SHB: Type I (EXP): Context-aware Ubiquitous Human Health Monitoring

PI: Weihua Sheng, Co-PI: Qi Cheng

School of Electrical and Computer Engineering
Oklahoma State University, Stillwater, OK 74078, USA

Laboratory for Advanced Sensing, Computation & Control (ASCC Lab)
http://ascc.okstate.edu

I. Motivation

Recent years have seen a growing demand for ubiquitous health monitoring systems that can be deeply integrated into human's daily life. During the last few years considerable research efforts have been made in wearable health monitoring. However, researchers nowadays still face several fundamental challenges, which should be tackled before the full potential of these new health monitoring technologies can be exploited in real healthcare practice.

- Most of the existing wearable health monitoring systems only collect vital sign data, while ignoring human's behaviors and the environmental context. Study shows that knowledge about human daily activity and environmental context complements vital sign data, and is important to conducting accurate assessment of human health conditions.
- It is highly desirable that such a health monitoring system can function in an everyday life setting, which implies that (1) it should minimize its obtrusiveness to the human subject; (2) it should not require significant infrastructure support, such as beacons around the residence.
- Combing the large volume of vital sign and human status data for anomaly detection will be a daunting task for the caregivers. It is very important to develop data mining algorithms that can provide early warning of abnormal patterns or signs to support health assessment. More importantly, such anomaly detection should take the human status into consideration.

II. Objective and Long Term Goal

The objective of this project is to develop a ubiquitous human health monitoring system that collects not only vital signs, but also daily activities and environmental context of a human subject in an everyday life setting. From these collected data, higher level knowledge such as anomalies will be extracted to assist health evaluation, medical diagnosis/prognosis or healthcare delivery. Such a system is called a ***Smart Health Monitoring (SmartMon) System***. The PIs' long term goal is to develop smart, human-friendly and low-cost wearable human health monitoring and healthcare delivery systems which can revitalize a wide spectrum of existing healthcare practice.

III. Hardware Platform

The overview of the SmartMon system is shown in Figure 1. The hardware platform consists of two parts: a wearable wireless ECG sensor kit (Figure 2) and a set of wearable wireless motion sensors (Figure 3).

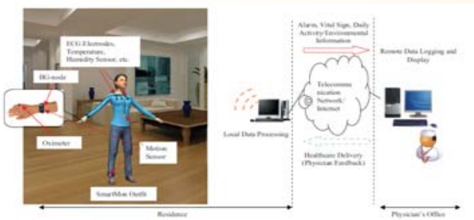


Fig 1. The SmartMon system overview.

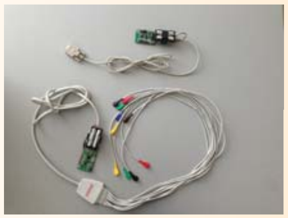


Fig 2. The wearable ECG sensor kit.

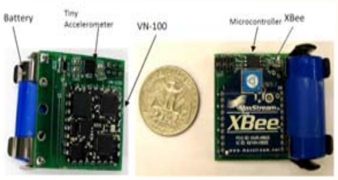


Fig 3. The wearable wireless motion sensor.

- The ECG sensor kit consists of a data collection/transmission unit carried by the human subject and a receiving unit attached to a computer. These two units talk to each other through Zigbee protocol.
- The motion sensor consists of a VN-100 orientation sensor module and a Zigbee communication module. It collects 3D acceleration, angular velocity and orientation data at a rate of 20HZ.

IV. Theoretical Framework

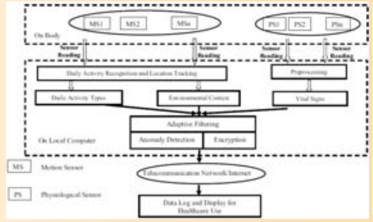


Fig 4. Overview of SmartMon operation.

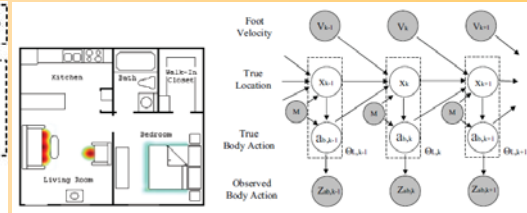


Fig 5. Stand-alone simultaneous tracking and body activity recognition.

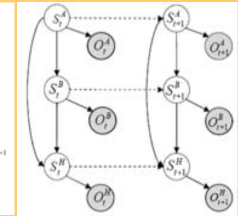


Fig 6. Daily activity recognition.

V. Results

- **Daily Activity Recognition**

We have implemented human activity recognition in indoor environments. Our algorithm can recognize body activities such as sitting, standing, walking, lying, etc. Our algorithm can also recognize complex daily activities such as eating, cooking, reading, using computer, etc.

