# Intelligent Manipulation of Human Activities using Cloud Computing for u-Life Care

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***Abstract*— Ubiquitous Life Care (u-Life care) is one of the most focus area of research. To provide robust healthcare services, recognition of patient daily life activities is required. Context information with real-time daily life activities can help in better services, service suggestions, and change in system behaviour for better healthcare. Human health, profile, as well as activities are monitored and processed intelligently for better care with low cost. In this paper, we focus on intelligent manipulation of activities using Context-aware Activity Manipulation Engine (CAME) core of Human Activity Recognition Engine (HARE), recognized using video-based, wearable sensor-based and location-based activity recognition engines for context analysis of the activities performed. The objective of CAME is to receive real-time low level activity information from Activity Recognition Engines and infer higher level activities, make situation analysis, and after intelligent processing of activities with their corresponding information take appropriate decisions. To achieve this objective, two phase filtering technique for intelligent processing of information (represented in ontology) is used and appropriate decisions based on description logic rules (incorporating expert knowledge). The experimental results for intelligent processing of activity information showed relatively good accuracy.***

## I. INTRODUCTION

With increasing life style, people are more interested in their better health and desire healthy life. As a result, the cost of life care or healthcare system is increasing. To maintain quality and availability level of life care services with minimum cost, a powerful, flexible, and cost-effective infrastructure for life care services that can fulfil the vision of *ubiquitous life care (u-life care)* is required. Cloud Computing can potentially provide huge cost savings, flexible high-throughput, and ease of use for different services [2] as well as for life care services. For this reason, we have developed a platform architecture, called Secured Wireless Sensor Network (WSN) - integrated Cloud Computing for u-Life Care ($SC^3$) [6]. Different wireless sensors are deployed that collect real-time data and transmit that to Cloud Server though Cloud Gateway. Based on this real-time data collected by different sensors, $SC^3$ provides real-time home care and safety monitoring services, 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) (see Fig. 1). This engine is necessary and important because in order to provide improved daily medical care and real-time reaction to medical emergencies, identifying patient's activities, so-called Activity Recognition (AR) is a prerequisite.

The existing systems are based on simple condition and action [11], not using context information or in some cases using imperfect context information [5] where the result of system is unpredictable. Their focus is more on environment sensors (e.g., smoke detector, infrared control, and GPRS modem) rather than on real-time human performed activity. Human 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 vision with motion, environment, location, and time to infer human intentions. Our focus in this paper is on CAME component of our proposed HARE (see Fig. 1). The proposed CAME can integrate all the activity information together with context and profile information of subject and help in enhancing capabilities and provides tremendous value for intelligent/efficient service provisioning and recommendation.

Considering context during decision making is an important factor [5]. For CAME implementation, we use all possible sources of information to avoid possibility of missing information or imperfect context information. For context representation and profile information, we use ontology and have developed a semantic structure for representation of information. Ontology is formally defined as *an explicit and formal specification of a shared conceptualization* [4].

Sensors are deployed to collect real-time data about the person activities and the environment information. Then with the use of ontology (containing expert knowledge of medical domain) these detected activities are intelligently manipulated to infer higher level activities and also make the situation analysis. The experimental results of match making process of our CAME showed good results and then with rule based filtering for situation analysis and decision making has verified our claims. The results of activity recognition and manipulation are very encouraging in term of accuracy.

This paper is arranged as follows: Section II is related work. Section III is our proposed CAME architecture. In Section IV we present preliminary results that we have achieved. We conclude our discussion in Section V.

