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on Wearable
Computers
October 11–14, 2006

Student Colloquium Proposals

http://www.iswc.net/colloquium.html Montreux, Switzerland

Index

Foreword

Cue the TV-show announcer: "*Previously.. on ISWC..*". With this being its 10th edition, this symposium is getting to a stage where many of the student volunteers from the early editions have now completed their PhDs and have become experts in their own domain of wearable-related research.

Think of a student colloquium as another way of introducing young students and budding researchers to the world of ISWC, with a bit more focus on research, compared to student volunteers. Instead of dragging buckets of coffee around and pointing attendees to the nearest toilets, these newcomers to wearables research got their proposals read by experts in their domains and the best are given the opportunity to present their research to the community at its main annual event.

This year's ISWC Student Colloquium selected six student proposal papers out of twelve submissions for you – a very tough acceptance rate! The panel of experts (listed on the next page) made sure that the proposals contained interesting and valuable research that would be of interest to attendees of ISWC, both now and in the future. The proposals which were not selected for inclusion in these proceedings still received a lot of expert advice to improve their proposals, and these will hopefully find their way to a future ISWC.

Speaking of which. I'm confident that the proposals in these proceedings will grow into quality full papers in ISWC in the near future, so "*stay tuned*" and read the following pages as exclusive previews of future research in wearable computers.

The ISWC Student Colloquium Chair:

Kristof Van Laerhoven
September 2006
Darmstadt University of Technology, Germany

Panel of Experts

The following people made sure that the submitted student proposals received tons of feedback on their proposed research:

- **Sharon Baurley** University of the Arts London, UK
- **Mark Billinghurst**, HitLab, New Zealand
- **Ozan Cakmakci**, University of Central Florida, USA
- **Lucy Dunne**, University College Dublin, Ireland
- **Francine Gemperle**, MAYA Design, USA
- **Tobias Hollerer**, University of California Santa Barbera, USA
- **Nicky Kern**, Darmstadt University of Technology, Germany
- **Gerd Kortuem**, Lancaster University, UK
- **Mat Laibowitz**, MIT Media Lab, USA
- **Kent Lyons**, Georgia Tech, USA
- **Walterio Mayol**, University of Bristol, UK
- **Wayne Piekarski**, University of South Australia, Australia
- **Albrecht Schmidt**, LMU Munich, Germany
- **Tsutomu Terada**, Osaka University, Japan
- **Jukka Vanhala**, Tampere University of Technology, Finland
- **Jamie Ward**, ETH Zurich, Switzerland

Wearable Communicator Badge: Designing a New Platform for Revealing Organizational Dynamics

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Abstract

We are developing a new wearable electronic badge that will enable people working in large organizations to communicate, find information, and interact in more efficient and intelligent ways. The badge will perform speech analysis and speech recognition using a microphone and state-of-the-art micro-power electronics. It will be capable of playing audio messages and reminders through a speaker. An accelerometer will allow us to study how people move and behave throughout the day: Are they walking to a meeting? Are they talking to someone? Are they sitting in front of their computers? An infrared sensor will be used to capture face-to-face interactions and study social networks. A 2.4 GHz radio transceiver will send and receive information from base stations distributed along a specific area and a Bluetooth module will enable it to interface with cell phones, PDAs, portable computers, and other Bluetooth-enabled sensors and devices.

1 Introduction

The vision that Mark Weiser and his colleagues at Xerox PARC had in the early 1990's of ubiquitous computing has become a reality [9]. Pervasive cell phones, PDAs, personal computers, and other portable electronic and wearable devices are commonplace in the workplace.

Wearable badges are common gadgets that employees wear in large organizations to identify themselves to others or to gain access to certain locations or information. The Active Badge developed at Xerox PARC was one of the first attempts to augment inanimate nametags with electronics. Containing only a small microprocessor and an infrared transmitter, this badge could broadcast the identity of its wearer and trigger automatic doors, automatic telephone forwarding, and computer displays [8].

We are currently developing the first prototype of a *Wearable Communicator Badge* that will allow us to integrate different research efforts at MIT Media Lab. This new research platform will allow us to study how members of different teams interact, exchange information, communicate their ideas, and form social networks within large organizations.

2 Related Work and Motivation

More complex badge platforms have been developed after the first Active Badge. One example is the SocioMeter, a wearable sensor package designed at MIT Media Lab to measure face-to-face interactions between people with an infrared transceiver, a microphone, and two accelerometers [1]. This badge was used to learn social interactions from sensory data, and model the structure and dynamics of social networks.

The UbER Badge is the most recent research platform developed at MIT Media Lab for facilitating interaction in large groups of people. This badge has both RF and IR communication, a 5 x 9 LED display capable of presenting graphics and scrolling text that users in the vicinity can read, an onboard microphone for 12-bit audio sampling, a 12-bit audio output available at a headphone jack, a pager motor for vibratory feedback, 3 onboard processors, capacity for up to 256 MB of flash memory, provisions for connecting LCD displays, and connectors that allow a variety of different sensors to be integrated [4]. It measures 8.25 x 10.5 cm and weights 100 grams. Its average current consumption is 100 mA and batteries last for about 15 hours of continuous usage.

The best known commercially available badge system is the 802.11-based Vocera communications system. With it, users interact through wearable badges that can be clipped to coat pockets, worn as pendants, or carried in holsters. The system architecture centers on a server that maintains voice dialing phrases, badge session identifiers, email addresses, telephone numbers, and names. The Vocera badge provides a voice-controlled user interface and enables instant, hands-free conversations among people throughout the workplace. It weighs 53.9 grams and measures 10.6 x 3.5 x 1.5 cm. The standard battery (Li-ion 600 mAh) lasts for 2 hours of talk time and 44 hours of standby time, and it is rechargeable through a single bay or 8-bay charger [7].

In addition to some of the main features offered by previous badge platforms, we want to add social intelligence to the *Wearable Communicator Badge* so that it will be capable of:

- Recognizing common daily human activities in real time using a single accelerometer [3].
- Performing speech feature analysis in real time to measure non-linguistic social signals and identify the social context [5].
- Interacting with the user through voice commands to find resources and information in a timely fashion.
- Communicating with radio base stations in the 2.4 GHz radio band for sending and receiving information from different users, and processing data.
- Performing indoors tracking and user localization by measuring the received signal strength and implementing triangulation algorithms.
- Communicating with Bluetooth enabled cell phones, PDAs, and other devices to study user behavior and routine through proximity sensing [2].
- Capturing face-to-face interactions using an infrared sensor to determine how much time users spend talking face to face [1].

The new badge must have a small form factor, be comfortable to wear for long periods of time (at least 8 hours a day), and have a long battery life so that it doesn't need to be charged every day. To achieve this, the badge is designed for very low power wake-up directly from sensor stimuli. We are currently evaluating the total power consumption and battery life.

3 Functional Description

In this section we present the concept of the *Wearable Communicator Badge* and describe the choice of electronic components that will be used in the first prototype implementation.

The output of an omnidirectional electret condenser microphone (currently evaluating a MEMs microphone) is connected to the non-inverting input of a micro-power single-stage non-inverting operational amplifier (AD8542), with a high-pass filtering cutoff frequency of 85 Hz realized via its feedback loop. The amplified microphone signal is then applied to an array of micro-power single-op-amp Sallen-Key band-pass filters with constant Q. A diode-capacitor peak detector is used after each band-pass filter to obtain the spectral envelope in each frequency band. These four spectral envelopes (85 to 222, 222 to 583, 583 to 1527, and 1527 to 4000 Hz) are applied to A/D inputs on the microcontroller and will be used for extracting different speech features such as energy and pitch. The output of a full audio band-pass filter also feeds an A/D input on the microcontroller directly for digital audio applications.

