Activity Manipulation using Ontological Data for u-Healthcare

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Abstract*— Ubiquitous Healthcare (u-Healthcare) is the intelligent delivery of healthcare services to user anytime and anywhere. To provide robust healthcare services, recognition of patient daily life activities is required. Context information in combination with user real-time daily life activities can help in better personalized services, service suggestions, and change in system behaviour based on user profile for better healthcare services. In this paper, we focus on intelligent manipulation of activities using Context-aware Activity Manipulation Engine (CAME) core of Human Activity Recognition Engine (HARE). The activities are recognized using video-based, wearable sensor-based and location-based activity recognition engines. We fuse these detected activities with user profile information for context analysis of the activities performed. An ontology is developed with standard specifications to help using the context information and generate personalized system response. The objective of CAME is to receive real-time low level activities and infer higher level activities, situation analysis, personalized service suggestions, and take appropriate decisions. Two phase filtering technique is applied for intelligent processing of information (represented in ontology) and taking appropriate decisions based on description logic rules (incorporating expert knowledge). The experimental results for intelligent processing of activity information showed relatively good accuracy. Moreover, CAME is extended with activity filters and T-Box inference, and we get better results in comparison to initial results of CAME in terms of accuracy and response time. [1]

I. Introduction

With increasing lifestyle, people are more interested in their better and healthy life, which results in high cost of healthcare systems and services. To maintain good quality and availability of healthcare services with minimum cost is a challenging issue [12]. Home healthcare system is becoming more important form of healthcare services delivery. The management, maintenance, and coordination of healthcare services, educating users, and empowerment of individuals to manage their own health are the main focused issues. To support this, a powerful, flexible, and cost-effective infrastructure for healthcare services that can fulfil the vision of *ubiquitous healthcare (u-healthcare)* is required. Cloud Computing can potentially provide huge cost savings, flexibility, high-throughput, and ease of use for different services [2] as well as for healthcare services. For this reason, we have developed a detail architecture, called Secured Wireless Sensor Network (WSN) - integrated Cloud Computing for u-Life Care (SC^3) [8]. 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 homecare 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) [12] (see Fig. 1). This engine is necessary to provide improved daily medical care and real-time reaction to medical emergencies, identifying patient’s activities (i.e., Activity Recognition (AR)).

The existing systems are based on simple condition and action model [17], not using context information including time, location, and user profile. In some cases the existing systems use imperfect low level context information [9] which makes the result of system unpredictable. Their focus is more on environment information using 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 profile information, vision with motion, environment, location, and time to infer human intentions. Our focus in this paper is on CAME [11] component of our proposed HARE [12] (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.

For CAME implementation, we use different sources of information to avoid possibility of missing information or imperfect context information [9]. For context representation and profile information, we use ontology and have developed a semantic structure for representation of information where ontology is *an explicit and formal specification of a shared conceptualization* [7].

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

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domain and user profile information) these detected activities are intelligently manipulated to infer higher level activities and for the situation analysis. The experimental results of match making process of our CAME showed good results. 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. We have also extended our proposed CAME [11] for the analysis and decision making process. The Extended CAME use both A-Box and T-Box inference techniques that helps in better accuracy against CAME. A filter is also implemented in extended CAME to filter out the unknown activities during match making phase. This helps not only in better accuracy of extended CAME against CAME but also help for better response time of the system.

This paper is arranged as follows: Section II is related work. In Section III we discuss our proposed CAME architecture. Section IV presents the results that we have achieved and discussion on these results. We conclude our findings in Section V.

