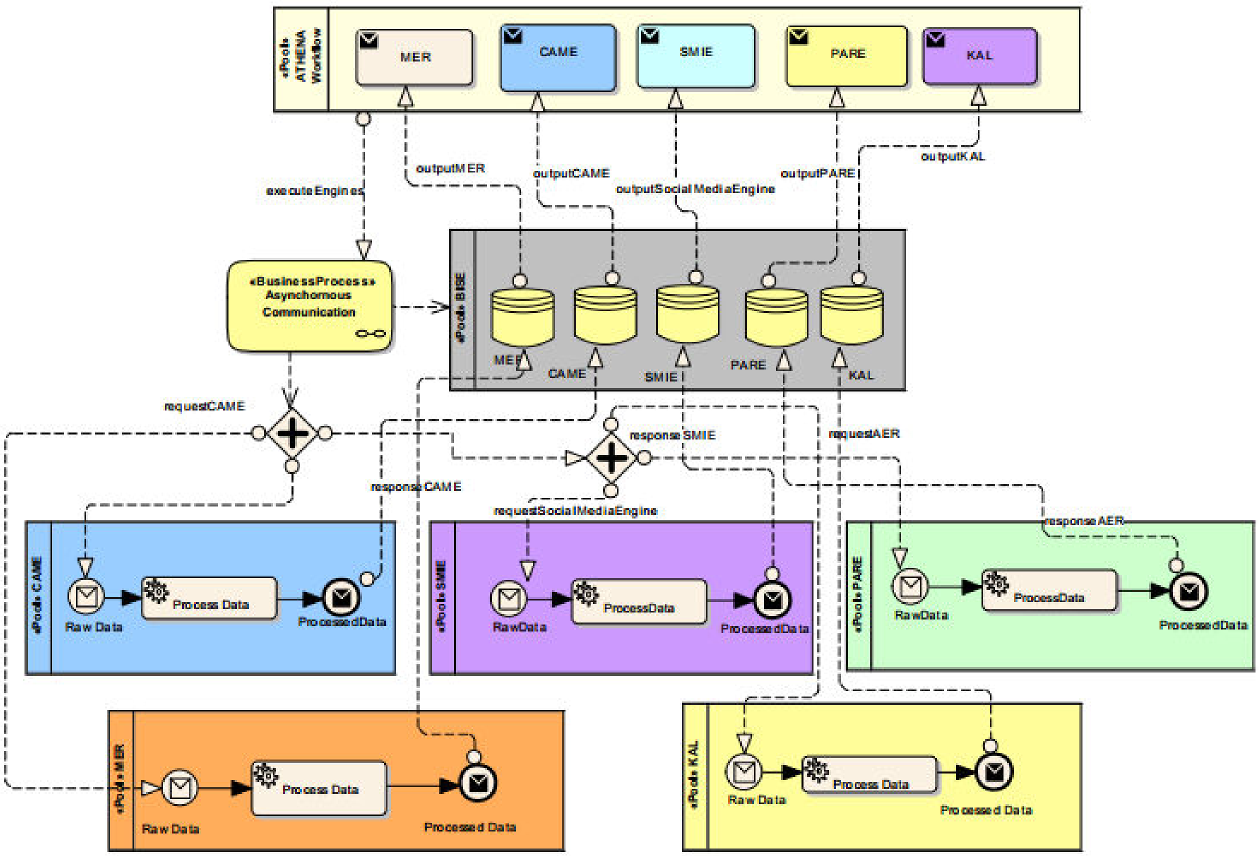


Figure 79 System information workflow

4.3 System Deployment Diagram

The deployment diagram is divided into three layers consumer side, smartphone and cloud infrastructure. These are described as follows:

- Physical activity recognizer and Kyung hee action logger are deployed on the smartphones to recognize the physical activities.
- To reduce the cost, our private cloud infrastructure is utilized to process the MER, CAME and SMIE data.
- Hadoop file system based infrastructure is deployed to store the different forms of dataset.
- Well-being services are accessible through the web-services of the cloud that made it easy to utilize in different devices ranges from smartphone, tablets, smart TV and PC systems.

