Proceeding of International Conference on
Ubiquitous Healthcare

# uHealthcare 2010

October 28-30, 2010
Jeju Grand Hotel, Jeju, KOREA

## Extending the Realm of u-Healthcare

### Conference Hosts

Institute of Medical & Biological Engineering, SNUMRC
Chungbuk National University Medical Research Institute
Personalized Tumor Engineering Research Center, Chungbuk National University
Advanced Biometric Research Center, Seoul National University

### Technical Co-sponsors

Korean Society of Medical & Biological Engineering
KIEE Information and Control Society
Japanese Society for Medical & Biological Engineering
IEEE EMBS

11:15 ~ 11:30:

**(5.2) Real-time Removal of Motion Artifacts from Photoplethysmographic Signal Using a Kalman Filter with Accelerometry**

Boreom Lee (GIST, Korea), Jong-Hee Han(Hanyang University, Korea)
Won Jin Yi (Seoul National University, Korea)

11:30 ~ 11:45:

**(5.3) Towards Efficient Analysis of Activities in Chronic Disease Patients**

Asad Masood Khattak, Zeeshan Pervez, Iram Fatima, Sungyoung Lee, Young-Koo Lee
(Kyung Hee University, Korea)

11:45 ~ 12:00:

**(5.4) Automation of Non-intrusive Nasal Breathing Detection by Using Far-Infrared Imaging**

Dai Hanawa, Yohei Yaginuma, Yusuke Enomoto, Taisuke Koide, Shuhei Terada, Kimio Oguchi
(Seikei University, Japan)

13:30 ~ 15:00

## Oral Session 6: Activity Monitoring and Evaluation

Chairperson: **Stacy J. Morris Bamberg**, University of Utah

13:30 ~ 14:00: Invited Lecture 6

- **Just Enough Measurement' to Enable Accessible Rehabilitation Technology**

Stacy J. Morris Bamberg(University of Utah, USA)

14:00 ~ 14:15:

**(6.1) Active Contour Based Human Body Segmentation with Applications in u-Life Care**

Muhammad Hameed Siddiqi, Muhammad Fahim, Phan Tran Ho Truc, Young-Koo Lee,
Sungyoung Lee (Kyung Hee University, Korea)

14:15 ~ 14:30:

**(6.2) 2D Image based Anthropometric Parameters Extraction Method**

Jang-Ho Park, Dae-Geun Jang, Umar Farooq, Seung-Hun Park
(Kyung Hee University, Korea)

14:30 ~ 14:45:

**(6.3) Feature Representation for Abnormal Human Activity Recognition**

Zafar Ali Khan, Won Sohn (Kyung Hee University, Korea)

14:45 ~ 15:00:

**(6.4) Gait Assessment for Parkinson's Patients using Spatial-Temporal Image Correlation**

Hyo-Seon Jeon, Sang-Kyong Kim, Won-Jin Yi, Beom Seok Jeon , Kwang Suk Park (Seoul
National University, Korea) Jonghee Han(Hanyang University, Korea)

# Towards Efficient Analysis of Activities in Chronic Disease Patients

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*Abstract— Ubiquitous Healthcare (u-Healthcare) is a* collaborative process incorporating work from diverse fields of *computer engineering as well as the knowledge from* medical science domain. One of the main targeting services of u-Healthcare is to enable people to live independently longer through the early detection and prevention of chronic disease and disabilities. To provide robust healthcare services, recognition of patient daily life activities is very important. Real-time daily life activities with context information can help in better services of overall system. Now-a-days with increasing life standards and styles, people are more interested in their better health and desire healthy life. This resulted in increase of cost for life care or healthcare system. To maintain quality and availability level of healthcare services with minimum cost, 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, flexible high-throughput, and ease of use for different services [2] as well as for healthcare 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) [7]. 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 [1, 3, 9], not using context information or in some cases using imperfect context information [5, 8] 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.

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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 for the performed activity. Our focus in this paper is on better accuracy and performance efficiency of Context-aware Activity Manipulation Engine (CAME) component of our proposed HARE [7] which in first phase is deployed for Alzheimer disease patients. 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]. With the use of ontology (containing expert knowledge of medical domain) these human activities detected using different sensors [7] are intelligently manipulated to infer higher level activities and also make the situation analysis. The experimental results of CAME in [7] showed fairly good accuracy and then with rule based filtering for situation analysis and decision making. Here we have made some extensions in match making process to enhance the accuracy and performance of CAME.

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. 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.

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. 1, y-axis is the % of Precision for match making process while x-axis represents the number of experiments. The graph in Fig. 1 shows that precision of CAME initially

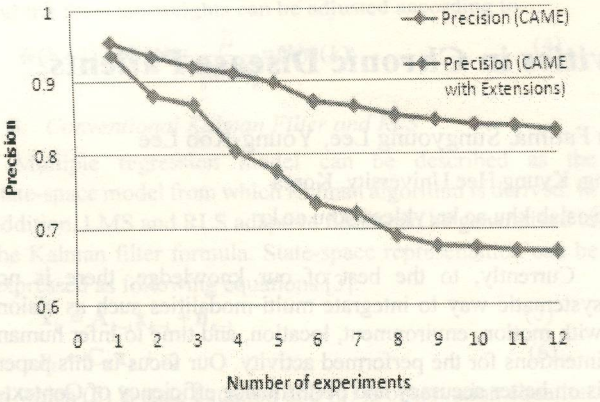


Fig. 1. Comparison between CAME and extended CAME precision for 12 different experiments with increasing number of activities.

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 0.6680 and .8310 respectively.

In CAME development, we used A-Box inferring that only involve instances. 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 was the unknown activities detected by the sensors. As we focused 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 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.

After the extensions made to the CAME, we tested both CAME and extended CAME for their response time. As shown in Fig. 2, the extended CAME in initial tests takes more time (time is in milliseconds) 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. All the experiments for response time of both CAME and extended CAME were conducted on machine with 2.66 GH Quad Core and 4 GB of primary memory.

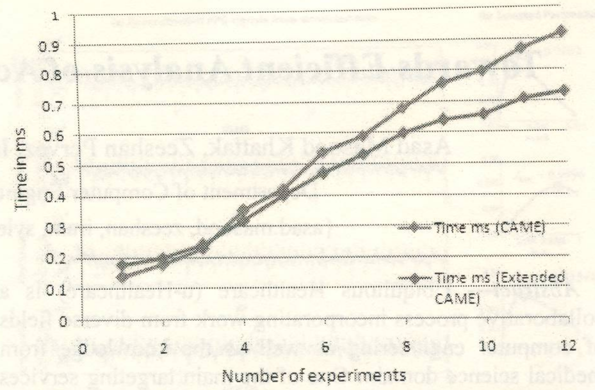


Fig. 2. Response time comparison between CAME and extended CAME.

We used 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 used the description logic rules refer to [7] compiled with the help of experts (Doctors) knowledge 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.

## 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] 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.

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

[5] 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.

[6] 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.

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

[8] 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.

[9] 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.