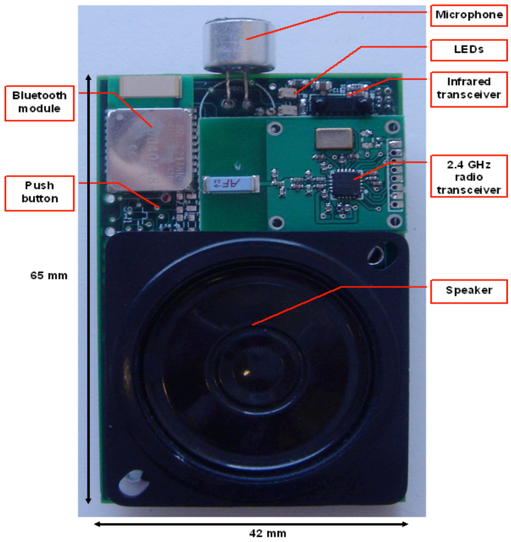

Figure 1. PCB front view

A microcontroller wake-up is also provided by a passive inertial component conditioned by a micro-power comparator. A 3-axis MEMS accelerometer (ADXL330) and infrared transceiver module (TFDU4300) are also powered up by the processor's power gate to save energy. All sensor electronics are powered up only when a significant sound is detected (indicating a possible conversation) or the passive inertial components detect significant motion. A bridged-output audio power amplifier (SSM2211) drives an electromagnetic speaker on the badge.

A 2.4GHz radio transceiver (CC2500) together with an ARM microcontroller (AT91SAM7S64) are being evaluated. A Bluetooth module (BR-C29A) has also been incorporated. A trans-flash memory card socket has been included for storing data when the user is out of range or when the badge is used as a self contained sensor package. The badge will be powered by a 1950 mAh Lithium-ion battery (CGA103450A) that measures 3.4 x 5.0 x 1.0 cm, weights 40 grams, and will be rechargeable through USB (BQ25010). The dimensions of the printed circuit board (PCB) are 4.2 x 6.5 cm. Figures 1 and 2 show the front and back views of our first prototype's PCB.

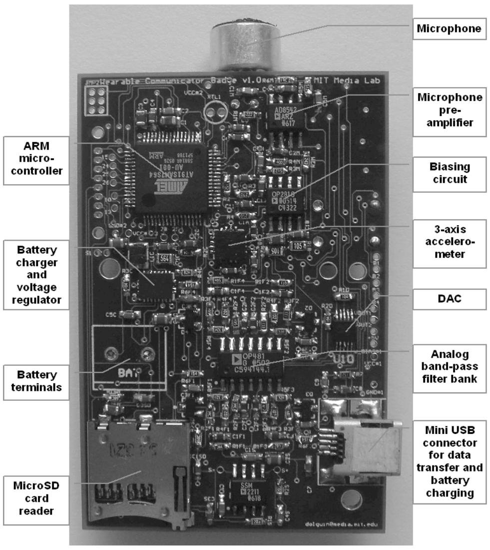

Figure 2. PCB back view

4 Applications

Sensible Organizations This is a new concept of social sensor network technologies that will help improve organizational practices. The *Wearable Communicator Badge* will allow us to quantitatively and qualitatively measure, analyze, and reveal organizational dynamics by closely looking at interactions and social behavior among employees of an organization. Companies will have a better understanding of how they work and how they can improve their daily routines in order to increase productivity, innovation, and job satisfaction.

Personal Sales Coach Recent experiments in the Human Dynamics Group at MIT Media Lab have shown that it is possible to measure how persuasive a person is being when talking to others, how interested a person is in a conversation, how much attention a person is paying to someone, and how effective someone is at negotiating all by measuring different voice features and body motion [5]. The *Wearable Communicator Badge* will be used to track individual and global sales performance in retail stores and give advice on how to make interaction with clients more effective.

Healthcare The *Wearable Communicator Badge* will also be used for a variety of healthcare monitoring applications, such as depression state tracking, eldercare, triage in the emergency room, and others. Sung et al [6] showed that non-invasive behavioral measures such as voice features and body motion are correlated to depression state and can be used to classify emotional state and track the effects of treatment over time.

5 Conclusions and Future Work

The first version of the badge is currently under revision. We are building ten of them for our initial studies. We will then make it as efficient as possible and reduce power consumption to a minimum by adding a nano-power comparator to detect the presence of significant audio and wake up the microcontroller. A vibration sensor will also indicate when there is significant motion. Migration to a low power microcontroller is also being considered in case the battery life needs to be significantly extended.

We plan to build several hundred badges and use them in real organizations both to study everyday social dynamics and to experiment with the different applications described in this paper. We will attempt to measure variables such as creativity, efficiency, productivity, and innovation using this research platform, with the goal of redefining current management practices.

6 Acknowledgements

We would like to specially acknowledge Hitachi LTD for their support as member of the Things That Think Consortium at MIT Media Lab. We would also like to thank Mat Laibowitz and Mark Feldmeier for their insightful help and advice in the design and testing of our first prototype.

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A system architecture for the gathering and distribution of wireless sensor data in wearable computing

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Abstract

This paper describes a system architecture for a power-efficient wireless sensor network platform that can be used for wearable computing. Current wearable sensor platforms and applications are discussed and evaluated, after which requirements for successful, cost-effective solutions are defined. A system architecture for small, power-efficient wearable sensor nodes is then proposed and discussed.

1. Introduction

Research in wireless sensor networks can be seen as an interdisciplinary approach to solving problems in multiple domains. The obvious reason for utilizing wireless sensor networks in wearable computing is to eliminate the need for wires to connect sensors to a communication unit that transmits the sensor data off the body.

There are numerous applications for wireless sensor networks in wearable computing, for example:

- Health monitoring, e.g. using electrocardiograph (ECG) sensors to monitor heart rate and accelerometers to measure physical activity.
- Context awareness, e.g. estimating a person's location and proximity to other people and nearby devices by measuring received signal strength from other wireless devices like cell phones and laptops.
- Auto-event recording, e.g. monitoring the work flow of a medical nurse's activities by making use of tilt sensors, a pedometer and a microphone.

A device called a polysomnograph consists of various kinds of physiological sensors and is often used for patient monitoring. Advanced Medical Electronics Corporation has manufactured a wearable polysomnograph, but it only transmits data off the body with a short-range wireless connection, is quite bulky to wear and the batteries only last about 12 hours [1].

The MIT Media Laboratory has several research projects geared toward interactive media and entertainment, for example footwear that detects and responds to dance movements and gestures [2].

In a recent survey [3] end-users and system integrators where asked whether they would consider deploying a wireless sensor network in the near future. The two main reasons for not deploying a sensor network were expense and reliability. The following aspects constitute requirements for a wireless sensor node used in wearable computing – it must be small, lightweight, rugged, energy-efficient, cost-effective, and reliable.

2. Related work

IBM Research's Personal Mobile Hub (PMH) was originally conceived as a personal wearable gateway that would act as an access point for a user's wearable devices, like health sensors or audio players. It includes a GSM/GPRS module, Bluetooth transceiver and a microprocessor that acts as a personal server. In the end it was replaced by a platform that provided most of the capabilities of the original PMH - a Sony Ericsson P800 cell phone. As they noted, customers are more comfortable trying new software on a platform that has good support and is readily available [4]. This is why it is necessary to augment existing cell phone hardware with the required functionality, instead of developing dedicated platforms that essentially perform similar functions.

While a wireless Personal Area Network (PAN) of intelligent sensors has been proposed [5], the authors make use of a separate platform called a personal server to communicate the sensor data off the body.

