Context-aware Human Activity Recognition and Decision Making

Asad Masood Khattak, La The Vinh, Dang Viet Hung, Phan Tran Ho Truc, Le Xuan Hung, D. Guan, Zeeshan Pervez, Manhyung Han, Sungyoung Lee, Young-Koo Lee
Dept. of Computer Engineering, Kyung Hee University, Korea,
{asad.masood, vinhlt, dangviethung, pthtruc, lxhung, donghai, zeeshan, smiley, sylee}@oslab.ac.kr, yklee@khu.ac.kr

Abstract— **Ubiquitous Life Care (u-Life care) nowadays becomes more attractive to computer science researchers due to a demand on a high quality and low cost of care services at anytime and anywhere. Many works exploit sensor networks to monitor patient's health status, movements, and real-time daily life activities to provide care services to them. Context information with real-time daily life activities can help in better services, service suggestions, and change in system behavior for better healthcare. Our proposed Secured Wireless Sensor Network - integrated Cloud Computing for ubiquitous - Life Care (SC^3) monitors human health as well as activities. In this paper we focus on Human Activity Recognition Engine (HARE) framework architecture, backbone of SC^3 and discussed it in detail. Camera-based and sensor-based activity recognition engines are discussed in detail along with the manipulation of recognized activities using Context-aware Activity Manipulation Engine (CAME) and Intelligent Life Style Provider (*i*-LiSP). Preliminary results of CAME showed robust and accurate response to medical emergencies. We have deployed five different activity recognition engines on Cloud to identify different set of activities of Alzheimer's disease patients.**

I. INTRODUCTION

As the standard of living rises, people are more interested in their health and desire healthy life. Due to aging of population, rising cost of workforce and high quality treatment, the cost of life care or healthcare system is increasing worldwide. According to OECD[1] (Organization of Economic Cooperation and Development) Health data 2008, total health spending accounted for 15.3% of GDP in the United States in 2006. Korea was 6.4% of GDP to health in 2006. The United States also ranks far ahead of other OECD countries in terms of total health spending per capita, with spending of 6,714 USD (adjusted for purchasing power parity (PPP)), more than twice the OECD average of 2,824 USD in 2006. For Korea it was 1480 USD.

Cloud Computing can provide a powerful, flexible, and cost-effective infrastructure for life care services that can fulfill the vision of "ubiquitous life care" that is providing life care to people anywhere at any time with increasing coverage and quality. Because of its elasticity, scalability, pay-as-you-go model [1], Cloud Computing can potentially provide huge cost savings, flexible, high-throughput, and ease of use for life care services. For example, with life care providers looking at automating processes for lower cost and higher gains, Cloud Computing can act as an ideal platform. For this reason we have developed Secured Wireless Sensor Network (WSN) - integrated Cloud Computing for u-Life Care (SC^3) [9] that provide all the above discussed facilities.

Our focus in this paper is on Human Activity Recognition Engine (HARE) component of SC^3 architecture highlighted in Figure 1. HARE can help in enhancing capabilities and provides tremendous value for smarter service provisioning. HARE can provide efficient model for managing real-time data from various sensors, efficiently detection of human activities, and better manipulation of detected activities using ontologies. System accuracy in healthcare systems is the most important issue. The existing systems are based on simple condition and action [19], not using context information, or in some cases use imperfect context information [7] where the result of system is unpredictable. Their focus is more on environment sensors rather than on real-time person activity.

Due to space limitation, we have provided the details of each HARE component and its preliminary results achieved with the help of Context-aware Activity Manipulation Engine (CAME). Experimental results of the proposed HARE framework showed robust response for health care services in emergency situations. As a proof of concept, in initial phase HARE is deployed on Cloud server for an Alzheimer's disease patient's for his better life care using five different activity recognition modules. The demonstration[2] was very successful for a set of 14 different real time activities that Alzheimer's disease patients commonly perform.

This paper is arranged as follows: Section II provides the overview of the overall SC^3 architecture. Section III is detail description of proposed HARE architecture and its subcomponents. Section IV comprises of the implementation and results details. Finally we conclude our findings in Section V and talk about future directions and applications of HARE.