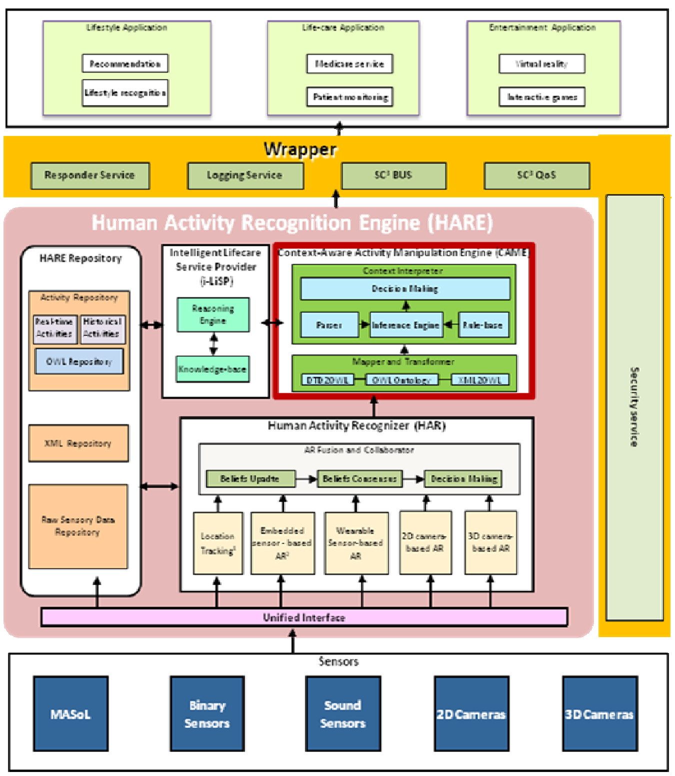

Fig. 1. The system model of HARE [12]

II. RELATED WORK

Many wireless technologies are in use nowadays for healthcare. CodeBlue [6] is one of the systems that is developed by Harvard Sensor Network Lab. CodeBlue works on publish/subscribe model for its different services. CodeBlue mainly supports physician and nurse that keep their watch on the patients. Research on reminders for elders to perform daily life activities [14] is getting more focus. They are mostly 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 [16], 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 [13] 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 [4] 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.

The idea in [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 the 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. The system in [17] is a more realistic system that not only uses ontology to incorporate context in intelligent processing of the collected information but also focus on the information collected from sensors like Smoke Detector, GPRS Modem, Infrared Control and X10 Appliance that actually facilitate more in homecare 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 single 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 systems, while the important thing is to facilitate in healthcare where these systems failed to perform.

III. CONTEXT-AWARE ACTIVITY MANIPULATION ENGINE

Use of ontology in activity recognition is relatively a new area of research. It helps in better understanding 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 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.

We define an ontology for information representation comprising the domain expert knowledge;

$$O = \{C, S, I, R, A\}$$

O is the ontology containing *C* concepts with *I* instances connected with one another using *S* slots. *R* is the restrictions applied on different *C*, *I*, and *S*. *A* is the auxiliary axioms and annotations used to enrich information in the knowledgebase that can later be used in match making and decision making processes. The concepts represent different diseases, symptoms, daily life activity allowed to be performed in a particular disease, patient detail information including profile information, and patient's daily activity schedule. Ontology with the rules 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, see Fig 2 while the Description Logic rule is given in Fig 3. The detail representation of the activities and related information is given in Fig 4.

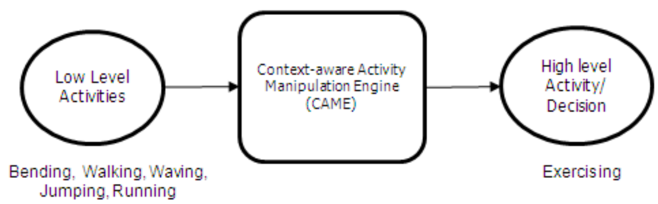

Fig. 2, Abstract model of CAME for activity manipulation.

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. 3, DL rule for exercising based on detected activities.

CAME is one of the main components of HARE, it is 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 5, while the detail description of all the components are given below.