3. Proposed solution

In this paper a system architecture for a wearable sensor network platform is described that utilizes existing technologies and hardware. Since the sensor node will be worn on the body, it is either integrated into a piece of clothing, or attached to the body without causing discomfort to the wearer.

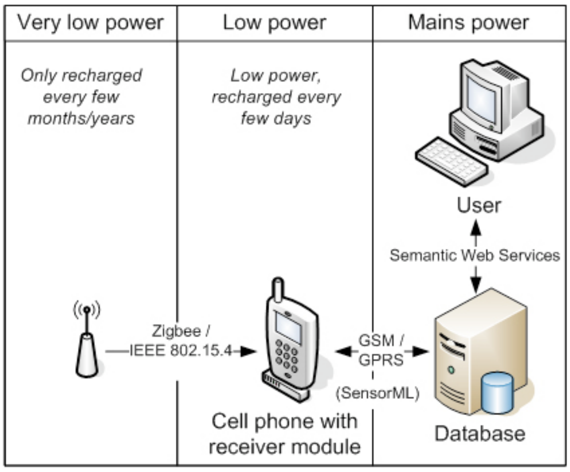

Figure 1. System architecture

With the radio transceiver being responsible for more than two-thirds of the total power consumption in a sensor node, it is imperative that its power consumption is minimized. In [6] it is shown that high-bit rate, low duty cycle radio transceivers are on average more power-efficient than the low-bit rate transceivers currently implemented in wireless sensor networks. By minimizing the message packet size (see section 4) the duty cycle is kept low. A medium to high bit rate of 250 kbps is achieved by implementing an IEEE 802.15.4 compliant radio transceiver. The limitation of such an approach is that typical data transfer rates may only be ~60kbps. If a large number of sensors will be used, signal processing must already be done on sensor node level.

In Internet protocols, the data packets being sent usually include a lot of information specifically catered for wired networks that are usually not constrained by any power limitations. The Internet architecture and its component protocols are well suited to their purpose, but trying to migrate the design to other architectures with completely different requirements (like wireless sensor networks) can only prove disastrous [7]. Since we want to keep the advantage provided by low duty cycle transceivers, message sizes are kept at a minimum.

The sensor node has to be physically small, not only for comfort, but also for privacy. In the case of medical monitoring devices, the user may not wish to disclose that he/she is wearing such a device. Through the utilization of System-on-Chip (SoC) devices, like Chipcon's CC2430 (that integrates a microprocessor, RF transceiver and flash memory onto one microchip), we can sufficiently miniaturize even prototype designs, without resorting to much larger designs that is currently the norm in wireless sensor network research efforts.

While some cell phone manufacturers like Pantech & Curitel have already implemented the Zigbee communication protocol on their devices, it is not expected that these devices will achieve the same cell phone market penetration that Bluetooth currently enjoys. This is why a wireless Zigbee transceiver module is required to interface with cell phones already owned by users. The module allows the cell phone to act as a micro-server and micro-router to the various mobile devices and sensors worn by the user.

Zigbee is set to become the standard for wireless PANs and devices that require low data bit rates and minimal power consumption. Due to Bluetooth's wide market acceptance, some researchers made the effort to indicate that it can be made power efficient through proper power management [8]. The problem is that Bluetooth was designed to replace wired connections between mobile devices and a computer, not for wireless PANs or wireless sensor networks.

While a database approach is useful for scientific applications, sensor data needs to be aggregated and properly managed. [9] and [10] describe sensor information systems to properly mine and manage large amounts of sensor data. Semantic services' primary role is to extract new semantic information from existing data streams. Semantic services allow a user to access sensor data by referring to "vehicle speed at garage entrance" instead of accelerometer values and break-beam events.

To enable semantic access to sensor data the sensors have to be properly described. This is done by making use of standards like the Sensor Modeling Language (SensorML) [11]. SensorML not only describes individual sensors, but also the geometric, dynamic and observational properties of the sensors.

4. System architecture

A system architecture for the proposed solution as described in the previous section is displayed in figure 1. The sensor nodes transmit the sensor data to the Zigbee receiver module that is directly connected to the cell phone. The cell phone transmits the sensor data via the cell phone network to a database server, from where the data is accessed using semantic web services. Whereas the power consumption of ubiquitous sensor nodes is of utmost importance (so that they can be integrated into clothing or remain on the body), people are used to recharging their cell phones every few days.

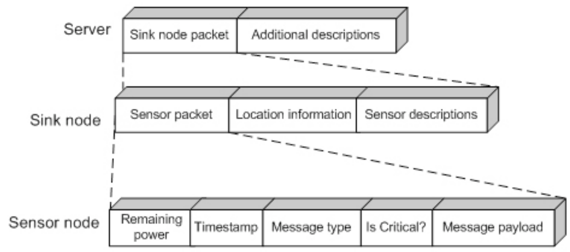

Figure 2. Packet structure

Only acquired sensor data and the occasional location updates are sent from the sensor node to the sink node (receiver module and cell phone) to minimize the amount of traffic and to maintain a low duty cycle.

Users query the database and not the individual sensors or even the cell phone, as this will lead to an unnecessary increase in power consumption due to the additional amount of traffic on the network.

While IP addressing is based on the Internet architecture, wireless sensor networks require location information more than the actual ID or address of the node [7]. Instead of increasing the message packet size by including location information, the location coordinates are encoded into the 64-bit extended address that complies with the Zigbee addressing scheme. Location information is obtained by implementing a SoC solution with an integrated location estimation engine.

To conserve power, querying is only done on database or sink node level. Messages from the sink node to the sensor nodes are kept to a minimum, so that the sensor nodes only have to transmit data to the sink node at certain intervals or when certain events occur.

When IEEE 802.15.4 beaconed mode is used, nodes can switch off their transceivers during an inactive period, wake up just before the beacon packet is to be received to ensure time synchronization, and go back to sleep if there is no data to send.

Figure 2 describes a message packet structure for wireless sensor networks in wearable computing, with a minimum amount of data communicated by the sensor node to keep the duty cycle low. The packet structure is a modified version of that of our SEER routing protocol as described in [12]. As the remaining battery power will affect many software layers the battery power is communicated across layers, even when a routing protocol is not required. This field can be made optional, or may only be transmitted every few cycles. A timestamp is used to indicate the time the sensor reading was taken, while the "Message type" field indicates whether the messages are data messages or broadcast messages. The "Is critical?" field provides a rudimentary form of Quality of Service (QoS).

Time synchronization is required at sink node level to be able to provide timestamp information. IEEE 802.15.4 beaconed mode uses a frame beacon packet that can be used for time synchronization.

Since the system adheres to the IEEE 802.15.4 standard, the address and sequence information is already included in the MAC sublayer frame. The sink node adds extra information to the packet, such as coarse grained location information and descriptions of the sensors (in SensorML format, for example). Once the message packet from the sink node reaches the server, additional information can be added as the length of the packet is not of great concern anymore.

Interference from other sensor networks can be minimized by communicating on different channels (IEEE 802.15.4 in the 2.4 GHz band can use 16 channels) and by having each sink node (cell phone) operate as a different Zigbee device coordinator.

5. Conclusion

In this paper a system architecture was proposed for a small and power-efficient wearable wireless sensor platform.

We are currently developing a small, wearable sensor node that has the capability to interface with different sensor types through a standardized connector interface. We are also developing a Zigbee receiver module that directly interfaces with a cell phone. A wireless sensor network for indoor localization is also being developed.

By augmenting existing wearable devices already owned by users with wearable sensors, cost effective solutions can be developed for wearable computing.