[1] http://www.oecd.org/statsportal/0,3352,en_2825_293564_1_1_1_1_1,00.html

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

978-1-4244-6375-6/10/$26.00 ©2010 IEEE

II. SC^3 OVERVIEW

The system architecture for SC^3 is shown in Figure 1, proposed in [9]. In this architecture, WSNs are deployed in home environments for collecting data. This sensed data is either human health data and/or data to be used for detection of human activities for care services. To detect human activities, we propose novel approaches: embodied-sensor based activity recognition [18], video-based activity recognition, wearable sensor-based activity recognition, location tracking, and ontology based intelligent activity logging and manipulation [13]. The sensors are either attached to a person or to the walls in the home environment. The video-based approach is based on images collected from camera, extracting the background to get the moving object and inferring activities such as walking, sitting, standing, falling down, bending, jacking, jumping, running, siding, skipping, one hand waving, both hands waving, and exercising. Location tracking helps in properly locating the subject's current position. On top of these, ontology engine is implemented to deduce high level activities and make decisions according to situation based on user profile information.

Sensed data is transferred to Cloud by using *sensor data dissemination and WSN-Cloud integration mechanisms* [6]. To access medical data on Cloud, the user must be authenticated and granted access permission. An image-based authentication and activity-based access control are proposed to enhance security and flexibility of user's access [12 and 8].

For Independent Clouds Collaboration (ICC) with each other, we proposed a dynamic collaboration procedure [6]. Numerous u-life care services can access Clouds to provide better and low cost care for end-users such as secure u-119 service, secure u-Hospital, secure u-Life care research, and secure u-Clinic.

In SC^3, we mostly focused on WSN, WSN-Cloud, activity recognition, authentication and access control to Cloud data, and a sample care service for different disease patients at home environment. We have implemented SC^3 for Alzheimer disease discussed in Section VI. First of all, human activity data is captured from sensors and videos, and then transmitted to the Cloud Gateway. After data filtering, it transmits the data to the Cloud via TCP/IP socket. In the Cloud, raw data is used to deduce user activity and location information such as patient is walking, eating, and staying in the kitchen. Activity and location information are forwarded to ontology for representation and inferring higher level activity and situation analysis. The decisions are also made based on the situation to respond to some context; for example, if patient is reading a book then TV should be turned off.

To access patient data, doctors and/or nurses are first authenticated based on their access permission. Some of the main services of SC^3 are (1) *Safety monitoring services for home users:* SC^3's WSN can monitor home user's movement; WSN can monitor home user's movement, location by using various sensors. The sensory data is then disseminated to the Clouds.

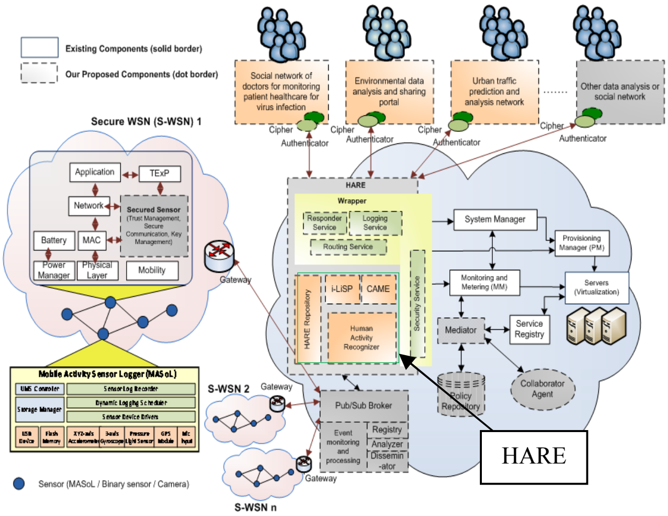

Figure 1, The system model of SC^3

From that, SC^3's Life care services such as emergency service, caregivers can monitor and has immediate responses in case of emergent situations. (2) *Information sharing services:* With SC^3, patient information and data can be accessed globally and resources can be shared by a group of hospitals rather than each hospital having a separate IT infrastructure. It can help in the early identification and tracking of disease outbreaks, environment related health problems, and other issues. (3) *Emergency-connection services:* SC^3 can be deployed to real-time monitor home environments, including gas, fire, and robbery. Through SC^3, an alarm system connects to users, u-119, police department can give an emergency alert in case any emergent situation occurs. (4) Users can monitor their home, their family health anywhere, any time with any kind of connected devices over Internet such as cell phone, PDA, laptop, and computer.