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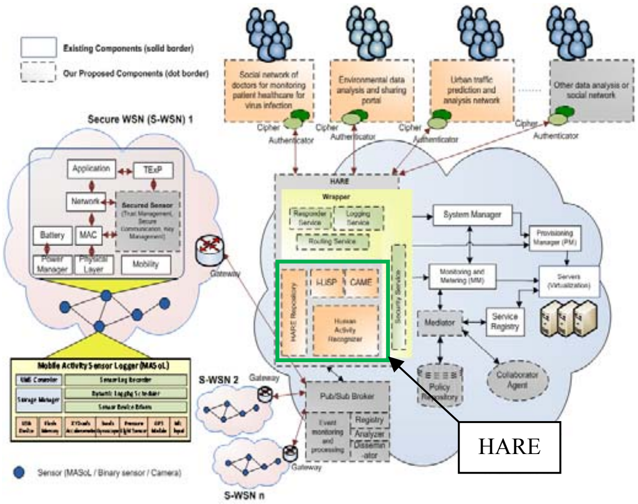


**Fig. 1. The system model of SC$^3$ [6]**

## II. Related Work

Research on reminders for elders to perform daily life activities [8] is getting more focus. These are plan-based approaches to decide when and how to prompt subjects effectively, hence focusing on time-based activities. To overcome the limitations of this system, a Location-based reminder system was introduced [10], where key element for reminders in this system is the location of subject. But in fact, context for reminders is more important than simple location or time and context includes both location and time as subset. ComMotion [7] is an example of context-aware system that supports reminder applications that use only one sensor and mainly based on time. They facilitate on how and when to prompt the subjects. HYCARE [3] is the most recent reminder systems that takes context in consideration and develop a novel scheduling mechanism that can coordinate various reminder services and remedy the possible conflicts.

[1] is based on Markov decision process (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) for decision making. The system is designed to monitor elderly dementia patients and provide them autonomous guidance to complete their activities of daily life. They focused on facilitating in hand washing activity of daily life using video camera. A conceptual model/space is developed for hand washing activity and then used by the system during the activity performed by patients and give reminders for different steps from the conceptual model/space. [11] is a more realistic system that not only uses ontology to incorporate context in intelligent processing of the collected information. They also focus more on the information collected from sensors like Smoke Detector, GPRS Modem, Infrared Control and X10 Appliance that actually facilitate more in home care for the person than person healthcare. It is basically based on Event-Condition-Action (ECA) model. But for support in healthcare, the system also needs to collect human performed activities with addition to the environment information.

The above discussed systems do not use real-time activities or only use one type real-time activity performed by subject and then generate reminders or even make decision based on that. They only consider the context to the level of time and location, which results in inflexible system behavior. These systems can mostly be categorized for reminder systems or homecare system, while the important thing is to facilitate in healthcare where these system failed to perform.

## III. Context-aware Activity Manipulation Engine

Use of ontology in activity recognition is relatively a new area of research. Using ontology helps better understand the activity in a given context. Activities recognized with the help of different sensors (i.e. body, location, motion, and video sensors) are low level activities and they are not in a capacity to be used for certain types of analysis and decision making. With the help of ontology, where we use the context information and link all the related activities in a chain, then with the help of customized rules we get the higher level activities that are more usable for decision making. Ontology helps in properly extracting the higher level activity of a set of activities in a series, e.g. series of low level activities like bending, sitting, jumping and walking with the help of ontology will result in a higher level activity i.e. exercising. CAME is one of the main components of HARE, it's the process of inferring high level activities from low level activities recognized by different sensors. The component based framework architecture diagram of CAME is given in Fig 2, while the detail description of all the components are given below.

