

Emergency Alarm System: Prototype and Experience

Meng-Che Teng Ju-Peng Chen Tsung-Han Lin Polly Huang
Department of Electrical Engineering
National Taiwan University
{b89901097, b90901002, b90901046}@ntu.edu.tw phuang@cc.ee.ntu.edu.tw

Chia-Li Huang
Department of Computer Science and Information Engineering
National Chi Nan University
s0321006@ncnu.edu.tw

Chia-Hui Chen
School and Graduate Institute of Nursing
National Taiwan University
cheryl.chen@ha.mc.ntu.edu.tw

Heng-Shuen Chen
Department of Family Medicine
National Taiwan University Hospital
chenhs@ntu.edu.tw

Abstract – Finding fusion in the domain of engineering and healthcare, we propose a wearable emergency alarm system that 1) monitors continuously the activity levels of the patient and 2) detects anomalies, in particular unconsciousness, in a timely fashion to alert the caregivers of the emergencies. In this summary, we share our experience building the first prototype and the preliminary results that support the feasibility of the system and give rise to a number of design choices towards better energy efficiency and emergency event detection accuracy.

I. INTRODUCTION

The advances in sensor and electronic manufacturing technologies have enlightened a future of intelligent and pervasive computing. In that, specialized, optimized, miniature computers will be able to detect and communicate the *situation* of the environment and in turn help with the daily livings. For example, auto-detection of the room temperature allows tuning of the air conditioning to the level just as necessary. Furthermore, detection of the pulse anomalies allows prevention of irreversible damages caused by diseases that are preceded by arrhythmia.

Seeking applications of such miniature sensor computers in the healthcare domain, we target the stroke-prone population that includes the very high-risk transient ischemic attack (TIA) patients and the general high blood pressure group. For these patients, the earlier the stroke is identified and the treatment is applied, the lower the degree of irreversible damage to the brain there is. Aiming to facilitate automatic early detection of serious strokes of which loss of consciousness is often the consequences, we propose a wearable emergency alarm system that monitors constantly the motion and audio levels of the patients. From the motion and audio data, the system can potentially infer states of unconsciousness by observing an abnormal amount of low motion and audio periods. We present in this paper summary the prototype experience and the preliminary results that demonstrate the wearability and feasibility of the system. Also from the preliminary results, we are able to identify a number of design choices towards better energy efficiency and emergency event detection accuracy.

II. SERVICE MODEL

Stroke is well recognized as a major cause of death and long-term disability. The amount of grief and medical expenditure due to stroke is virtually incomprehensible. In the US, stroke is the top 3rd cause of death. It would take the lives of 275,000 people and disable another 370,000 every year. The situation is similar in Taiwan where stroke has been the top 2nd cause of death since 1992. There are about 2.5 million stroke patients in the US population. About two third of the patients are under the age of 65 and 10 % of the patients need to be situated in long-term nursing facilities. The American Heart Association estimated [14] that the total annual cost due to stroke amounts to 53 billion dollars in 2004.

To focus on well-understood stroke-prone population, we target patients who suffered from transient ischemic attacks (TIA). A TIA is the result of a temporary interruption of blood flow to the brain and is sometimes referred to as a mini-stroke. The lack of oxygen to the brain will cause the same symptoms as those produced during a full stroke. These might include confusion, numbness or weakness in the face, blurred vision, severe headache, dizziness or trouble walking. TIAs are one of the best indicators of future stroke. Researchers have found that 11% of patients diagnosed with TIA in an emergency room will have a stroke within the next 90 days and about 30% of the TIA patients will have a stroke within three years.

The emergency alarm system wearable by the TIA patients can monitor the activity levels of the patients and alert the caregivers if an abnormally low amount of activity level is detected, i.e. going unconscious after having a stroke attack. We think that the similar service model might be extended to help other stroke-prone patients or patients of other diseases that would benefit from such automated unconsciousness detection systems, for example heart attack and diabetic coma.

III. RELATED WORK

The general idea of constructing the automated emergency

alarm system is not new. Systems such as [7][8] share our vision. Concerning specifically the service model, [10] investigates the strategy for emergency prevention and management. Concerning the system design, there exist commercial products, such as [13] providing a safety button for the patients to call for help. Wearable multi-sensor systems are closer to our approach. There have been such systems built for various purposes, for example, tracking location [5][9], annotating recorded conversations [4], and recognizing human activities [12]. Human activity recognition is close to what we plan to achieve in detecting unconsciousness. Researchers have taken different sensing and system architecture to detect human activities. Some use vision-based sensors, such as cameras [15][23]; some use motion sensors, such as accelerometers [1][6]. The emergency alarm system is close to the motion sensor based systems in the choice of sensor technologies. Our system is unique in that we aim to infer unconscious states of patients and unconsciousness detection, as opposed to fall detection [2], is a topic that has not yet been addressed by the research community.