III. HARE ARCHITECTURE

Core of SC^3 is a Human Activity Recognition Engine (HARE) as shown in Figure 2. HARE is composed of various sub-components such as; *Location Tracking:* to track human location, *Activity Recognizer (including embedded, wearable, 2D camera, and 3D camera based activity recognition)*: to recognize human activities. *Schema Mapping and XML Transformer:* to transform activity output in a machine-understandable and flexible OWL format, and *Context-Aware Activity Manipulation Engine*: to infer high level activities or make decisions based on subject performed activity and profile information.

In addition, a number of supporting components are also integrated to make HARE work properly, to mention these: *AR Fusion and Collaborator:* is to make collaboration among different activity recognition engine approaches. It is necessary to increase the accuracy of activity recognition. For example, if wearable sensor-based AR detects a person is taking medicine with 70% accuracy, and 2D camera-based AR also detects the person is taking medicine with 80%, so the collaborator can ensure that he is taking medicine. *HARE Repository:* is back bone of HARE, it stores raw data collected by sensors and cameras, stores real-time activities recognized by activity recognition engines, activity history and activities in machine understandable format (OWL) to infer high level activities. We have developed successfully a Mobile Activity Sensor Logger (MASoL) (see Figure 1). MASoL serves in the infrastructure layer under HARE to collect and monitor human and environment information.

In this section we briefly discuss the main components of HARE namely: Video Based Activity Recognition, Sensor Based Activity Recognition, Intelligent Life-care Service Provider (*i*-LiSP), and Context-aware Activity Manipulation Engine (CAME). The activities are detected by Video based and Sensor based AR engines and then given to *i*-LiSP and CAME for further manipulation and decision making.

A. Video Based Activity Recognition

The accuracy of the video-based AR depends significantly on the accuracy of human body segmentation. In the field of image segmentation [15], active contour (AC) model has attracted much attention. Recently, Chan and Vese (CV) proposed in [3] a novel form of AC based on the Mumford and Shah functional for segmentation and the level set framework. The CV AC model utilize the difference between the regions inside and outside of the curve, making itself one of the most robust and thus widely used techniques for image segmentation with energy function;

$$F(C) = \int_{in(C)} |I(\mathbf{x}) - c_{in}|^2 \, d\mathbf{x} + \int_{out(C)} |I(\mathbf{x}) - c_{out}|^2 \, d\mathbf{x}$$

where $\mathbf{x} \in \Omega$ (the image plane) $\subset R^2$, $I : \Omega \to \mathcal{Z}$ is a certain image feature such as intensity, color, or texture. c_{in} and c_{out} are respectively the mean values of image feature inside $[in(C)]$ and outside $[out(C)]$ the curve C, which represents for the boundary between two separate segments. Considering image segmentation as a clustering problem, we can see that this model forms two segments (clusters). However, the global minimum of the above energy functional does not always guarantee the desirable results, especially when a segment is highly inhomogeneous, e.g., human body, as can be seen in Figure 3(b). It is due to the fact that CV AC is trying to minimize the dissimilarity within each segment but does not care for distance between different segments. Our methodology is to incorporate the Bhattacharyya distance [2] to the CV energy functional such that not only the differences within each region are minimized but the distance between the two regions is maximized as well. The proposed energy functional is;