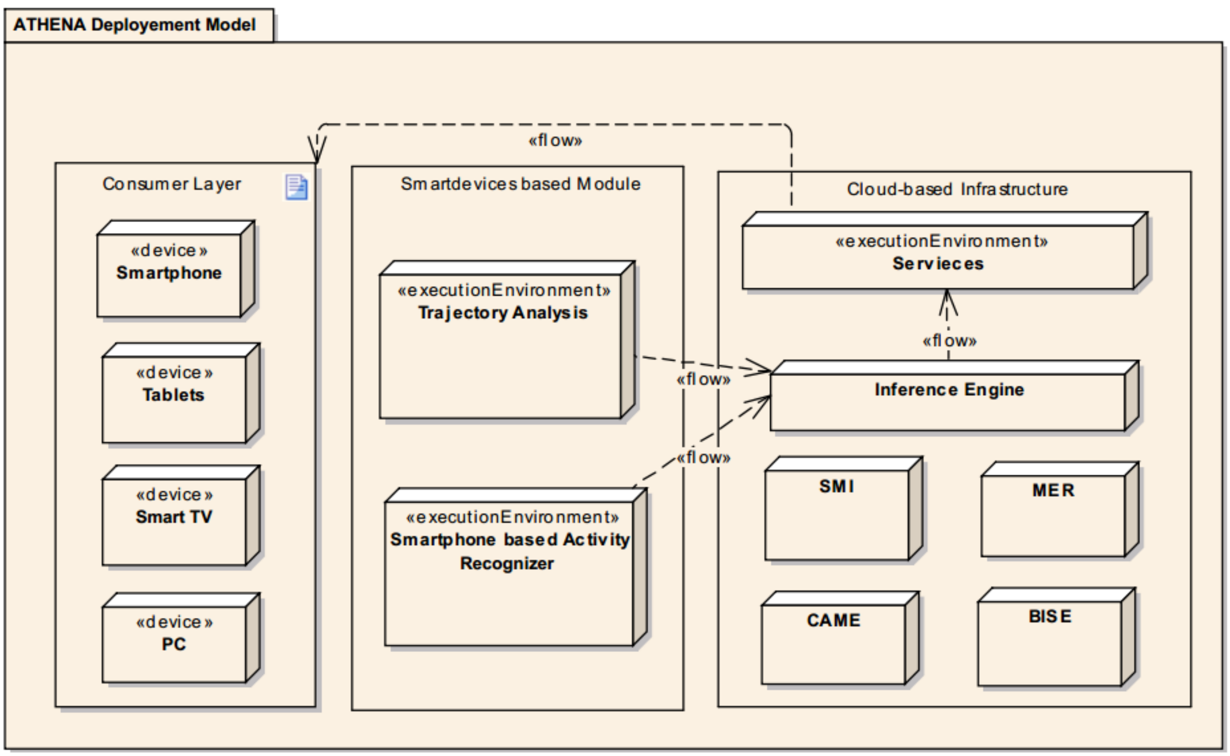


Figure 80 ATHENA deployment diagram

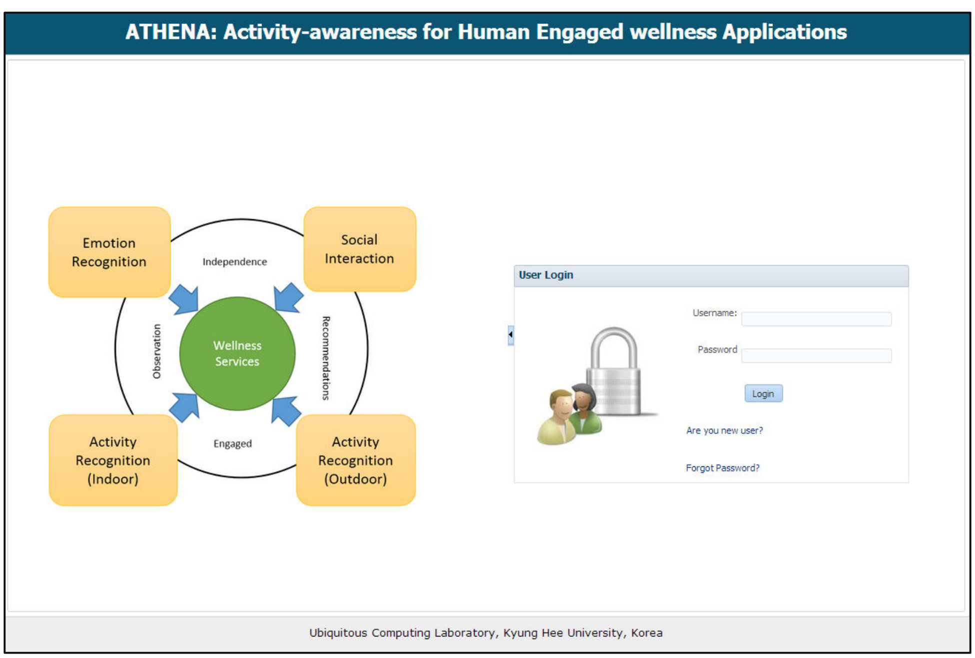
Chapter 5: Case Study

5.1 Active Lifestyle

An important application scenario is "Active Lifestyle" for promoting self-management. It is a proactive approach to adopt healthy lifestyle in our daily routines. For instance, daily exercise, diet, sleep and social relationships are the wellbeing indicators. A progressive health effects can be observed if they are well managed. Activity recognition system can recognized the amount of exercise and some motivation factor to keep it as a part of daily routines. Social media plays an important role to share exercise routines to motivate others as well as himself in terms of appreciation by comments and likes. ATHENA can provide some nutrition guide as a service for daily meal preparation and may sharing over the social media with family and friends. Social media groups play an active role by announcing events and attracting many people to join them for remain themselves actives. Suggesting such groups to other people ATHENA can find the socializing trends that are increasing through social media and provide to the users as a recommended service. The case study scenario is described as follows.

5.1.1 ATHENA Login

To provide a secure way to access the services and analytics about the activities is bounded by user's credentials. Following screenshot elaborate the user login.



5.1.2 User Profile

To manage the user's profile and know about his/her preferences we provide the interface to visualize the subject's preferences and may change their preferences according to the seasonal changes or interests. Such updates are reflected while system recommend them services.

5.1.3 Update Stats

To make the system more accurate in terms of recommendations, system also provide the interface to update the user stats in terms of height, weight, and age with the passage of time. Similarly preferred activity, therapy and food.