IV. SYSTEM DESIGN

The emergency alarm consists of the hardware, communication and software components. In the system hardware component, we aim at building a system integrated with sensors, wireless communication, and processing capabilities. The system uses more affordable sensors such as accelerometers, microphones to monitor the motion and audio levels at the two wrists and the back of the neck. The hardware can be customized to the physical forms that optimize the wearability, for example as watches, necklace or other accessories.

In terms of communication, data from the various sensors are transmitted over a wireless sensor network and gathered at a personal gateway, for example the patient's mobile phone or PDA. The data could further be transmitted over the wide-area wireless network, for example, GPRS, to combine with the patient's medical record online as the patient lives the average mobile lifestyle.

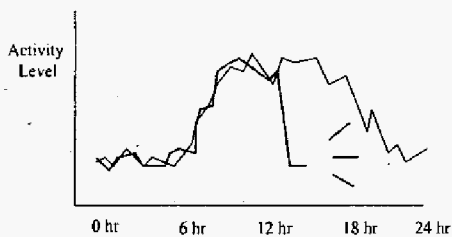


Figure 1. Principle of Detecting Anomalies

To detect unconsciousness, we take an adaptive learning approach, commonly used in artificial intelligence or signal processing, to infer abnormal amount of motionless or quiet periods from the activity level data. Figure 1 illustrates the general idea of unconsciousness detection. When the

potential unconsciousness is detected, the system will trigger the confirmation mechanism, which is designed mainly to suppress reports due to false positives. The confirmation mechanism will signal the patient by means of vibration or alarming sound. This emulates how we verify the state of unconsciousness in real life, i.e., stimulating the patients by calling the names or slapping at the faces. If the patients are conscious, they will respond and suppress reports of the inferred unconsciousness events.

V. SYSTEM PROTOTYPE

The prototype is built on the Berkeley Mote/TinyOS platform. A Mica Mote is a wireless sensor device which consists of an embedded microcontroller, low-power radio, and a modest amount of local storage in a small (5.7 cm × 3.2 cm × 2.2 cm) package, powered by 2 AA batteries. Motes attached on human body collect motion and audio data and transmit them to a more resourceful computer for further analysis and anomalies recognition. When an emergency event occurs the system will recognize it and notify the medical center.

A. Hardware Components

We used MicaZ (Figure 2) and Stargate (a PDA-scale embedded system) to implement the system. Three MicaZ nodes are attached on user's neck, left wrist, and right wrist, and a Stargate is placed in the user's pocket. MicaZ is the sensing unit which contains accelerometer, acoustic sensor and other sensors. All three of them are set to collect acceleration data. And we also collect acoustic data from the sensing board on the neck to determine if the user is speaking. The Stargate in user's pocket works as a personal gateway. It collects accelerometer and acoustic data from MicaZ and sends it back to a personal computer for further analysis. MicaZ and Stargate communicate at 2.4 GHz in 250 kbps through a protocol called Zigbee, and Stargate then transmits data to a PC through WLAN.

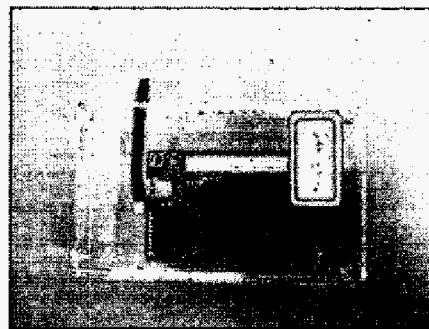


Figure 2. MicaZ

B. Software Components

The MicaZ runs an operating system called TinyOS and the applications are written in NesC. NesC is a new language for programming structured component-based applications. The

nesC language is primarily intended for embedded systems such as sensor networks. nesC has a C-like syntax, but supports the TinyOS concurrency model, as well as mechanisms for structuring, naming, and linking together software components into robust network embedded systems. We implement the sensing function on MicaZ by utilizing an opponent called TestSensor which activates all the sensors on MicaZ and collect data from them. Our personal gateway, Stargate, runs Linux and uses the C language. We implemented a function called Xlisten to get data from MicaZ. Then the Stargate transmits the data back to computer through WLAN for further analysis.