$$E_0(C) = \beta F(C) + (1 - \beta) B(C)$$

where $\beta \in [0,1]$,

$$B(C) \equiv B = \int_z \sqrt{p_{in}(z) \, p_{out}(z)} \, dz$$

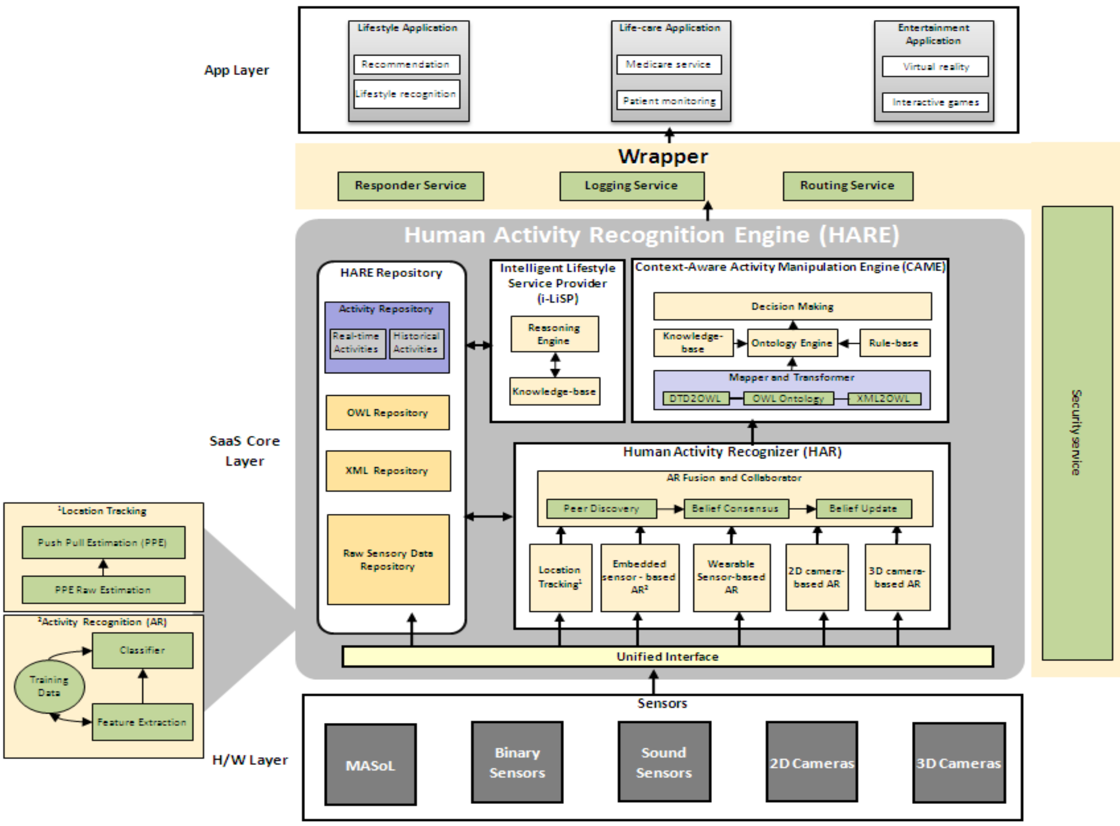

Figure 2, Framework architecture of Human Activity Recognition Engine (HARE)

the Bhattacharyya coefficient with

$$p_{in}(z) = \frac{\int_\Omega \delta(z - I(\mathbf{x}))H(-\phi(\mathbf{x}))d\mathbf{x}}{\int_\Omega H(-\phi(\mathbf{x}))d\mathbf{x}}$$

$$p_{out}(z) = \frac{\int_\Omega \delta(z - I(\mathbf{x}))H(\phi(\mathbf{x}))d\mathbf{x}}{\int_\Omega H(\phi(\mathbf{x}))d\mathbf{x}}$$

$\phi : \Omega \to R$ the level set function, and $H(\cdot)$ and $\delta(\cdot) \triangleq H'(\cdot)$ respectively the Heaviside and the Dirac functions. Note that the Bhattacharyya distance is defined by $[-\log B(C)]$ and the maximization of this distance is equivalent to the minimization of $B(C)$. Note also that to be comparable to the $F(C)$ term, in our implementation, $B(C)$ is multiplied by the area of the image because its value is always within the interval $[0,1]$ whereas $F(C)$ is calculated based on the integral over the image plane. In general, we can regularize the solution by constraining the length of the curve and the area of region inside it. Therefore, the energy functional is;

$$E(C) = \gamma\int_\Omega |\nabla H(\phi(\mathbf{x}))|\, d\mathbf{x} + \eta\int_\Omega H(-\phi(\mathbf{x}))d\mathbf{x} + \beta F(C) + (1-\beta)B(C)$$

where $\gamma \geq 0$ and $\eta \geq 0$ are constants.