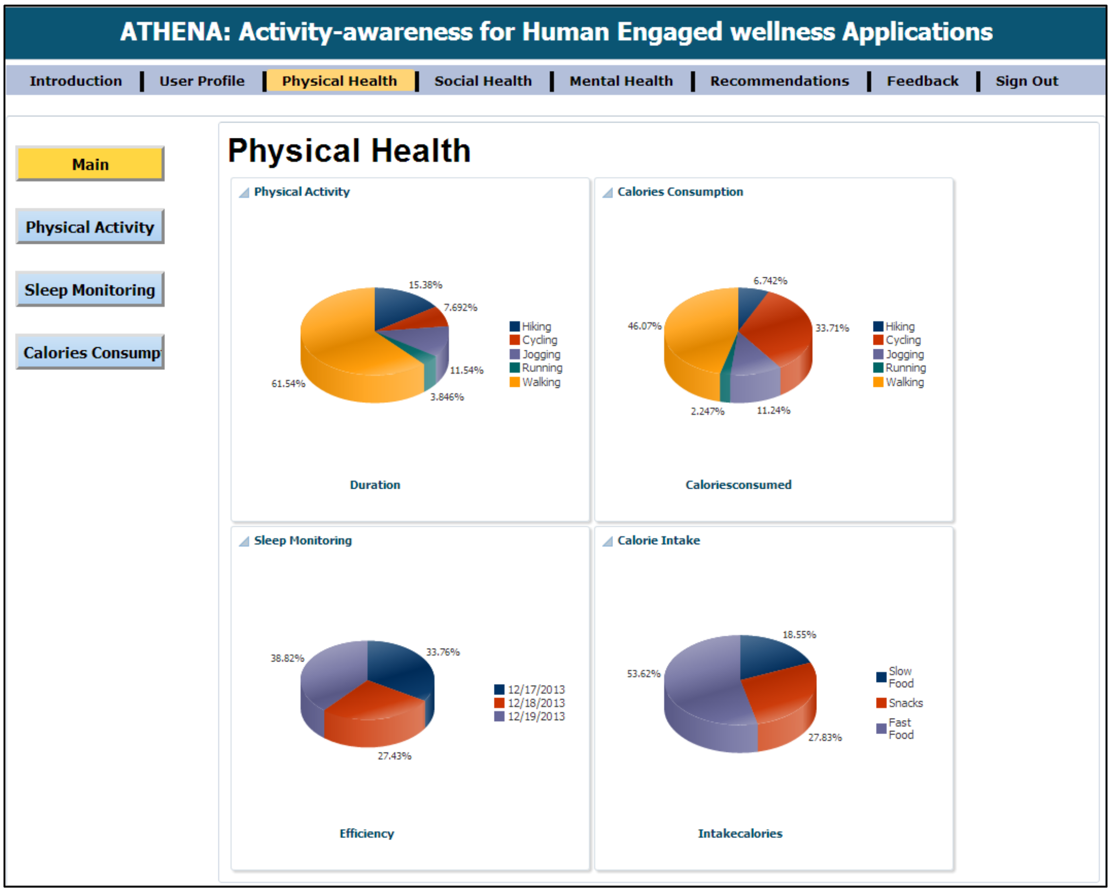
5.1.4 Update Activity

5.1.5 Update Therapy

5.1.6 Update Food

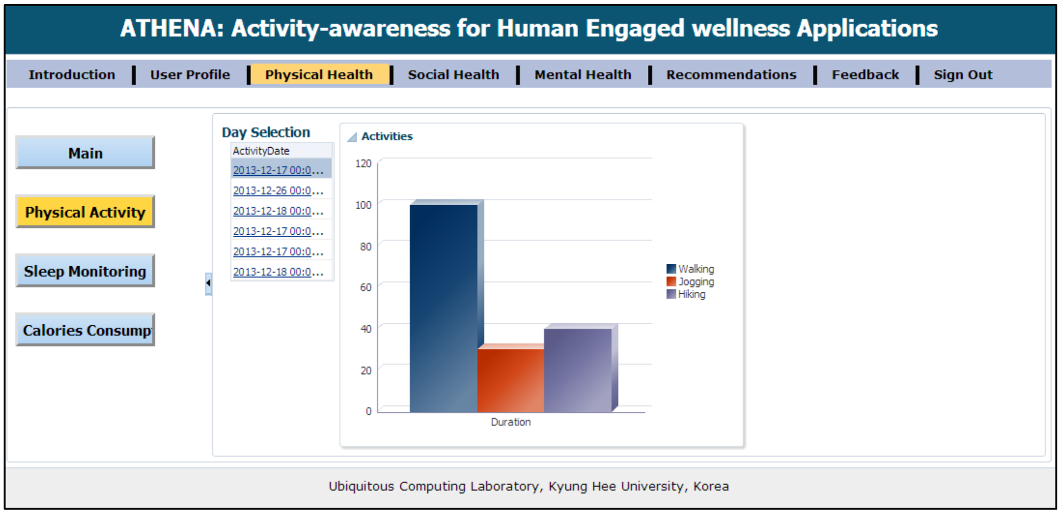
5.1.7 Physical Health

User can visualize the overall analytics on the basis of his/her performed activities. Our system calculate the calories consumed during the exercise as well. Sleeping patterns are also one of the important key provided the recommendations accordingly.