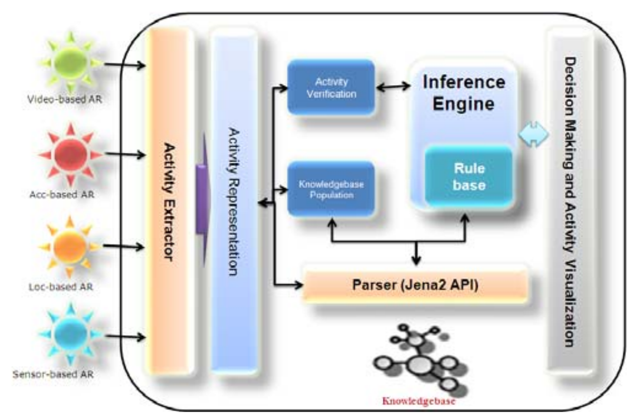


**Fig. 2, Context-aware Activity Manipulation Engine (CAME); Inferring High Level Activities From Low Level Activities**

*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 possible types of activities that a human body can perform in different context/situations, with the information of different activities priority for different users and group of users. Proper engineering of the KB is most important activity in the development of CAME. To engineer the KB we have to look at the same problem from different angles. We have developed a Knowledgebase for activity representation and have divided activities into *Temporal* and *Non-Temporal Activity* classes. The same way we have modelled all the other concepts in Knowledgebase related to activity as well as to the subject that performs the activities. *Activity Extractor* component extract activity related information from XML and Text files. So the activity needs to be formally represented in predefined semantic structure [9]. For this reason, the *Activity Representation* component formally represents (see Fig. 3) the activities that are extracted in the previous module, while the representation is provided by the Knowledgebase.

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

**Fig. 3, OWL representation (using N3 notation) of Activity (Person entering in a class)**

*Activity Verification* is important for two reasons; (1) Check for the consistency of the newly recognized activity against the Knowledgebase developed for the activities. (2) After consistency verification, the existence verification is done for the activity i.e., is this activity already present in the Knowledgebase or not? If not present then it is given to *Knowledgebase Population* module to store it in the Knowledgebase (KB). For 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 verity of different reasons like verification of activity and decision making, Parser is also used to populate the KB for newly recognized activities.

To understanding the context of an activity and to extract high level 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. It uses the activities information with respect to their context information and infers high level activities. To facilitate the decision making, we have incorporated the experts (Medical Doctors) knowledge with the help of description logic rules. To infer high level activities and make decisions, we developed Two Phase Algorithm. The first phase is match making process. Here newly detected activity is matched against the already existing activities in Knowledgebase and for this purpose we use semantic matching techniques. Second phase is the rule based filtering of the matched results returned from Knowledgebase for the newly detected activity. After the process of inferring, according to the Description Logic (DL) rules incorporating expert knowledge, the system can take decisions or give suggestion against different activities. So *Decision Making* module is responsible for performing/executing actions against the suggestions made by the Inference Engine.

## IV. Implementation and Results

Ontology defines a formal semantics for information allowing information to be process-able by computer system agents. It defines real-world semantics for resources, allowing them to link machine process-able content in a meaningful way based on consensual terminology. Researchers have different approaches to use ontology for introduction of context in the system. In [11] the authors only focused on the location and time information of an activity (where context means a lot more than only time and location) and use the method of Event-Condition-Action (ECA) to respond to particular activity. In our approach, we not only use the location and time information but also use information about the subject profile and information about the environment in which the subject is currently.

Activities recognized with sensors (i.e. body, location, motion, and video sensors) and context information from ontology, link all the related activities in a chain, then with the help of customized rules we get the higher level activities that are more usable for decision making. For instance, low level activities in a series, e.g. bending, sitting, jumping, and walking with the help of ontology will result in higher level activity e.g. exercising, where its DL rule is given in Fig. 4. To implement CAME with all its components, we used Jena2, Protégé, Protégé-OWL, Arq, and Pellet 3.4 (for inference). The outcome of CAME is partially dependent on the results of activity recognition modules that are responsible to detect activities from the raw data collected with sensors.

**Rule**

Exercise ⊑ ∀ Activity ⊓ Activity.performedBy.Person = 1 Person ⊓ (∃Activity.hasContents(bending) ⊔ ∃Activity.hasContents(jacking) ⊔ ∃Activity.hasContents(jumping) ⊔ ∃Activity.hasContents(runing) ⊔ ∃Activity.hasContents(skiping) ⊔ ∃Activity.hasContents(siding) ⊔ ∃Activity.hasContents(walking) ⊔ ∃Activity.hasContents(waveing) = ∃ 2 Activity.distinctContents

**Fig. 4, DL rule for exercising based on detected activities.**

We have tested CAME for 8 different experiments with increasing number of activities for one after another, where these activities are all real-time activities detected by different sensors discussed above. Sensors are deployed in the Test Bed environment and all real-time activities data is collected. The video demonstration of our overall system deployment and working is available online[1]. To get information about some specific activity and their consequent actions, we wrote SPARQL queries that are executed using Jena2 API while using the functionality of Arq API. Fig. 5 is a query of getting the information for some particular activity and their consequent action. For this query, the activity is provided by the system or user and then its corresponding information are