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Human Activity Recognition: Accuracy across Common Locations for Wearable Sensors

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Abstract

In recent years much work has been done on human activity recognition using wearable sensors. As we begin to deploy hundreds and even thousands of wearable sensors on regular workers, hospital patients, and army soldiers, the question shifts more toward a balance between what information can be gained and their broad immediate user acceptance. In this paper we compare the activity classification accuracy of four different configurations of accelerometer placement on the human body using hidden Markov models (HMMs). We find the classification accuracy of a single accelerometer placed in three different parts of the body and evaluate whether there is a significant improvement in recognition accuracy by adding multiple accelerometers or not. We also find the number of hidden states that best models each activity by achieving the lowest test error using K-fold cross-validation.

1 Introduction

Being able to automatically recognize human motion patterns using unobtrusive wearable sensors can be useful in monitoring the elderly in their homes and keep track of their daily activities and behavioral changes. This could lead to a better understanding of numerous medical conditions and treatments. Other applications of human activity recognition range from context aware computing to physical training, physical rehabilitation, and military applications such as intelligent outfit design for soldiers.

In this paper we study different configurations of accelerometer placement to classify human activities that are frequent in at least one of these application areas. Eight different activities were modeled using HMMs and continuous Gaussian observation vectors. Three wireless accelerometers (*MITes: MIT Environmental Sensors*) [6] were placed on different parts of the body: right wrist (A1), left hip (A2), and chest (A3). We selected these locations on the basis of lengthy discussions with three potential user groups (office workers, hospital patients, and army soldiers) concerning their general acceptance of wearable sensors. We found that there was broad consensus about the acceptability of the chest and hip locations, and so we are developing a wearable electronic badge that will be worn on the chest. This badge will be able to share information with a Bluetooth-enabled cellular phone that could be worn on the hip and might have a second accelerometer.

2 Related Work

Previous work in human activity recognition using accelerometers has shown that it is possible to classify several postures and activities in real time. In [3], the authors developed a two-layer model that combined a Gaussian mixture model with first-order Markov models to classify a range of activities including: sitting, walking, biking, and riding the subway. A single 3-axis accelerometer placed on the torso was used. In [4], the authors combined data from three accelerometers and two microphones placed on different body locations to classify activities performed in a wood shop with 84.4% accuracy. They modeled most of the activities using single Gaussian hidden Markov models. The number of hidden states to model each activity was selected through visual inspection. In [1], several algorithms to classify twenty different physical activities from data acquired using five 2-axis accelerometers were evaluated with an overall recognition rate of 84%.

In [5], the authors used decision trees to classify six different activities with a single accelerometer, placed on six different body positions commonly used for wearing electronic devices, with accuracies ranging from 16.7% to 92.8% depending on the position of the accelerometer and the features used.

3 Data Collection and Processing

Three different subjects were asked to perform the following sequence of activities: 1) Sit down, 2) Run, 3) Squat, 4) Walk, 5) Stand, 6) Crawl, 7) Lay down (on the chest), and 8) Hand movements (while standing). The data collection process was repeated three times for each subject. 90 seconds of data were collected for each activity and labeled according to the start and stop times of each activity performed. The data were divided into nine datasets, each of them containing 80 observation sequences of one-second duration. An HMM was trained for each activity using eight datasets (640 observations) and tested on the ninth dataset (80 observations). This process was repeated nine times, each time using different training and test sets to obtain the K-fold cross-validation classification accuracy.

We resampled each dataset at $f'_s = 50$ Hz. The mean and variance of the acceleration in the x, y, and z axes from each of the three accelerometers were calculated over 200-millisecond time slices.

4 Activity Classification Using HMMs

Given a training set of labeled observation sequences (features extracted from the acceleration readings in the x, y, and z axes from three accelerometers placed on different parts of the body), corresponding to each of the activities that we want to classify, we first want to estimate the model parameters $\lambda = (\mathbf{A}, \mathbf{B}, \pi)$, where $\mathbf{A} = \{a_{ij}\}$ is the the state transition probability distribution, $\mathbf{B} = \{b_j(k)\}$ is the observation symbol probability distribution in state j, and $\pi = \{\pi_i\}$ is the initial state distribution for each activity. Given a new set of observations we would like to classify each sequence according to the model that gives the maximum likelihood for that particular sequence.

We modeled each observation sequence as a 5-state left-to-right HMM with continuous Gaussian observation vectors and two hidden states. Each observation vector was formed by combining the mean and variance in the x, y, and z axes from each accelerometer. These features were previously used in [2]. An HMM was trained for each class $(\lambda_1, \lambda_2, ..., \lambda_C)$, where λ_c indicates the learned HMM model for class c, and $C = 8$ is the total number of classes, using the labeled data from eight datasets as training dataset $\mathcal{T}_k$. The ninth data set was used as the validation dataset $\mathcal{V}_k$.

The HMM toolbox for Matlab developed by [7] was used to train and test the different models. The log-likelihood of each model was calculated for each observation sequence in the ninth dataset. Each observation sequence $O^l = \{O^l_1 O^l_2 ... O^l_T\}$ (with $T = 5$ time slices) in the validation dataset $\mathcal{V}_k = \{O^l\}_{l=1}^{L}$ was classified according to the model that gave the maximum likelihood.

The final classification was obtained as

$$\hat{G}(O^l) = \arg\max_c \mathcal{L}(\lambda_c). \quad (1)$$

The classifier $\hat{G}$ takes values in the class set $G = \{1, 2, ...C\}$.

This process was repeated $K = 9$ times using k-fold cross-validation. The average cross-validation classification accuracy per class is compared for the four possible configurations of accelerometer placement shown in table 1.

	Configuration			
	C1	C2	C3	C4
Right wrist	YES	YES		YES
Left hip	YES		YES	YES
Chest		YES	YES	YES

Table 1. Accelerometer configurations

5 Results

Figure 1 shows a comparison of classification accuracy when a single accelerometer was used for activity classification. We are able to discern activities such as walking (65.68%) and performing hand movements (56.30%) using only accelerometer A1 (right wrist). Accelerometer A2 (left hip) played the most important role when classifying activities such as sitting(66.05%), running (97.78%), crawling (69.26%), and lying down (87.04%). Accelerometer A3 (chest) was best for classifying activities such as squatting (75.8%) and standing (77.78%).

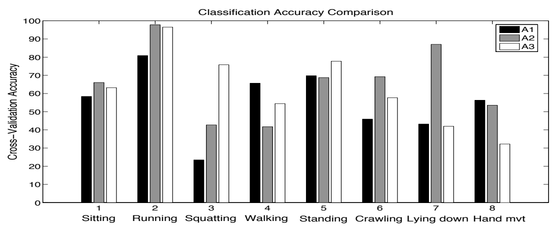

Figure 1. K-fold cross validation accuracy comparison using a single accelerometer.

Figure 2 shows the average classification accuracy per activity when combinations of two and three accelerometers were placed in the four different configurations described in table 1. Table 2 shows a comparison between the classification accuracy obtained when a single accelerometer (A1 to A3) was used, and the classification accuracy obtained when multiple accelerometers were used (C1 to C4).

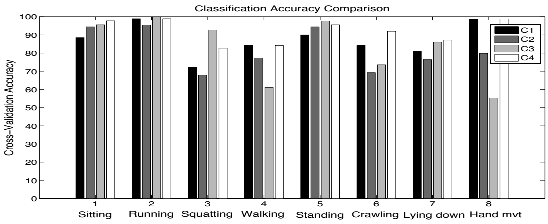

Figure 2. K-fold cross validation accuracy comparison for the four different configurations of accelerometer placement.