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 KB 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 KB related to activity as well as to the subject that performs the activities. Activity related information are extracted from the XML and Text files generated by *Activity Recognition Engines*. So the activity needs to be formally represented in predefined semantic structure [15]. For this reason, CAME formally represents (see Fig. 4) the activities that are extracted in the previous step, while the representation is provided by the *Knowledgebase*.

```
activityOnto:Person_Instance_654
 a       activityOnto:Person ;
 activityOnto:has activityOnto:Patient , activityOnto:PhD , activityOnto:High_Age;
activityOnto:hasAge                     68;
activityOnto:hasDesignation             activityOnto:Professor;
activityOnto:hasID                      654;
activityOnto:hasName                    "Mr. Raazi".

activityOnto:Activity_Instance_20090614140013345
a       activityOnto:Activity ;
activityOnto:hasConsequentAction     activityOnto:Rule;
activityOnto:hasID                   345;
activityOnto:hasName                 "Running";
activityOnto:hasType                 "Motion";
activityOnto:isA                     activityOnto:Room_Instance_Living;
activityOnto:performedAtTime         2010:11:14:14:00:13;
activityOnto:performedBy             activityOnto:Person_Instance_654.

activityOnto:Activity_Instance_20090614140013347
a       activityOnto:Activity ;
activityOnto:hasConsequentAction     activityOnto:Rule;
activityOnto:hasID                   347;
activityOnto:hasName                 "Walking";
activityOnto:hasType                 "Motion";
activityOnto:isA                     activityOnto:Room_Instance_Living;
activityOnto:performedAtTime         2010:11:14:14:00:18;
activityOnto:performedBy             activityOnto:Person_Instance_654.

activityOnto:Activity_Instance_20090614140013346
a       activityOnto:Activity ;
activityOnto:hasConsequentAction     activityOnto:Rule;
activityOnto:hasID                   346;
activityOnto:hasName                 "Jumping";
activityOnto:hasType                 "Motion";
activityOnto:isA                     activityOnto:Room_Instance_Living;
activityOnto:performedAtTime         2010:11:14:14:00:15;
activityOnto:performedBy             activityOnto:Person_Instance_654.

activityOnto:Activity_Instance_20090614140013348
a       activityOnto:Activity ;
activityOnto:hasConsequentAction     activityOnto:Rule;
activityOnto:hasID                   348;
activityOnto:hasName                 "Bending";
activityOnto:hasType                 "Motion";
activityOnto:isA                     activityOnto:Room_Instance_Living;
activityOnto:performedAtTime         2010:11:14:14:00:22;
activityOnto:performedBy             activityOnto:Person_Instance_654.
```

Fig. 4, OWL representation (using N3 notation) of Activities that result in Exercise Activity

The activities detected are then verified for two reasons; (1) Checked for the consistency of the newly recognized activity against the KB 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 KB? If not, then it is populated in the 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 parses 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.

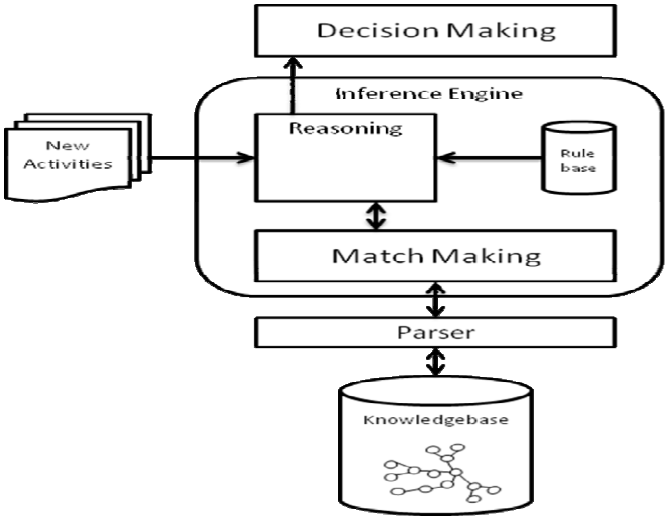

Fig. 5, Context-aware Activity Manipulation Engine (CAME); Inferring High Level Activities From Low Level Activities

To understand 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 personalized 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 KB 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 using inference engine. 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 systems and 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 [17] 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 user profile and information about the environment in which the user is currently to make the system more personalized.