[1] http://www.youtube.com/watch?v=FfRpsjD3brg

all extracted. In Fig. 6, % of Precision and Recall for match making process is presented. From the result shown in Fig. 6, it is quite obvious that the precision and recall of CAME for match making process is a little low, but interestingly, with the increasing number of experiments, both precision and recall are becoming stable. The average precision and recall for CAME match making in 8 different experiments is 0.802 and 0.666, respectively.

```
"SELECT ?activityName ?hasConsequentAction ?type ?performedBy ?performerName ?time ?actionD
es ?performedAt ?performedAtLoc ?hasType ?actionTime WHERE { <" +
 strNS + strActivity + "> <" + strNS +  "hasName>  ?activityName ." +
"<" + strNS + strActivity + "> <" + strNS + "hasConsequentAction> ?hasConsequentAction ." +
 "<" + strNS + strActivity + "> <" + strNS + "hasType> ?type ." +
 "<" + strNS + strActivity + "> <" + strNS + "performedAtTime> ?time ." +
"OPTIONAL {<" + strNS + strActivity + "> <" + strNS + "performedBy> ?performedBy} ." +
 "OPTIONAL {?performedBy <" + strNS + "hasName> ?performerName} ." +
 "?hasConsequentAction <" + strNS +  "hasActionDescription>  ?actionDes ." +
"?hasConsequentAction <" + strNS + "hasType> ?hasType ." +
"?hasConsequentAction <" + strNS + "hasTime> ?actionTime ." +
"OPTIONAL {?hasConsequentAction <" + strNS + "hasPerformedAt> ?performedAt} ." +
"OPTIONAL {?performedAt <" + strNS + "hasName> ?performedAtLoc}}";
```

**Fig. 5, SPARQL query to extract all the corresponding information of an activity**

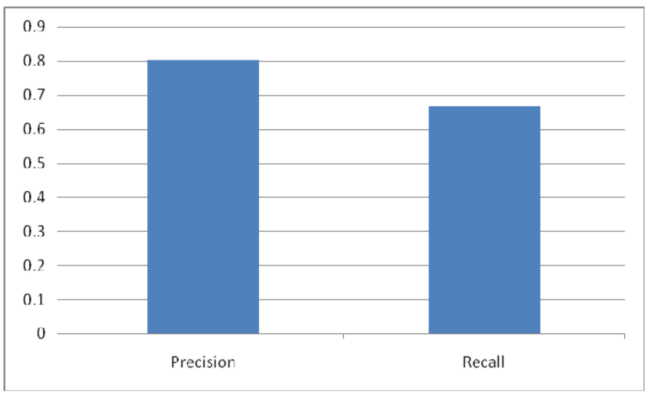


**Fig. 6. Precision and Recall of CAME for match making against number of performed experiments with increasing number of activities.**

CAME result is highly dependent on the results of Activity Recognition Engines discussed above. We use two phase filtering for decision making as using only the results of match making is not sufficient in health care systems. In the second phase we apply the DL rules (see Fig. 4) compiled with the help of expert knowledge (Medical Doctors) over the extracted activities in previous phase to filter out appropriate information from those of match making process. The output of 2nd phase filter is then used for decision making or suggestions about current situation.

## V. Conclusions

Context-aware Activity Manipulation Engine (CAME) has been presented for inferring high level activities from low level real-time daily life activities detected by sensor of a subject. By making use of ontologies to model the domain and expert knowledge (including activity, location, time, and environment information), better service provisioning, and intelligent healthcare facilities (i.e. activity information, reminders, and emergency situation analysis with decision making) have been achieved (see video demonstration).

Currently, we have worked on A-Box level inferring while in future we are planning for A-Box with integration to T-Box inferring that will ultimately increase the overall performance of CAME.

## VI. Acknowledgement

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