Class	A1	A2	A3	C1	C2	C3	C4
1	58.40%	**66.05%**	63.21%	88.52%	94.44%	95.56%	**97.78%**
2	80.86%	**97.78%**	96.54%	98.89%	95.43%	**100.0%**	98.89%
3	23.46%	42.72%	**75.80%**	72.10%	67.90%	**92.72%**	82.72%
4	**65.68%**	41.73%	54.44%	**84.32%**	77.28%	61.11%	84.20%
5	69.75%	68.77%	**77.78%**	90.00%	94.44%	**97.65%**	95.56%
6	45.93%	**69.26%**	57.65%	84.20%	69.26%	73.58%	**91.98%**
7	43.21%	**87.04%**	41.98%	81.11%	76.42%	86.05%	**87.16%**
8	**56.30%**	53.51%	32.22%	**98.77%**	79.85%	55.28%	**98.77%**
Global	55.45%	65.86%	62.45%	87.24%	81.88%	82.74%	92.13%

Table 2. Classification accuracy comparison

Our results show that it is possible to to recognize some of the most common activities using a single accelerometer on the chest (with 62.45% average accuracy). Adding a second accelerometer on the hip or the wrist improved our classification accuracy by approximately 20%. Adding a third accelerometer improved the global classification accuracy by an additional 10%.

The results presented so far were obtained by modeling each activity with an HMM having two hidden states. However, we think that classification results could be improved by modeling each activity with a different number of hidden states. In some cases, two hidden states might not be enough for capturing the different stages of a particular activity, especially when the activity involves different movements and body positions. Previous studies have not taken this into consideration and have modeled all activities using the same number of hidden states.

Table 3 shows the K-fold cross-validation accuracy when modeling each activity with two-hidden-state HMMs and when using the number of hidden states, Q_{min}, that gives the minimum test error for configuration C4 of accelerometer placement. Based on these results, we select the number of hidden states, Q_{opt}, that best models each of the activities studied in this paper.

Class	$Q = 2$	Q_{min}	Var	Q_{opt}
1	97.78%	93.33%	-4.45%	2
2	98.89%	98.89%	0%	2
3	82.72%	82.72%	0%	2
4	84.20%	88.64%	+4.44%	4
5	95.56%	96.67%	+1.11%	4
6	91.98%	86.29%	-5.69%	2
7	87.16%	87.26%	+0.1%	4
8	98.77%	99.01%	+0.24%	5

Table 3. Classification accuracy variation and optimal number of hidden states.

6 Conclusions

We found that the best global classification performance was achieved when using configuration C4 (92.13%), although it might be possible to obtain similar results using only two accelerometers. We showed that the global classification accuracy that can be achieved using a single accelerometer is around 60%, and determined the activities that are best classified with each accelerometer placed on three different parts of the body. Modeling each activity with a different number of hidden states improved the results. We are convinced that a minimum system formed by a wearable badge and a cellular phone can achieve fairly good results in daily activity recognition (80%).

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Wearable Games - An Approach for Defining Design Principles

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Abstract

This paper describes the efforts on designing games for wearable computing technology taken by the 23 students of the project PEnG - Physical Environment Games. Creating wearable game concepts we are faced with a lack of good design principles and therefore found out that some of our concepts are not very playable. Finding out where our concepts failed will result in knowledge about what rules a good design principle for wearable games must follow.

1. Introduction

The design of games for wearable computing technology plays a strong role in the students' project *PEnG - Physical Environment Games*, established at the University of Bremen. The project's goal is to create wearable games, that is, games mixing the real and the virtual world by the explicit use of wearable computing technology to play a game that is set in the real environment.
Usage of wearable technology is a required but not exclusive aspect of the game as we are not intending to create wearable video consoles but new gaming concepts.
The qualifying games are therefore partitioned into virtual and real aspects that need to interact with, resp. that are modified by the player.
During the course of the project we examined several game designs. Each design demanded different amounts of interaction between the player and the worn equipment. Therefore the player has to concentrate on the interaction on the one side and the game-play on the other side. The player's attention is divided and not focused on one task often leading to hectiness and or confusion. This knowledge soon became a design factor limiting but also improving the possible games by identifying ideas where the user interaction needed would effectively spoil the game.

2. What is a wearable game ?

When defining wearable games, it makes sense to look at the definition of mobile games. Mobile games are played with mobile devices like cell-phones or PDA's with small and limited input and output possibilities [2]. But still it is possible to convert games, that were implemented for desktop computers, more direct and easier to a mobile game than to a wearable game because the in/output devices are even more limited. It is similar to the effect that occurs when desktop applications in general are converted to a wearable computing application [3]. Thus, except for the used devices, the way of interaction distinguishes wearable games from mobile games.

According to Steve Manns definition of wearable computing [1], we define wearable games as follows:
The player wears a computer, that is seamlessly integrated into the the game. Therefore the used devices have to be small and well mounted to the body. The computer system must be available all the time and support the player during the game. Furthermore the game is not playable without this system.
To maintain the mobility character, the player needs to have the possibility to move freely in a certain area or even everywhere, depending on the radius of the communication techniques (e.g., WLAN hotspot vs. UMTS).

The wearable game itself consists of real and virtual components, were the wearable devices are used for interaction between the two environments. To enable the user to be immersed into the given game scenario, there have to be two different ways of interaction. Firstly, whenever possible, functionalities should be automatically performed by the system. Therefor methods of context-awareness can help to realise these aspects. Furthermore functionalities can be hard coded (e.g., *when an event has taken place, the system performs an action*) or realised with sensors (e.g., *the player arrived at special GPS coordinates*). Secondly, there are functionalities, were the player has to interact directly within the game. He/She has to fulfil quests and consider how to go on in the story line or about strategic means by manual input. The decision how to act in the game is based on information the system provides either by displays (e.g. HMD (*head-mounted display*) or attached to the body), acoustic signals, speech and/or tactile interfaces (e.g., vibration signal at a special event).

3. The Project - A Progress Report

Initially our project followed four different gaming ideas in order to evaluate their qualities as wearable games.

With *Stratego* we have a strategic game with two teams rival each other. It is adapted from the eponymous board game by Jumbo [4]. All players have an individual *rank* with special abilities. Each team also has virtual *bombs* distributed in the virtual game area. Scoring in the game is realised by collecting *flags* that are also embedded in the virtual game area. Each teams aim is to locate the other teams virtual flag and capture it. If two players from opposing teams get in contact, a game server calculates the winner based on the rank. The inferior player is not allowed to take part in the game for a certain time.
The wearable computer equipment is used to display a map with the locations of all players, the *rank* of the own team members and the virtual objects discovered so far.

Run 4 The Pilot (R4TP) is mixture of a strategic game and an action game. It was created by the project group based on the idea of paper chases. Like in *Stratego* we have two opposing teams. Each team's goal is to find and rescue a virtual aircraft pilot who crashed in the game area and possesses valuable information. The games area is covered with previously placed real items that represent wreckage from the aircraft. Every piece of wreckage provides information by using wireless technology (Bluetooth). This information needs to be analysed by team members and holds clues about the location of the pilot. By collecting and analysing wreckage the pilot's location gets more precise for the teams.

With *Hot Spotting* one project group created a pure action game. Again two teams are rivalling for points. Collecting points is done simply by standing near a WLAN-Hotspot, but each player is equipped with an *Infrared-Weapon* (realised with remote controls) and can *harm* a player virtually by *shooting* with it. A shot taken reduces a players virtual energy level maintained by the wearable computer. If the energy is depleted a player has to return to the team base to recover.

TROIA is a different approach in setting up a game environment.
The players are equipped with a wearable device is used to locate the player by infrared signals. The game area is defined by an artificial room where the walls and the ceiling are covered by low resolution LED-displays. We have created a multi-player version of the classic *Pong*-game concept where each player in the room has an own paddle and scores by hitting targets with a moving ball. The paddles, targets and the ball are virtual objects displayed on the walls. By moving, the players move their paddle in order to deflect the ball.