VI. PRELIMINARY RESULTS

We tested the prototype and collected preliminary acceleration and audio data. The further analysis and anomalies recognition are yet to follow.

A. Experimental Design

We attached three MicaZ on the neck and wrists of the tester, and collected data continuously for one hour. The test subject is asked to be active and inactive in interleaving 10 minutes intervals. So we can observe if there is obvious difference between normal data and data collected when the test subject is unconscious.

B. A First Look at the Data

The acceleration and sound data collected from one of the three MicaZ nodes are shown in Figure 3. The Y-axis represent the amount of acceleration and the X-axis represents time. In the graph, we can see clear distinction between active and inactive periods. However, the level of the values does not indicate the level of activities. For example, higher accelerometer values do not necessarily mean higher activity levels and vice versa. The data processing mechanism should look for the relative difference. Therefore, variance of the signal will be a better indication of the activity level.

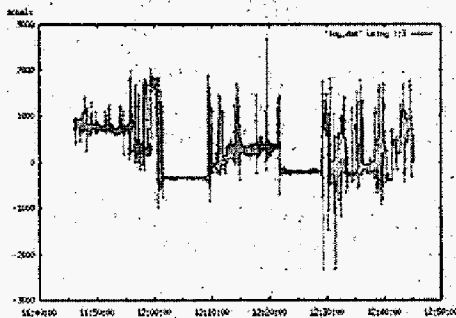


Figure 3. On-Off Patterns Observed from the Motion Sensors

We also observed distinction between active and inactive period in acoustic data. Especially the acoustic data collected from sensor attached on the neck show clear difference when the test subject is speaking. It allows us to detect conversation and could thus be a very useful indication of unconsciousness.

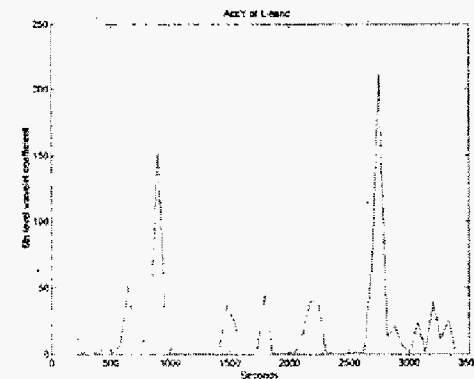
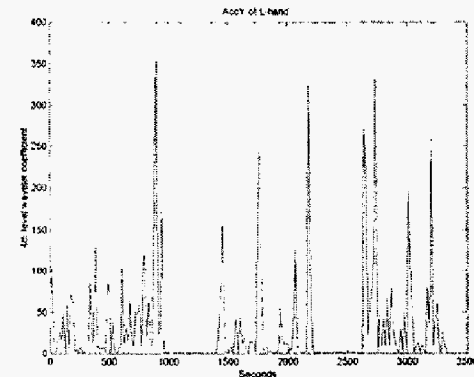
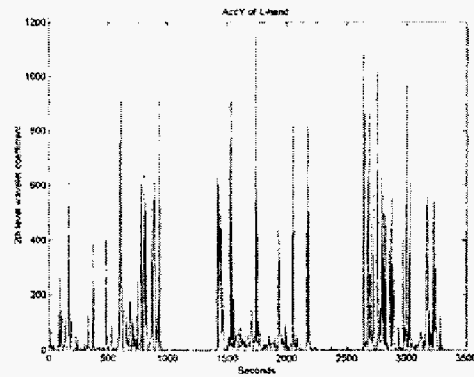


Figure 4. Top to bottom: Wavelet Coefficients of the Sensor Data at the 4-second, 16-second, and 64-second Levels.

The data collected during one hour amount to 1MB, thus for longer period of activity monitoring, a data compression algorithm might be necessary concerning limited storage on Stargate. Replacing the wired power, we hook the Stargate up with a battery pack that holds 2 AA high capacity batteries. The Stargate collecting data from 9 sensors and each samples at once-per-second rate drains batteries in about half an hour. This implies that in order for the system to function in a

continuous basis, we need to reduce the rate of data sampling and the amount of sensor data transmissions as much as possible.

C. Extracting Variances

We use the discrete wavelet transform [15] to extract the variance of the signal. There are major two reasons to our choice of the variance extraction technique. The first one is that the wavelet transform is computationally efficient and easy enough to be implemented on MicaZ to processing on the spot and avoid excessive transmissions of raw data. The second reason is that it allows us to observe the variances in the signal at different resolutions in time.