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. 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. 6 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 all extracted.

```
"SELECT ?activityName ?hasConsequentAction ?type ?performedBy ?performerName ?time
?actionDes ?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. 6, SPARQL query to extract all the corresponding information of an activity

We tested CAME using 12 different experiments with increasing number of activities, where all activities are real-time activities detected by sensors discussed above. In Fig. 7, y-axis is the % of Precision and Recall for match making process while x-axis represents the number of experiments. The graph in Fig. 7 shows that precision and recall decreases with increasing number of activities, however, with the increasing number of experiments, both precision and recall are smoothening with average of 0.759 and 0.636, respectively. The video demonstration of our overall system deployment and working is available online[2].

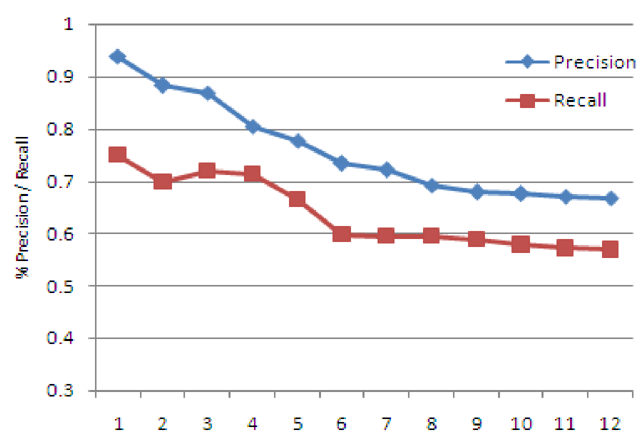

Fig. 7. Precision and Recall of CAME for match making against number of performed experiments with increasing number of activities.

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

For match making process, different algorithms for ontology matching i.e., Falcon [10], FOAM [5], and H-Match [3] are tested for their accuracy and performance in our given situation (see Fig 8-a and Fig 8-b for accuracy and execution time). The algorithms are also tested on the real dataset that is collected in real time system working. These algorithms have their own pros and cons which are out of the scope of this paper. In our given customized situation, we found Falcon to be more suitable for the match making process, though there is little difference among the results. The results of these algorithms for both i.e., accuracy and execution, highly depends on the *threshold* value set for the match and the number of *iterations* for finding the match. We used Falcon for the purpose of match making of newly detected activities against the already stored activities and related information in the knowledgebase.

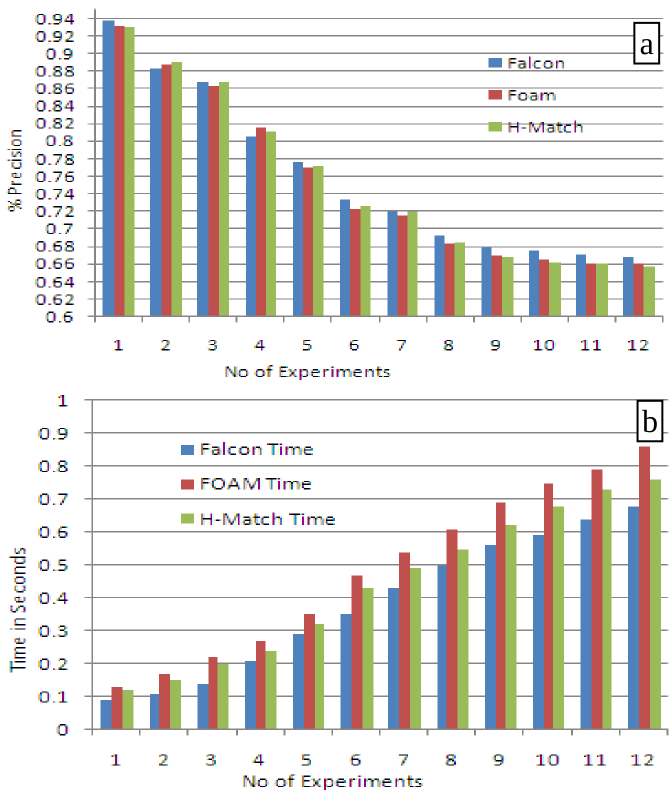

Fig. 8. a) Shows the precision of Falcon, FOAM and H-Match algorithms, while b) is the execution time comparison of these algorithms.

In CAME development, we used A-Box inferring that only involve instances. So we have extended CAME and for extended CAME we used the integration of A-Box with T-Box and before applying A-Box we used T-Box to limit the number of instances by using the structure of knowledgebase. Another main cause for low precision of CAME is the unknown activities detected by the sensors. As we focus only on set of 18 activities, so any other activity performed by Alzheimer patient not included in the set of 18 activities was reported as unknown activity. We have also modified CAME for unknown activities by implementing a filter to avoid selecting unknown activity during match making process, which resulted in better system precision. Though, we still need to store these activities as they may figure out some interesting new activities for system enhancement. For instance; in taking bath there were always two unknown activities one before and one after. After continuous pattern it was figured out that locking and unlocking the bath room door activities were detected as unknown activities. Still the precision of extended CAME depends more on the sensors deployed to detect human activities on timely manner.