Studying the different games, we found that the players were exhausted in a short period of time. This effect can be attributed to the high importance of movement for the gameplay. Additionally this also leads to a higher possibility of damaging worn equipment during the game. While the ideas looked promising in the beginning we found out that the dynamical behaviour of interaction between virtual and real game elements is very hard to predict. Moving with wearable equipment is a limiting factor for wearable games and great care has to be taken to balance the weight of movement and the physical limits of players in gameplay. This can be seen as a design principle yet to be developed but with a strong effect on game design for wearable games.

4. Methods

In our project we initially started to collect ideas for physical environment games that are supported by wearable computing devices.
In order to evaluate our concepts, the games were played without using wearable devices where the device's tasks were carried out by project members (that is, guiding the players if needed and ensuring conformance to the rules of the game).
Additionally, some game aspects were evaluated by creating software prototypes.

Along the four mentioned games we see that the adaption of board and desktop games on wearables fails!

Based on this experience we try to find new design principles for wearable games. In doing so we decided to borrow and adapt design patterns used for mobile games. The book *Game Design Patterns for Mobile Games* by Ola Davidsson, et. al. [5] shows some important models which have to be taken in account when creating games on mobile platforms. Keeping this knowledge in mind we try to take new approaches in analysing game concepts and scenarios.

Our current approach in game concept analysis is to divide the whole concept into different atomic constituent sub-concepts. These sub-concepts would be analysed from three distinct points of view. Also these analysis where independent from each other the results will be taken in account for finding a game concept.

TEC-Analysis:
First we analyse a concept along technical feasibility. We look at the target platform and the resources we have to acquire in order to realise it. Therefore several technical possibilities to implement a concept and their effects on the game are analysed.

BIZ-Analysis:
The second analysis is taking into account economical feasibility. Because we have limited financial capacities in our project this is a very limiting criterion. If a sub-concept needs a platform which is unaffordable the whole game concept cannot be further followed.

FUN-Analysis:
The final inspection is considering the amount of fun a concept brings into a game concept. Each sub-concept is assigned a score and a *high-score* is formed by summing them up. The high-score gives us an indication of the overall fun factor of the game concept.

If we find a game sub-concept that is technically feasible, affordable and has a high fun factor it makes sense to implement it.
When the analysis was finished, a library of usable sub-concepts was created, of which each sub-concept can be easily appended to an implementation of a game concept or makes it easy to analyse the sub-concepts of a new game idea for the technical, economic and fun factors.

5. Related Work

ArQuake [6] is an adaption of the desktop first-person shooter Quake from iD Software. When developing this game, they primarily concentrated on user interfaces, tracking and the conversion of desktop applications to AR environments. The game that arised from their work fulfils all these requirements and truly shows, that an adaption of a desktop game to an AR application is possible. What this project did not take into account, is the physical strain of the users.
The WUI Toolkit [7] is an approach to design a toolkit for adaptive, context-aware user interfaces for wearable devices. Therefore, guidelines are proposed to develop a toolkit that satisfies the requirements of wearable computing user interfaces.
In *Game Design Patterns for Mobile Games* [5] mobile games are analysed according to their game-play mechanics. Game design patterns were used to evaluate existing games for mobile devices.

6. Conclusion

In this paper, based on our prototypes, we have showed the adaption problems of traditional computer game concepts to wearable computers, which need to be very dynamic to interact with the physical environment. Therefore, our suggestion is to solve this adaptation problem at the design stage. Besides, we have described how our analysing methods assist to find new design approaches for wearable games. Our next step in the future is to find and implement a concrete game concept with the use of these design principles.

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Design and Implementation of a Sensor Management Device for Wearable Computing

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Abstract

In wearable computing environments, a wearable computer runs various applications with various sensors (wearable sensors). Since conventional wearable systems do not manage the power supply flexibly, they consume excess power for unused sensors. Additionally, sensors frequently become unstable for several reasons such as sensor breakdown. It is difficult for application engineers to detect the instability. To solve these problems, we have developed a new sensor management device called CLAD (Cross-Linkage for Assembled Devices) that has various functions for power management and sensed data management. CLAD improves data accuracy and operational reliability.

1. Introduction

Recently, because of computer downsizing, wearable computing is attracting a great deal of attention. Wearable computing has the following three features compared to conventional computing, (1) Handsfree, (2) Power is always on, (3) Enhances people's daily lives[1]. With wearable sensors, wearable computers provide various services such as navigation, health care, and context-aware systems[2].

Conventional systems using multiple sensors have several problems. For example, a navigation system using GPS, accelerometer, and gyro sensor to acquire position[3] has high accuracy but heavy power consumption because it uses all sensors at all times. However, GPS is unavailable indoors, and sensors frequently become unstable because of breakdowns, power shortages, overcurrents and so on. It is difficult to detect the instability from only the sensed data.

To solve these problems, we have developed a new sensor management device called CLAD (Cross-Linkage for Assembled Devices) that has various functions for power management and sensing data management.

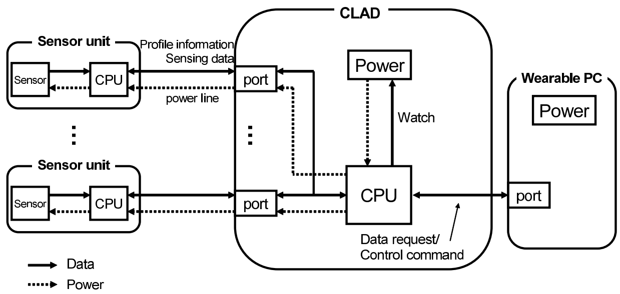

Figure 1. System structure of CLAD

2. System Design

In wearable environments, though a computer is always on, sensing is not always required. A user can equip multiple kinds of sensors, which consumes a lot of power. CLAD is placed between the wearable computer and wearable sensors, and it manages sensors to enable (1) flexible power-supply control to save energy, (2) flexible error control to achieve sensing accuracy and hardware error recovery.

2.1. System structure

Figure 1 shows the system structure of CLAD. CLAD has its own power source and manages sensors connected to it. Moreover, it monitors the voltage and current to detect power shortages and overcurrents. Each sensor unit has its own information about one sensor's type, accuracy, output range, start-up time, operating voltage, and operating current. Each unit has a CPU to hold this information and answer CLAD's calls.

Table 1 shows the control commands for CLAD. Table 1(a) shows the control commands from CLAD to sensors for managing power control and sensing data requests, Table 1(b) shows the commands from CLAD to PC for notifying CLAD status, and Table 1(c) shows the commands

Table 1. Command tables

(a)Sensor control command

Command
Power off
Sensing data request
Profile request
Power on

(b)PC control command

Command
Overvoltage
Overcurrent
Data anomaly
Sensor anomaly
CLAD Startup
CLAD End

(c)CLAD control command

Command	
Pseudo data generation	On
	Off
Filtering	On
	Off
Data merging	On
	Off
Change importance	High
	Low
Change criteria	Importance
	Rareness
	Power consumption
	Accuracy
	Startup time
Power supply	Start
	Stop
Sensing	Start
	Stop
Profile information request	
CLAD end	

from PC to CLAD for controlling CLAD functions. When a new sensor is attached to CLAD, it sends profile information to CLAD. Then, CLAD sends commands to the sensor for controlling it based on requests from the PC. When CLAD detects sensor errors or other troubles, it sends an alert to the PC and addresses them.

2.2. CLAD function

The functions of CLAD are divided into power management and data management. The features contributing to each function are shown in Table 2.