As shown in Figure 7, a mock apartment is constructed in our lab. A human subject `lives' in this environment. Three motion sensors are attached to one hand, the waist and one leg of the human subject, respectively.

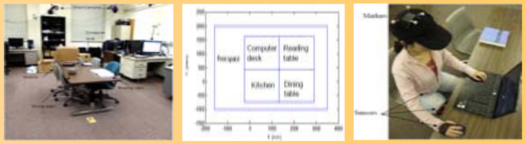


Fig 7. Experimental setup for activity recognition.

The results reveal that human daily activities can be recognized with high accuracy. Figure 8 shows the recognition results when the subject conducts various body activities. Table 1 shows the recognition results when the subject conducts daily activities in the mock apartment.

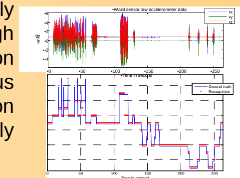


Fig 8. Body activity recognition result.

Ground truth	Decision type											Accuracy
	Sitting	Sit-to-stand	Stand-to-sit	Standing	Walking	Typing on keyboard	Using the mouse	Flipping a page	Cooking	Eating	Missed	
Sitting	**1.00**	--	--	--	--	--	--	--	--	--	--	1.00
Sit-to-stand	--	**0.92**	--	--	0.08	--	--	--	--	--	--	0.92
Stand-to-sit	--	--	**0.90**	--	0.06	--	--	--	--	--	0.04	0.90
Standing	--	--	--	**1.00**	--	--	--	--	--	--	--	1.00
Walking	--	--	0.02	--	**0.98**	--	--	--	--	--	--	0.98
Typing on keyboard	--	--	--	--	--	**0.83**	0.08	--	--	--	0.09	0.83
Using the mouse	--	--	--	--	--	0.05	**0.76**	--	--	--	0.19	0.76
Flipping a page	--	--	--	--	--	--	--	**0.85**	--	--	0.15	0.82
Cooking	--	--	--	--	--	--	--	--	**0.82**	--	0.18	0.82
Eating	--	--	--	--	--	--	--	--	--	**0.80**	0.20	0.80

Table 1. Confusion matrix for daily activity recognition.

- **Anomaly Detection**

Based on the data collected by the motion sensors, behavioral anomaly is detected. As an example, fall detection is implemented (Figure 9). Based on the data from the ECG sensors, vital sign anomaly is also detected. As an example, detection of sleep apnea is implemented (Figure 10).

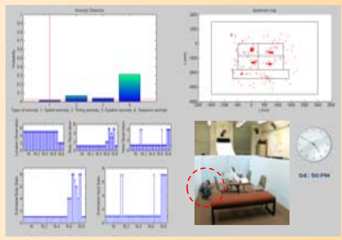
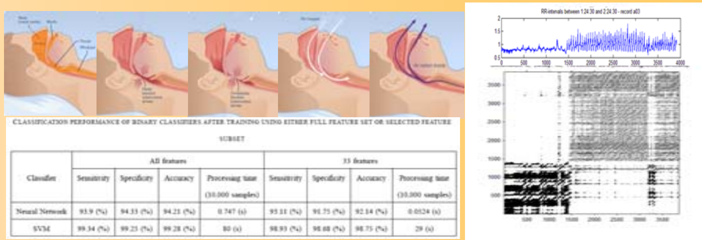


Fig 9. Fall detection as an example of behavioral anomaly.



CLASSIFICATION PERFORMANCE OF BINARY CLASSIFIERS AFTER TRAINING USING EITHER FULL FEATURE SET OR SELECTED FEATURE SUBSET

Classifier	All features				33 features			
	Sensitivity	Specificity	Accuracy	Processing time (10,000 samples)	Sensitivity	Specificity	Accuracy	Processing time (10,000 samples)
Neural Network	93.9 (%)	94.33 (%)	94.21 (%)	0.747 (s)	93.11 (%)	91.75 (%)	92.14 (%)	0.0524 (s)
SVM	99.34 (%)	99.23 (%)	99.28 (%)	80 (s)	98.93 (%)	98.68 (%)	98.75 (%)	29 (s)

Fig 10. Sleep apnea detection as an example of vital sign anomaly.

VI. Conclusions

We have developed the hardware platform of the SmartMon system to collect human motion and vital sign data. Daily activity recognition has been realized. Anomaly detection has been implemented for fall detection and sleep apnea detection. This SmartMon system exhibits the capability of identifying, predicting and adapting to dynamic human contexts, which reaches beyond today's technologies and significantly improves the accuracy, adaptability and usability of the next-generation health monitoring system.

VII. Acknowledgments

This project is supported by NSF grant CISE/IIS 1231671.