The intuition behind the proposed energy functional is that we seek for a curve which 1) is regular (the first two terms) and 2) partitions the image into two regions such that the differences within each region are minimized (i.e., the $F(C)$ term) and the distance between the two regions is maximized (i.e., the $B(C)$ term). The level set implementation for the overall energy functional can be derived as

$$\frac{\partial\phi}{\partial t} = |\nabla\phi| \left\{ \begin{array}{l} \gamma\kappa + \eta + \beta\left[(I-c_{in})^2 - (I-c_{out})^2\right] \\ -(1-\beta)\left[\frac{B}{2}\left(\frac{1}{A_{in}} - \frac{1}{A_{out}}\right) + \frac{1}{2}\int_z \delta(z-I)\left(\frac{1}{A_{out}}\sqrt{\frac{p_{in}}{p_{out}}} - \frac{1}{A_{in}}\sqrt{\frac{p_{out}}{p_{in}}}\right)dz\right] \end{array} \right\}$$

where A_{in} & A_{out} are areas inside & outside curve C.

As a result, the proposed model can overcome the CV AC's limitation in segmenting inhomogeneous objects as shown in Figure 3(c).

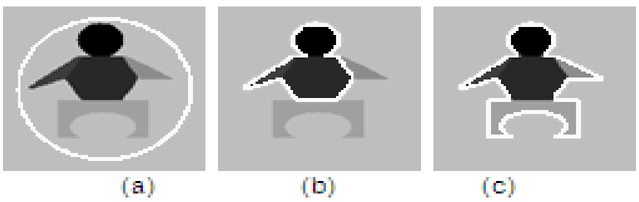

Figure 3, Sample segmentation of inhomogeneous body-shape object using active contours. (a) Initial contour, (b) result of CV AC [3], and (c) result of our approach.

After obtaining a set of body silhouettes segmented from a sequence of images; we propose to apply ICA (Independent Component Analysis) [10 and 11] to get the motion features of that sequence. The extracted features are then symbolized using vector quantization algorithms such as K-mean clustering [14]. Symbol sequence generates a codebook of vectors for training and recognition. The overall architecture of proposed framework is shown in Figure 4, where T represents the number of testing shape images, N number of trained HMMs, and L likelihoods.

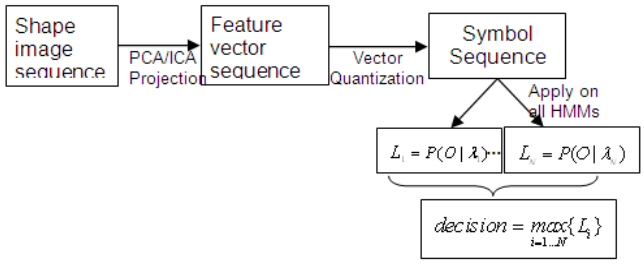

Figure 4, Architecture of the proposed approach for motion feature extraction and recognition.

B. *Sensor Based Activity Recognition*

Based on existing work [16], we develop our own recognition which is called "semi-Markov Conditional Random Fields (semiCRF)" [18], furthermore we propose a novel algorithm which helps to reduce the complexity of training and inference by more than 10 times in comparison with the original work. In our model, we assume that

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

are input signal and label respectively. We optimize the model parameter so that P (Y|X) is maximized. Where in CRF, P(Y|X) is calculated by

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

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

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

Where F is a vector of feature functions (which are often delta functions), W^T is a vector of model parameters, and ψ is called potential functions. Z_X (normalization factor), is computed by using forward/backward algorithm. However, conventional CRF is limited to Markov assumption which is not able to model the duration of activity as well as long-transition between activities. To overcome these, we introduce a semi-Markov model by defining a new state as $s_i = (y_i, b_i, e_i)$ where s_i is the i^{th} state, y_i, b_i, e_i in that order are label, begin and end time of the state. For example, given an input label sequence Y=(1,1,2,2,2,3,4,4), then the semi-Markov state sequence is (1,1,2), (2,3,5), (3,6,6), (4,7,8). Note that, in AR we consider states with expected label. With these definitions, potential function is rewritten as:

$$\Psi(s_{i-1}, s_i, X) = \begin{pmatrix} e^{Q^T(y_{i-1}, y_i)} \times \\ e^{Q^D(y_i, e_i - b_i + 1)} \times \\ e^{Q^O(y_i, b_i, e_i)} \times \\ e^{Q^O(IA, e_{i-1}+1, b_i - 1)} \end{pmatrix}$$