Figure 4 illustrates the variances in the sensor signal at the 4-second, 16-second, and 64-second levels. The most dominant resolution of human motions is at the 16-second frequency. Although the 16-second level coefficients lose some details that are at the 4-second level, they nonetheless capture the 4-second scale profile. The 64-second level coefficients are at an even coarser granularity, and to this point, some of the finer human motions are lost. Examining the variance of the signal at the 64-second level is, according to the preliminary results, too rough. The dominant 16-second scale suggests that the data sample interval is better set to 8 seconds such that the resolution is just good enough for observing interesting activities and in the meantime only a fraction of the energy, relative to 4-second scale monitoring, is required to sample at one quarter of the rate.

D. Emergency Detection

The characteristics for the inactive period are that the degree of variance is low and low for the whole duration of the inactive period. There might be some point in time experiencing a low degree of variance during the active period but this is only occasional. We thus take the majority vote approach and determine whether the user is non-active at a certain point in time by calculating whether the majority of the consecutive k points in time show a low degree of variance.

To establish the everyday profile as shown in Figure 1, we derive the probability of the user being active at the various points in time in a day from a long-term trace. A red-light alarm is triggered when an inactive event is detected but the profile shows a high probability of the user being active. Similarly, one may define the yellow-light or green-light situations as when an inactive event occurs at a point that is not quite as active or highly inactive.

VII. CONCLUDING REMARKS

At present stage, we managed to implement the prototype and have several preliminary experiments done. The data collected from the experiments have enlightened the system feasibility. The results also hint that the 'variance' of the signal will be a better indication of the activity level. More work on data analysis and pattern recognition is yet to be completed. In addition to recognizing the patterns, placement of the sensors, data storage, power consumption and hardware design remain important issues to pursue in a longer term.

REFERENCES

- [1] K. Van Laerhoven and H.-W. Gellersen. "Spine versus Porcupine: a Study in Distributed Wearable Activity Recognition". In Proceedings of the eighth International Symposium on Wearable Computers, ISWC 2004, Arlington.
- [2] Hammadi Nait-Charif and Stephen J. McKenna. "Activity Summarisation and Fall Detection in a Supportive Home Environment" In Proceedings of International Conference on Pattern Recognition, ICPR 2004.
- [3] Yang Song, Xiaolin Feng, and Pietro Perona. "Towards Detection of Human Motion" In the Proceedings of CVPR 2000.
- [4] N. Kern, B. Schiele, H. Junker, P. Lukowicz, and G. Troster. "Wearable sensing to annotate meeting recordings" In Proceeding of the Sixth International Symposium on Wearable Computers (ISWC'02).
- [5] A. R. Golding and N. Lesh, "Indoor navigation using a diverse set of cheap, wearable sensors". In Proceedings of the third International Symposium on Wearable Computers, 1999.
- [6] N. Kern and B. Schiele. "Multi-Sensor Activity Context Detection for Wearable Computing". In Proc. Of European Symposium on Ambient Intelligence, 2003, Eindhoven, The Netherlands.
- [7] N. M. Barnes, N. H. Edwards, D. A. D. Rose, and P. Garner. "Lifestyle monitoring: technology for supported independence". IEE Computing and Control Engineering Journal, August 1998.
- [8] S. Bonner. "Assisted interactive dwelling house: Edinvar housing association smart technology demonstrator and evaluation site". In Improving the Quality of Life for the European Citizen (TIDE), 1998.
- [9] M. Chan, H. Bocquet, E. Campo, and J. Pous. "Remote monitoring system to measure indoors mobility and transfer of the elderly". In Improving the Quality of Life for the European Citizen (TIDE), 1998.
- [10] K. Doughty. "Fall prevention and management strategies based on intelligent detection, monitoring and assessment". In New Technologies in Medicine for the Elderly, Charing Cross Hospital, London, November 2000.
- [11] C. R. Wren, A. Azarbayejani, T. Darrell, and A. Pentland. "Pfinder: Real-time tracking of the human body". IEEE Trans. PAMI, 1997.
- [12] Emmanuel Munguia Tapia, "Activity Recognition in the Home Setting Using Simple and Ubiquitous Sensors". Massachusetts Institute of Technology 2003.
- [13] American Senior Safety Agency, The "Button", 2002.
- [14] Heart Disease and Stroke Statistics, 2004 Update. American Heart Association (AHA), 2004
- [15] Ingrid Daubechies, Ten Lectures of Wavelets, CBMS-NSF Regional Conference Series in Applied Mathematics, No 61, 1992