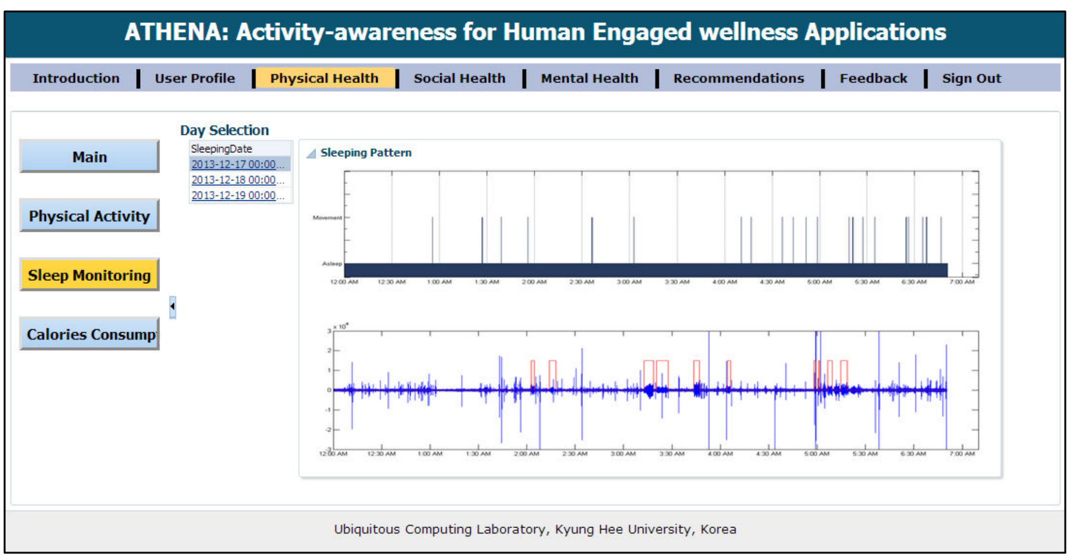


5.1.8 Physical Activity

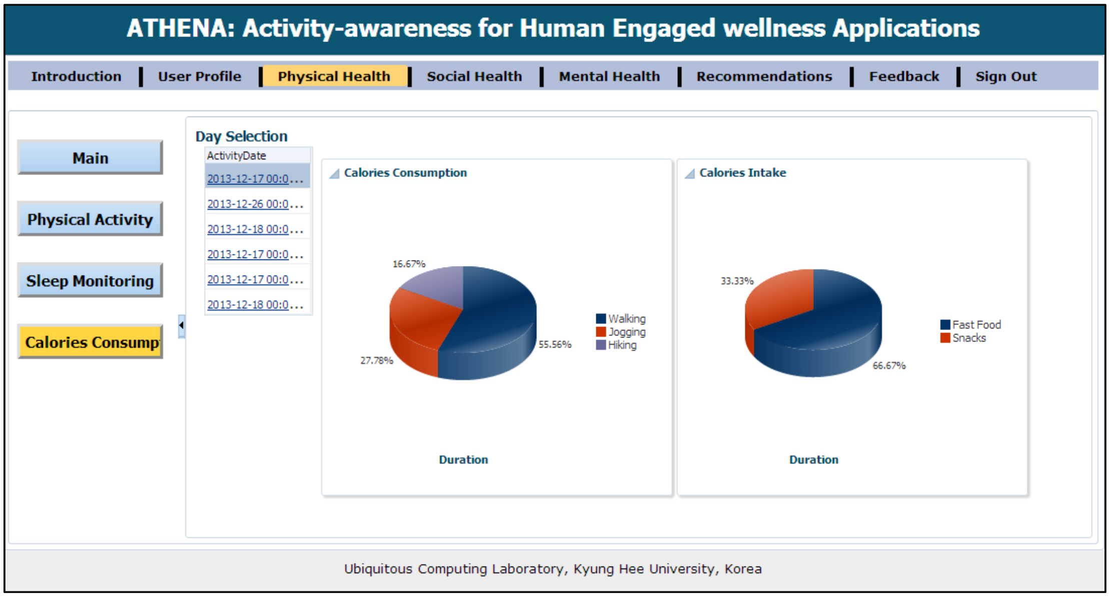
We also facilitate the user to visualize the specific activities, sleeping patterns and consumed calories.