Where

$$Q^T(y', y) = w^T(y', y)\delta(y_{t-1} = y', y_t = y)$$

is a weighted transition potential function, $w^T(y',y)$ is the weight of transition from y' to y.

Making use of semi-Markov conditional random fields, we proposed our algorithm for computing gradients of the target function by extending [16]. It reduces the complexity of computing each gradient from $O(TN^2D)$ to $O(TN(N+D))$, where T, N, D are length of the input sequence, number of label values, and maximum duration of a label respectively. For experiments, we used the dataset of long-term activities available at http://www.mis.informatik.tu-darmstadt.de/data. Then we show our result in comparison with the original one. The dataset contains 7 days of continuous data, measured by two triaxial accelerometers [18].

C. *Intelligent Life-care Service Provider*

Intelligent Life-care Service Provider (*i*-LiSP) module is responsible to provide intelligent services to the users by analyzing their context information. Service could be an act of help, assistance, and recommendations. Various kinds of services are considered in *i*-LiSP, such as entertainment, medication, and sport services. The context information used in *i*-LiSP is obtained from various sources. They mainly include: the activity information from low level sensors, the activity information from Human Activity Recognition Engine, and the high-level context information from CAME Engine (discussed later).

i-LiSP is designed to provide intelligent services/recommendations to users. The services can be divided into two types: (1) Service by long-term observations (SLO): This service is provided after *i*-LiSP module analyzed the long-term history data of users. For example, by analyzing one week data of a user, we can create the model for the user's toileting times per day (e.g., estimating the probability density function of the user's toilet times). Then the medical doctors can give some recommendations to the user by analyzing the generated model. (2) Service by current observations (SCO): This service is the immediate response/recommendations provided by *i*-LiSP by analyzing current context information. For example, the current context information of the user is: at 9AM, he is watching TV. Based on the knowledge (stored information) of *i*-LiSP, this time he should do the exercise. Therefore, the system will remind him to stop watching TV and do exercise.

i-LiSP have three sub modules that work using different techniques: (1) Topic Model Based Service Provider (TMSP): TMSP adopts topic model as the reasoning algorithm to provide SLO. Topic model is originally proposed to summarize (finding concise restatements) of spoken/text document to improve the navigation quality of speech/text collections. Here, TMSP use topic model to summarize the history information of users. (2) Rough Set Based Service Provider (RSSP): RSSP adopts rough set theory as the reasoning algorithm to provide SCO. Rough set theory is used here for the following reasons: it directly works on the data and does not require any other prior knowledge for the data (such as probability distributions); it can automatically filter out the irrelevant and redundant information from data. The knowledge of RSSP is represented by rules which are understandable by humans. Therefore, experts can flexibly manipulate the knowledge by adding or removing the rules. (3) Bayesian Network Based Service Provider (BNSP): BNSP uses Bayesian network as the reasoning algorithm. It can provide both SLO & SCO by varying the models it generates. A Bayesian network is a probabilistic graphical model that represents a set of random variables and their conditional independencies via a directed acyclic graph. For example, a Bayesian network could represent the probabilistic relationships between the user's diseases and symptoms.

D. *Context-aware Activity Manipulation Engine*

Ontology is formally defined as *an explicit and formal specification of a shared conceptualization* [5, 17]. Ontology defines a formal semantics for information allowing information to be process-able by computer system agents. Use of ontology in activity recognition is a new area of research and helps in better understanding the activity in a given context. In [19] the authors only focused on the location and time information of an activity 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 environment information.

Ontology helps in properly extracting the higher level activity of a set of activities in a series, e.g. an activity of fall down detected with low level sensor only will always generate alarm for emergency situation. On the other hand with the use of ontology having context information about the fall down activity like the location information, time information, profile information of the subject, and linked other low level activities can easily identify that it's an emergency situation or a jumping competition.