2.2.1 Power management

Alternative device retrieval and changeover
CLAD detects sensor anomalies from consecutive outlying data or sensor disconnections, etc. In such cases, CLAD refers to profile information and uses an alternative devices if they exsit.
Power saving
CLAD always monitors the internal power source. In

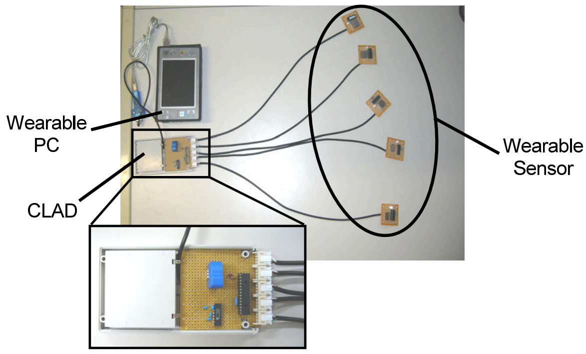

Figure 2. CLAD prototype

case of a power shortage, it cuts down on power consumption by stopping the power supply to part of the sensors according to a refusal policy.
Overcurrent detection
When detecting an overcurrent, CLAD stops all power supplies for safety.

2.2.2 Data management

Filtering
When sensed data is outlying based on the profile information, the data is automatically filtered.
Data merging
When the same kind of multiple sensors are attached to CLAD, it merges their data to improve accuracy.
Pseudo data generation
If CLAD finds no alternative device during alternative device retrieval, it generates pseudo data. The pseudo data is generated from learned data or relationships to other sensors' data. This function improves a operational reliability.
Error detection
CLAD detects errors and uses alternative devices or generates pseudo data. Additionally, since CLAD notifies the PC of these errors, applications can deal with the errors individually such as by displaying a message to induce a battery change.

3. Implementation

We implemented a CLAD prototype using a Microchip PIC16F873A as a processing unit. We implemented the system software on a Microchip MPLAB using CCS PIC C Compiler. The CLAD prototype and wearable sensors are shown in Figure 2. Table 3 shows the specifications of the prototype. Each wearable sensor has a processing unit that carries out communication control. CLAD measures the power source voltage using a Zener diode, and we use a

Table 2. Features of CLAD

Feature \ Function	Power managemet			Data management			
	Alternative device	Power save	Overcurrent detection	Pseudo data	Error detection	Filtering	Data merging
Power control	○	○	○				
Profile information	○	○		○	○	○	○
Voltage check		○		○	○		
Current check			○		○		
Sensing data management				○	○		

Table 3. CLAD specifications

Connection method		RS232C
Power source		4 dry batteries (AA)
Communication speed		9600 bps (Max.)
Size(main body)		W 76 × H 13 × D 70 mm
Weight	Without battery and cable	130 g
	With battery and cable	292 g
Power consumption		0.05 W

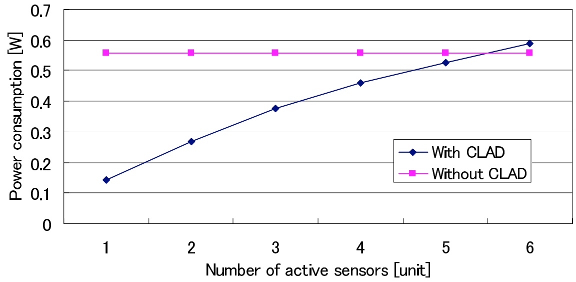

Figure 3. Active sensors vs. power consumption

Current Transducer LTS6-NP by LEM for current monitoring.

Figure 4 shows the power saving function of CLAD. Using five accelerometers, there are two lines in the graph, that indicating the power consumptions using CLAD and not using it. The power consumption does not change without CLAD because all sensors are always active. In contrast, CLAD decreases the power consumption by changing the number of active sensors.

4. Consideration

As an example of how CLAD is used, we consider a locating system using GPS, accelerometer, and gyro. GPS is not able to get information indoors and makes accidental errors. An accelerometer and a gyro sensor are able to detect users' actions in detail, but errors accumulate as we use them. CLAD automatically adapts to the situation.

Many context-aware systems employ probability-based matching with multiple accelerometers. If the amount of input data decreases due to sensor breakdown, cognitive accuracy drops off. We implemented a context-aware system using CLAD and evaluated cognitive accuracy with pseudo-data. We used 5 accelerometers and dropped them out in all combinations (31 patterns). The result shows that the use of pseudo-data achieves higher accuracy compared with not using pseudo-data (average improvement 7.46%).

In related work, Personal Mobile Hub[4] serves as the focal point for all devices worn by the user. Since it supports multiple wireless protocols, devices that have different protocols can communicate. It however does not work for problems such as power shortages or exothermic heat. Therefore, the hub serves only as a router and gateway.

5. Conclusion

We have designed and implemented CLAD, which is a management device for wearable sensors. CLAD saves power by dynamically managing sensor power and achieves high data reliability through management of sensed data and error control. It was clear from the evaluation experiment that CLAD saves power. By having sensors dynamically cover defects with each other, CLAD improves power efficiency and operational reliability.

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Situated Music: An Application to Interactive Jogging

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1. Introduction

Portable music player that stores many hours of music files have became very popular. But in typical portable music players, input and display devices are very small so that operations of user, such as selecting certain tune from a lot of music files by many times button pressed, impose burdens to users. Playing, pausing and selecting a tune according to user's situation and environmental, we can get rid of the burdens. For example, if detecting user's situation of walking and driving, a system stops playing a tune on the portable music player automatically, changes an output of sound from ear-phone to a car speaker, and selects a suitable tune for driving. In this paper, we define "Situated Music" as a framework that selects and plays a tune according to a user's situation. The selected and played tune itself is also referred to as Situated Music. And we propose Interactive Jogging as an application of the Situated Music for jogging.

Interactive Jogging is a framework of accomplishing an objective by an interaction loop of stimuli and responses (figure 1). The framework provides some stimuli, which are depending on a set objective and based on user's situation, to the jogger. The jogger reacts to the stimuli and then the situation is changed. Thereby next providing stimuli will be changed. As these stimuli, we can adopt sense of eye, hearing and pain. The responses are that a jogger speed up, keep up and slow down.

We apply the Situated Music as the stimuli of the Interactive Jogging to sense of hearing. This Interactive Jogging is comprised by two features that situations of a jogger are estimated with wearable sensors and selecting and applying an audio effect to a tune is depended on the estimated situations.

2. Interactive Jogging system

We propose the Interactive Jogging System, which are providing Situated Music as the stimuli to a user. A method of estimating situations of a jogger is necessary function because selected tune and a tune with audio effect are based on user's situation. Also a method of control a jogging activity is necessary function because encouraging a user consciously or unconsciously, the system let the user accomplish an objective very naturally.

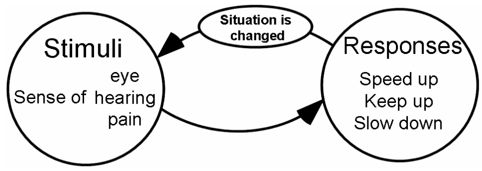

Figure 1. Interactive jogging.

In the System, to estimate user's situation, we use a jogging pitch. Analyzing measured raw accelerations, we can detect a jogging pitch. And observing the detected jogging pitch, we can estimate that user is jogging or walking and even how much speed the user is jogging. Also detected pitch is proper for user's steps rate per unit of time. Therefore we can calculate a roughly mileage of jogging to do multiplication of the detected pitch and user's step length measured before jogging starts. To detect the jogging pitch of a user, we attach an accelerometer to a user and conduct frequency analysis to measured acceleration.