We tested CAME and Extended CAME using the same 12 different experiments with increasing number of activities. In Fig. 9, y-axis is the % of Precision for match making process while x-axis represents the number of experiments. The graph in Fig. 9 shows that precision of CAME initially developed is less than the Extended CAME. Though the precision of both are decreasing with the increasing number of activities, however, extended CAME still maintain a good precision rate. Average precision of CAME and extended CAME for 12 experiments are 0.7590 and .8810 respectively.

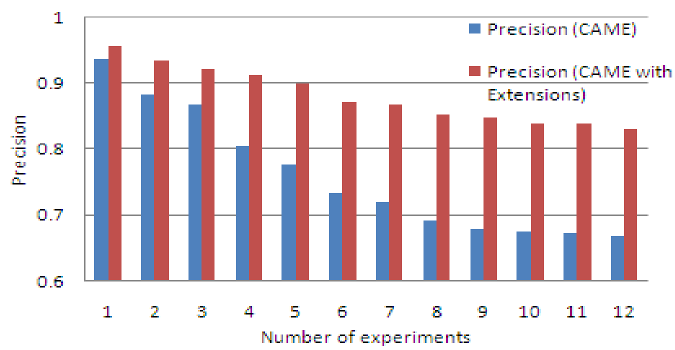

Fig. 9. Comparison between CAME and extended CAME precision for 12 different experiments with increasing number of activities.

After the extensions made to the CAME, we tested both CAME and extended CAME for their response time. As shown in Fig. 10, the extended CAME in initial tests takes more time (time is in seconds) in producing the results as the number of activities are less and the filtering criteria is taking more time. After some test and increasing the number of activities extended CAME shows better performance than CAME. The more the number of activities the better the response time of extended CAME will be against original CAME.

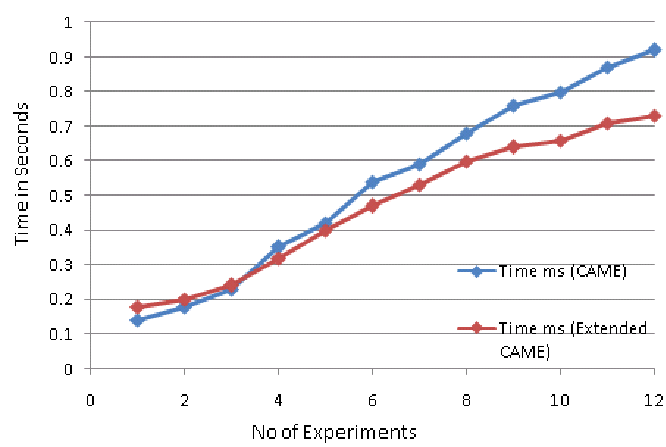

Fig. 10. Response time comparison between CAME and extended CAME..

CAME and extended CAME results are highly dependent on results of Activity Recognition Engines of HARE. Two phases filtering for decision making is used as only the results of match making are not sufficient in healthcare systems. In the second phase, DL rules (see Fig. 3) are applied 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), personalized service provisioning, and intelligent healthcare facilities (i.e., activity information, reminders, and emergency situation analysis with decision making) have been achieved (see video demonstration). In future we are planning to test the system on more activities with an extensive set of rules.

REFERENCES

[1] J. Boger, J. Hoey, P. Poupart, C. Boutilier, G. Fernie, A. Mihailidis, "A planning system based on markov decision processes to guide people with dementia through activities of daily living." IEEE Transactions on Information Technology in Biomedicine 10(2), 323–333, 2006.

[2] R. Buyya, C. S. Yeo, S. Venugopal, J. Broberg, and I. Brandic, "Cloud computing and emerging IT platforms: Vision, hype, and reality for delivering computing as the 5th utility". Future Generation Computing Systems, June 2009.

[3] S. Castano, A. Ferrara, and S. Montanelli. "Matching ontologies in open networked systems. Techniques and applications," Journal on Data Semantics (JoDS), vol. V, pp. 25-63, 2006.