All the activities are store managed in domain ontology. For manipulation of information (activities in ontological format) we used SPARQL, Pellet3.4, and for decision making we use Description Logic (DL) Rules. Table 1 represents the DL rules that we used in our system implementation. The list is not an exhaustive list of all the rules we used in project implementation.

Our HARE is designed in such a flexible manner that its client can easily communicate with it from a small hand held devices such sensors, PDA, or cell phones. Various entertainment applications can make use of HARE to apply in reality, such as online game and console game.

Table 1, Customized rules for making decisions

Rule1 ∃Activity(a1) ⊓ ¬hasContents(taking medicine) ⊓ hasNextActivity(a2) ⊓ ∃Activity(a2) ⊓ hasContents(eating) → Activity.Create(a1) ⊓ Activity.Create(a2) ⊓ reminder(take medicine)
Rule2 ∃Activity(a1) ⊓ hasContents(reading) ⊓ hasNextActivity(a2) ⊓ ∃Activity(a2) ⊓ hasContents(TV On) → Activity.Create(a1) ⊓ Activity.Create(a2) ⊓ turnOff(TV)
Rule3 ∃Activity(a1) ⊓ hasContents(unknown exercise) ⊓ hasNextActivity(null) → Activity.Create(a1) ⊓ reminder(movements are wrong)
Rule4 ∃Activity(a1) ⊓ hasContents(entering kitchen) ⊔ ∃Activity(a2) ⊓ hasContents(entering bedroom) → Activity.Create(a1) ⊔ Activity.Create(a2) ⊓ turnOn(lights)

IV. Implementation and Results

One of the main targeting services of u-Life care is to enable people to live independently longer through the early detection and prevention of chronic disease and disabilities. Computer vision, emplaced wireless sensor networks (WSN), and body networks are emerging technologies that promise to significantly enhance medical care for seniors living at home in assisted living facilities. With these technologies, we can collect video, physiological, and environmental data, identify individuals' *activities of daily living* (ADL), and act for improved daily medical care as well as real-time response to medical emergencies.

To achieve this, accurately identifying individuals' ADL, so-called activity recognition (AR) which can be based on both video and sensor (e.g., accelerometer, gyroscope, physiological) data, is of vital importance. However, it is a significant challenge, for instance; Video-based AR can be complex due to abrupt object motion, noise in images, non-rigid nature of human body, partial and full object occlusions, scene illumination changes, and real-time processing requirements [4]. In this paper we discuss the overall results of our HARE system. The activities are detected using camera based and sensor-based activity recognition engines. The detected activities are then forwarded to context-aware activity manipulation engine (CAME) to infer higher level activities and decision making.

The 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. For instance, low level activities in a series, e.g. bending, sitting, jumping, and walking with the use of ontology will result in higher level activity e.g. exercising. To implement CAME, Jena2, Protégé, Protégé-OWL, Arq, and Pellet 3.4 are used. The outcome of CAME is partially dependent on the results of AR modules. Figure 5 is the OWL (using N3 notation) of "Entering Kitchen" activity in Activity Repository.

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

Figure 5, N3 representation of 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 Figure 6, y-axis is the % of Precision and Recall for match making process while x-axis represents the number of experiments. The graph in Figure 6 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.

We use two phase filtering for decision making as using only the results of match making is not sufficient in healthcare systems. In the second phase we use the description logic rules (see Table 1) compiled with the help of expert knowledge (Doctors) to filter out appropriate information from those of match making process. The output of second phase filter is then used for decision making or suggestions about current situation.

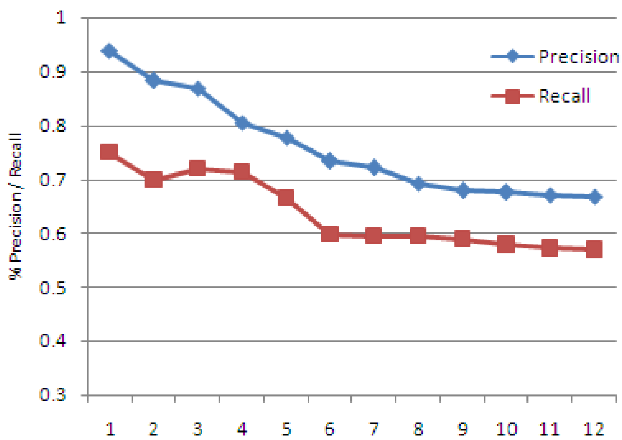

Figure 6, Precision and Recall of CAME for match making against number of performed experiments.