To control a jogging activity, we used the theory that inputting periodic sounds to sense of hearing induces a human to certain walking cycle [3]. By means of this theory, our system let a user listen the certain music, which has certain tempo, to induce the certain tempo. Finally a jogging activity of the user is controlled.

2.1. Estimating user's situation

Our Procedure of detecting a jogging pitch is shown as below.

1. Measuring an acceleration of vertical direction (Strictly, this direction is not vertical but in this method, this is enough).
2. Applying FFT to measured accelerations.
3. Frequency of highest peak is assumed the jogging or walking pitch. (Except for 0Hz zone.)

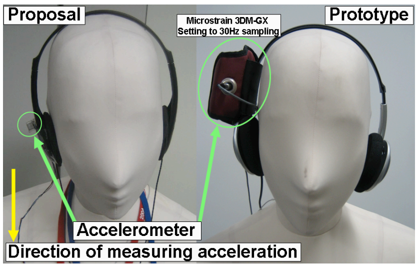

Figure 2. Sensor headphone.

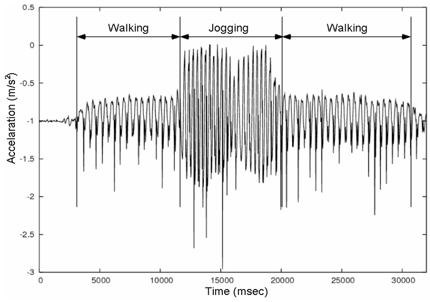

Figure 3. Acceleration of vertical direction when a user is walking, jogging and walking.

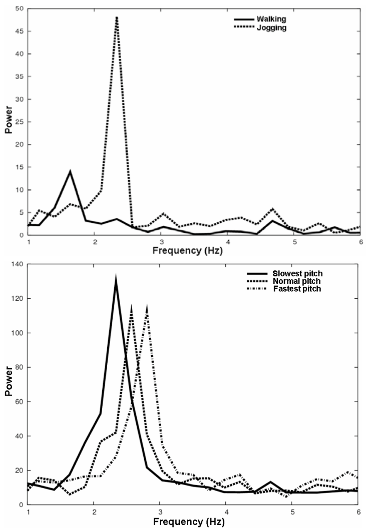

Figure 4. Power spectrum of vertical direction when a user walking, jogging and walking (TOP). Power spectrum of three levels jogging pitch (Bottom).

For measuring accelerations, we attached an accelerometer to an outside of headphone speaker (figure 2) [6]. We called the headphone attached an accelerometer a sensor headphone.

We made a prototype sensor headphone at the right side of figure 2 to experiment the procedure was working adequately. This prototype was that Microstrain 3DM-GX set to 30Hz sampling as an accelerometer is attached to the right side of a headphone.

Figure 3 shows measured acceleration of vertical direction when a user is walking (about 8 seconds), jogging (about 8 seconds) and walking (about 10 seconds) with the prototype sensor headphone. In this graph, there are different amplitude and frequency between walking and jogging. The top of figure 4 shows power spectrum that are 128 samples (corresponding about 4.2 seconds) taken from measured vertical accelerations of walking or jogging with applying FFT. Note that power spectrum of around 0 Hz zone does not include in both graphs because acceleration of gravity make very high peak around 0 Hz zone. When a user is walking, highest peak is detected around 1.6 Hz zone. Also when a user is jogging, highest peak is detected around 2.4 Hz zone.

A user with the prototype sensor headphone conducted “fastest pitch”, “normal pitch” and “slowest pitch” joggings based on user’s subjectivity. The bottom of figure 4 shows integrated power spectrum of three levels jogging pitch. When a user conducts “fastest pitch” jogging, highest peak is appeared around 2.8 Hz. When “normal pitch” jogging, it is appeared around 2.5 Hz. In case of “slowest pitch” jogging, it is appeared around 2.3 Hz.

As results, the procedure can distinguish a user is jogging or walking and detect a jogging pitch. Finally we can estimate that a user is walking or jogging, and a jogging activity as user’s situation. Also in these experiences, in case of the user banking own head and moving own head to look around, the sensor headphone can detect jogging pitch and situation of walking and jogging.

2.2. How to provide the Situated Music

In this subsection, we describe two methods of providing the Situated Music according to detected user’s situation. The first method is that the system let a user listen a tune or a play list based on detected jogging pitch. In case of providing play lists, the system divides a lot of tunes stored in a portable music player to several play lists by the tune’s pitch before jogging is starting. Due to this, the system can choose a play list comprised tunes whose tempo are similar to detected jogging pitch. Tune’s tempo is obtained from analyzing tune’s itself or the database on the Internet such as MoodLogic [4].

The second method is that the system applies audio effects, which augments an amusement aspect, to playing tunes. The effects are changing an original tempo of a tune to detected jogging pitch, low pass filter which can output only a basso, playing a tune as the tempo based on a jogging pitch, and overlapping additional sounds to a tune for augmenting a game aspect.

3. Application of the Interactive Jogging

This section describes two application of the Interactive Jogging. The first application let a user accomplish set objective to induce a user to certain pitch naturally. The second application is augmenting a game aspect to let a user listen the Situated Music based on detected pitch.

The first application is specifically that a user set a target mileage of jogging, a target time and a user's step length for calculating a mileage of jogging before jogging is starting. If the system estimated that a user cannot achieve the objective with current detected pitch, choosing certain play list comprised fast tempo tunes or applying an audio effect which makes a tune play faster, the system impose a user to a faster jogging pitch. On the other hand, if the system estimated a user will reach the target time too early, the system chooses a play list comprised slow tempo tunes or applying an audio effect which makes a tune play slowly. Also if the system estimated a user is jogging a very fast pitch comparing with the target pitch, the system chooses a play list matched walking pitch or applying an audio effect which makes a tune play very slowly. Due to theses, controlling a jogging activity, the system can prevent the overloading to a user and injuring a user before happen.

The second application is specifically that if a user was jogging a same pitch continuously, the system chooses a play list comprised similar tempo tunes and applying an audio effect which makes a tune play detected pitch. During a beginning of jogging, the system plays only a basso of a tune at small volume. If a user was jogging a same pitch continuously, the system plays diapason at large volume. And if a user was jogging a same pitch more continuously, the system plays additional sounds at full volume such as "Dance Dance Revolution" [5].

4. Outlook

Our system calculates a mileage of jogging from a detected pitch. By means of Kourogi and Kurata Personal Positioning System [1] based on inertial and GPS sensor, estimating a mileage of jogging have more accuracy compared with the current method.

The current implementation cannot estimate a load of a user by a detected pitch because there are individual differences of body capacity. Attaching a biological sensor, the system can finely control user's activity according to user's physical condition.

An explicit user's input doest not reflect to criteria of providing the Situate Music. Rekimoto proposed UniversalPlaylist [2] that has a function to select a favorite play list by only yes/no user's input in portable music player. Importing the function, a future system can select a favorite play list compared with the current system.

We can realize a Situated Music based on place, weather and landscape. In this case, the system can provide tunes based on situations estimated by information of network or attached GPS, magnetometer, humidity and air pressure sensor. For example a user link certain tune and certain place. After that other user come to the place and listen the tune. Finally the other user can share a mood felt by the user. Specifically, the system detects objects user headed and place with GPS sensor and magnetometer. A user links a tune matched a mood to detected information and preserve these data to a data base on the Internet. Other user come to the same place and head to the same object, the system finds out the tune from the data base and plays it. Finally both users can share the mood.

5. Conclusion

In this paper, we proposed and implemented the Interactive Jogging adopted the Situated Music. We confirmed that an accelerometer attached to headphone could detect a jogging pitch and situations of walking or jogging in the experiment. In the future, we confirm that using this system, a user can achieve a set objective naturally and feel an entertainment in a jogging.

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