5.1.9 Sleep Monitoring



5.1.10 Calories Consumption

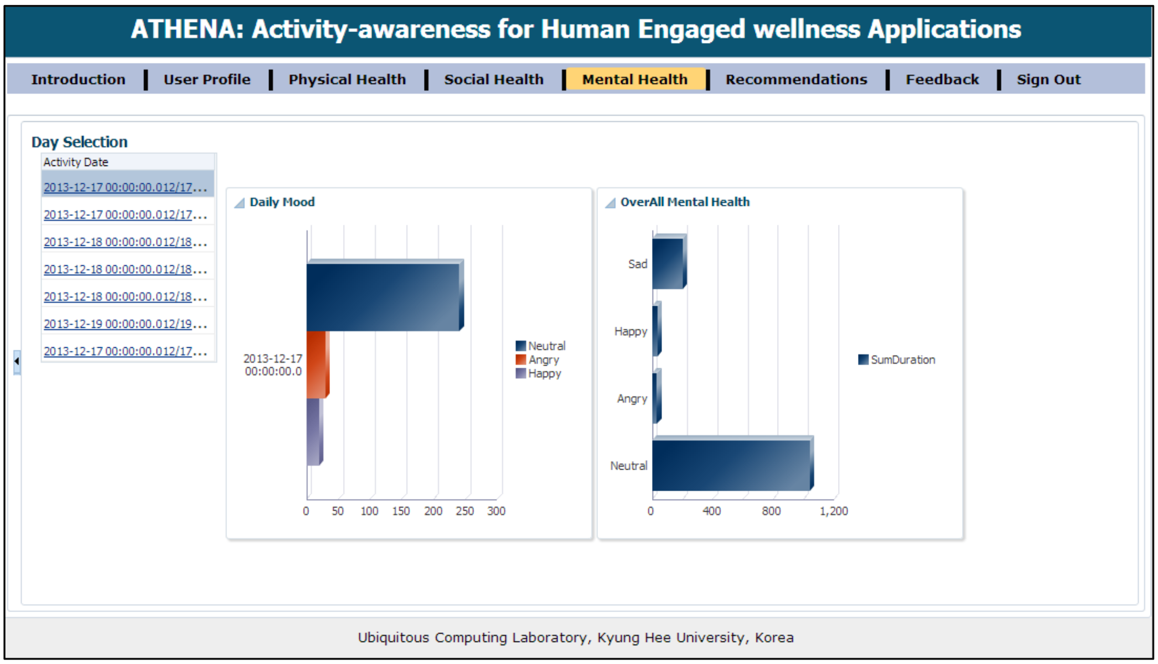


5.1.11 Social Health

Social health is also an important factor that is mapped to subjects visited locations.

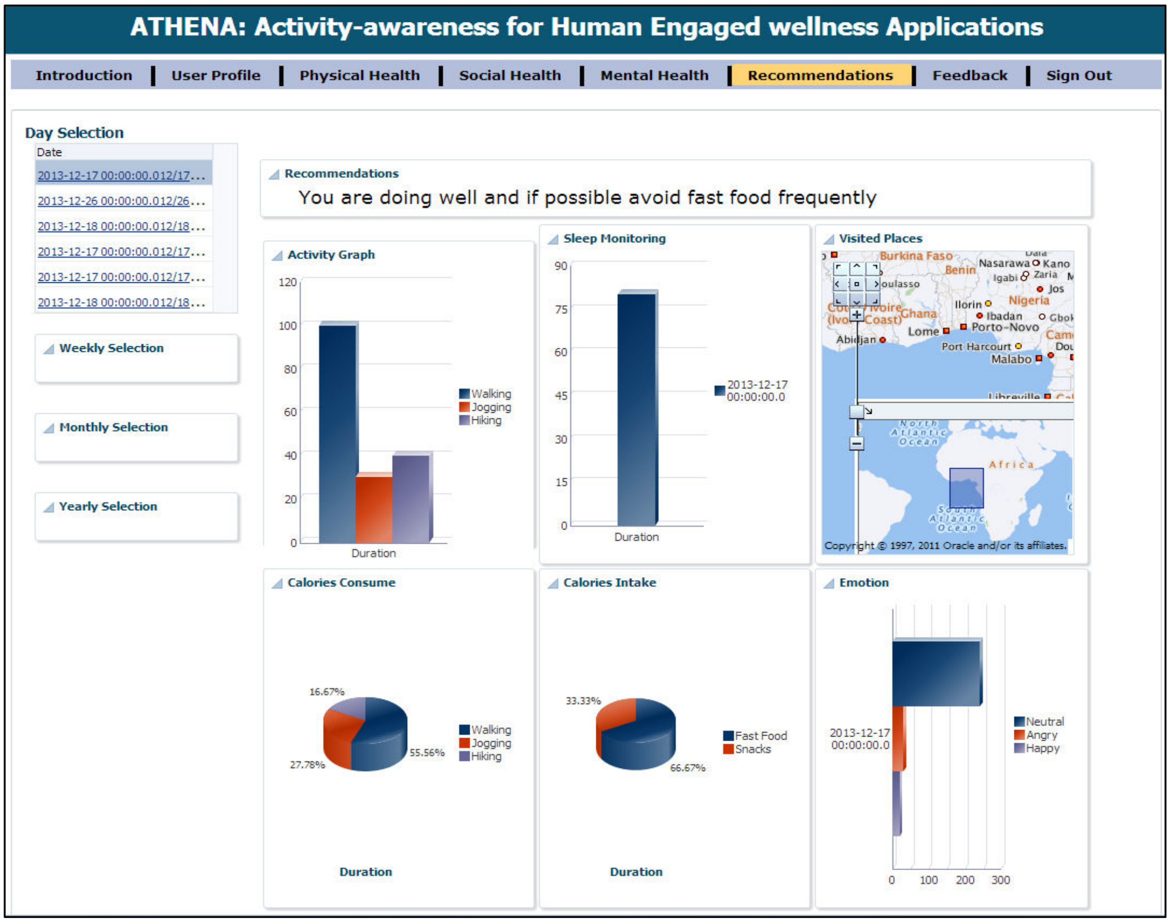
5.1.12 Mental Health

With the help of our developed audio sensor based application like "play emotion", and physiological and video based emotion recognition system recognize the user's mood and reflect in analytics on the daily and overall mental health basis as show below.