V. Conclusions and Future Work

Framework architecture of Human Activity Recognition Engine (HARE) has been presented for detecting real-time daily life activities of a person. 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 have been achieved. Detail discussion on HARE and its subcomponents with the experimental results is made. The support of HARE to doctors, care-givers, clinics and pharmacies are all elaborated using the capabilities of Cloud computing. From experimental results, it is observed the HARE component worked well in combination for a particular domain. We are looking forward to implement HARE for Alzheimer, Parkinson's, and Stroke patients in their normal daily life.

ACKNOWLEDGMENT

This research was supported by the MKE (Ministry of Knowledge Economy), Korea, under the ITRC (Information Technology Research Center) support program supervised by the NIPA (National IT Industry Promotion Agency)" (NIPA-2009-(C1090-0902-0002)). This work was supported by the IT R&D program of MKE/KEIT. [2009-S-033-01, Development of SaaS Platform for S/W Service of Small and Medium sized Enterprises].

REFERENCES

[1] 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.

[2] E. Choi, C. Lee, "Feature extraction based on the Bhattacharyya distance", Pattern Recognition, Volume 36, Issue 8, Pages 1703-1709, August 2003.

[3] T. Chan and L. Vese, "Active contours without edges", IEEE Trans. Image Proc. 10, pp-266-277, 2001.

[4] Gorelick L, Blank M, Shechtman E, Irani M, Basri R, "Actions as space-time shapes". IEEE Trans Patt Anal Mach Intell 29(12): 2247–2253, 2007.

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

[6] M. Hassan, E. Huh, B. Song. "A framework of sensor-cloud integration opportunities and challenges", 3rd International Conference on Ubiquitous information Management and Communication, Korea, January 2009.

[7] 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.

[8] L. Hung, S. Lee, Y. Lee, H. Lee, "Activity-based Access Control Model to Hospital Information," IEEE 13th Int. Conf. Embedded and Real-Time Computing Systems and Applications, pp. 488-496, Korea, 2007.

[9] 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.

[10] A. Hyvarinen, "New approximations of differential entropy for independent component analysis and project ionpursuit Adv. Neural Inform". Process. Syst. 10 273–9, 1998.

[11] Hyv¨arinen A, Karhunen J and Oja E, "Independent Compon. Anal". (New York: Wiley), 2001.

[12] H. Jameel, R. Shaikh, H. Lee and S. Lee, "Human Identification through Image Evaluation Using Secret Predicates", Topics in Cryptology - CT-RSA, 67-84, 2007.

[13] A. M. Khattak, K. Latif, S. Y. Lee, and et al., "Change Tracer: Tracking Changes in Web Ontologies", 21st IEEE International Conference on Tools with Artificial Intelligence (ICTAI), Newark, USA, November 2009.

[14] L. Kaufman and P. J. Rousseeuw, "Finding Groups in Data: An Introduction to Cluster Analysis," Wiley Series in Probability and Statistics. John Wiley and Sons, New York, Novemeber 1990.

[15] M. Kass et al., "Snakes: active contour models", Int. Journal on Computer Vision, 1 (4) pp-321-33, 1988.

[16] S. Sarawagi and W. Cohen. "Semi-markov conditional random fields for information extraction". Advances in Neural Information Processing Systems, 2004.

[17] M. Singh, and M. Huhns, "Service Oriented Computing: Semantics, Processes, Agents", John Wiley & Sons, West Sussex, UK, 2005.

[18] L. Vinh, L. Hung, S. Lee. "Semi Markov Conditional Random Fields for Accelerometer Based Activity Recognition", The International Journal of Artificial Intelligence, Neural Networks, and Complex Problem-Solving Technologies, (In Press).

[19] 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.