[4] K. Du, D. Zhang, X. Zhou, M. Mokhtari, M. Hariz, and W. Qin. HYCARE: A hybrid context-aware reminding framework for elders with mild dementia, ICOST 2008.

[5] M. Ehrig, Y. Sure, "Foam - framework for ontology alignment and mapping; results of the ontology alignment initiative". In Proceedings of the Workshop on Integrating Ontologies. Volume 156., CEUR-WS.org, pp-72-76, 2005.

[6] T. Gao, C. Pesto, L. Selavo, Y. Chen, J. Ko, J. Lim, A. Terzis, A. Watt, J. Jeng, B. Chen, K. Lorincz, M. Welsh, "Wireless Medical Sensor Networks in Emergency Response: Implementation and Pilot Results", The 2008 IEEE International Conference on Technologies for Homeland Security, May, 2008.

[7] Gruber, T. "A Translation Approach to Portable Ontology Specifications", Knowledge Acquisition , pp 199-220, 1993.

[8] L. X. Hung, P. T. H. Truc, L. T. Vinh, A. M. Khattak, and et al. "Secured WSN-integrated Cloud Computing for u-Life Care", 7th IEEE Consumer Communications and Networking Conference (CCNC), USA, 2010.

[9] K. Henricksen, and J. Indulska, "Modelling and Using Imperfect Context Information". In Proceedings of the Second IEEE Annual Conference on Pervasive Computing and Communications Workshops,Washington DC, March 14 - 17, 2004.

[10] W. Hu, and Y. Qu, "Falcon-AO: A practical ontology matching system." Journal of Web Semantics. 6, 3 (Sep. 2008), 237-239. DOI= http://dx.doi.org/10.1016/j.websem. 2008.

[11] A. M. Khattak, Z. Pervez, K. K. Ho, S. Y. Lee, Y. K. Lee, "Intelligent Manipulation of Human Activities using Cloud Computing for u-Life Care", The 10th Annual International Symposium on Applications and the Internet (SAINT 2010)", Seoul, Korea, July 2010.

[12] A. M. Khattak, L. T. Vinh, D. V. Hung, P. T. H. Truc, L. X. Hung, D. Guan, Z. Pervez, M. Han, S. Y. Lee and Y. K. Lee, Context-aware Human Activity Recognition and Decision Making, 12th International Conference on e-Health Networking, Application Services(IEEE HealthCom 2010), Lyon, France, July 1-3, 2010

[13] N. Marmasse, C. Schmandt, "Location-aware information delivery with commotion". In: Proceedings of the 2nd International symposium on Handheld and Ubiquitous Computing, Bristol, England, pp. 157–171 (2000).

[14] M. E. Pollack, L. E. Brown, D. Colbry, C. E. McCarthy, C. Orosz, B. Peintner, S. Ramakrishnan, I. Tsamardinos, "Autominder: an intelligent cognitive orthotic system for people with memory impairment. Robotics and Autonomous Systems 44(3-4), 273–282, 2003.

[15] P. Shvaiko and J. Euzenat, " Ten Challenges for Ontology Matching", In Proceedings of The 7th International Conference on Ontologies, DataBases, and Applications of Semantics (ODBASE), August 2008.

[16] T. Sohn, K. Li, G. Lee, I. Smith, J. Scott, W. Griswold, "Place-its: A study of location-based reminders on mobile phones". In: Ubicomp, pp. 232–250, 2005.

[17] F. Wang and K. J. Turner. "An Ontology-Based Actuator Discovery and Invocation Framework in Home Care Systems," 7th International Conference on Smart Homes and Health Telematics, pp. 66-73, LNCS 5597, Springer, Berlin, June 2009.

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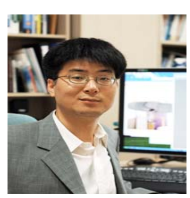

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