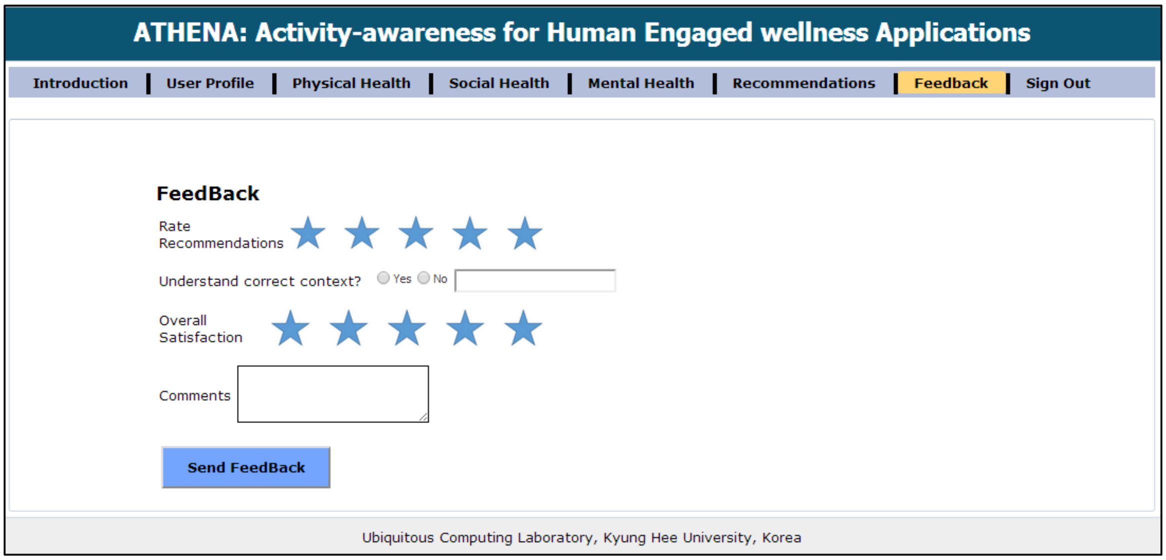
5.1.13 Recommendations

To provide the recommendations, about the user mental, physical and social health condition we also provide the analysis on the basis of day, week, month and over the year. Users can visualize their activities and corresponding consumed calories as well. We also place the geo tags over the map to show his visited location according to the selection of the days.



5.1.14 Feedback

One of the most important concept of ATHENA system is the feedback to maintain the system and provide the more robust services in the future. Once system delivered the recommendation according to his health conditions, same time ask about the feedback. Users can rate the provided recommendation, give the information about the context either system understand it correct or not. Similarly, feedback about the satisfaction level and comments about provided recommendation.



Chapter 6: Conclusion

6.1 Conclusion

To enable individuals, aging societies, and active lifestyle demands a smart and innovative way to stay active for a long time, prevent social isolation and assistance for performing daily life activities independently. We are developing activity-awareness for human engaged wellness application (ATHENA) to provide wellness services. In order to handle the huge amount of data Hadoop based file system is introduced along the cloud infrastructure to reduce cost and fast processing of massive data. Moreover, a complete system is proposed over these assistive technologies that can take care of mental health, physical health and social-wellbeing to provide a smart care for individuals as well as population levels. Following are the conclusions of ATHENA.

- We are considering human activities, emotions and social activities for providing the wellness services. These services results in improved quality of life.
- Our proposed algorithms solve the primitive challenges of recognition rate, cost and processing overheads. We are introducing novel light-weight classifiers that works properly inside the smart devices.
- Cloud computing infrastructure provide cost effective solution for computation intensive tasks. Hadoop based infrastructure is utilized to process the massive queries.
- We will release our overall framework as a commercially viable platform as a cloud service and a smart devices application. The cloud service will be hosted on a cloud maintaining the privacy of the personal data of the users.
- The underneath component of the context-aware processing will be able to work independently and flexible, so that it can be tweaked according to the targeted application domain.
- The system will have a full featured feedback analysis scheme as an important outcome which can be used for validating the knowledge bases and recommended services.

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