WearNET: A Distributed Multi-sensor System for Context Aware Wearables

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Abstract. This paper describes a distributed, multi-sensor system architecture designed to provide a wearable computer with a wide range of complex context information. Starting from an analysis of useful high level context information we present a top down design that focuses on the peculiarities of wearable applications. Thus, our design devotes particular attention to sensor placement, system partitioning as well as resource requirements given by the power consumption, computational intensity and communication overhead. We describe an implementation of our architecture and initial experimental results obtained with the system.

1 Introduction

Context awareness has repeatedly been singled out as one of the most important components of the vision of wearable computing (e.g.[1,2]). It can be broadly described as the ability of a computer system to adapt its functionality to the user's activity and the environment around him [3]. Currently, there are two complementary approaches to making computers context aware. One focuses on improving vision and audio recognition, trying to mirror the human's perception. The other relies on the fusion of information from different, simple sensors. The advantage of the second approach stems from the fact that it is in general much less computationally intensive. Also, using sensors that provide information not available by the human senses opens up the possibility of extending the human perception. While promising, deriving contextual information from a heterogeneous multi-sensor system is a hard problem. Open issues include sensor selection, system architectures, adaptation of the hardware system to the wearable environment, miniaturization and of course context recognition. This paper focuses on the first three problems.

Related Work. The use of multi-sensor systems for context recognition is an active research area. Clarkson and Pentland [4] used a wearable camera in combination with a microphone to recognize a person's situation. Picard's group has used a galvanic skin response sensor, a blood volume pulse sensor, a respiration sensor and an electromyogram sensor for recognizing affective patterns in physiological signals [5,6]. Gellersen et al. propose to use relatively simple sensors as a basis for the derivation of complex context information [7,8]. Other systems that

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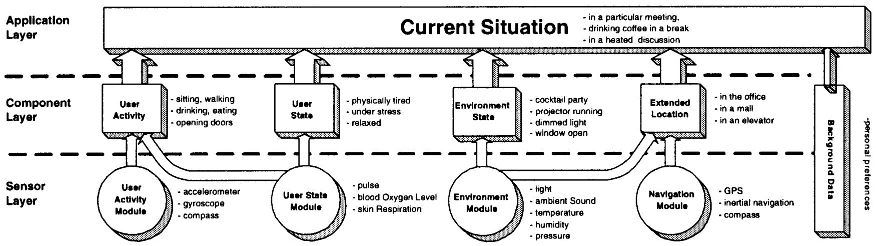

Fig. 1. Different context layers used in our approach.

use multiple low level sensors to capture context information include the Smart-Its sensor-board (*http://smart-its.teco.edu/*) and the KTH SmartBadge [9].

Paper Contributions. Our system extends the above work by integrating additional sensors and appropriately placing them on the user's body to detect the user's activity. In particular we use multiple, distributed motion sensors rather than a single accelerometer. Knowing the importance of power management, the system architecture takes into account the computation/communication tradeoff involved in adding processing power to the sensor nodes and combining sensors into modules and subnetworks. An important contribution of our work is also the actual implementation of a wearable platform and the presentation of real life data.

2 Context Components and Observation Channels

The design of a wearable context recognition system is a tradeoff between versatility and flexibility on one hand and efficiency for a particular narrowly defined task on the other. As a compromise between focusing our system on a single application and providing a generic assembly of sensors we target our architecture towards a loosely specified set of requirements defined on an intermediate level, the component layer (Figure 1). Leaning on different attempts of context classification and partitioning [10], the component layer consists of four context components: Extended Location, Environment State, User Activity and User State. For each of the above components the rest of this section describes the type of information that these components deliver and specifies the sensor combination that we have found appropriate (see Table 1).

Extended Location Component (EL). It is important to understand that there are two types of location information: (1) the position in physical coordinates and (2) a description of a place such as "in the train" or "in the office". Outdoors physical position is easily obtained with GPS. Extracting the position without GPS which is e.g. the case within buildings poses a greater problem. Unless a building is equipped with appropriate infrastructure there are two solutions: (1) using inertial navigation based on acceleration sensors, gyroscopes and magnetic field sensors and (2) relying on multi-sensor based location identification to determine the user's position. We propose to use inertial navigation (which alone is not accurate enough) and multi-sensor based location identification as complementary information sources for both the physical location and extended location recognition.

The identification of a location is based on three types of information: (1) ambient sound, (2) light conditions and (3) changes in other environmental parameters like temperature, humidity and atmospheric pressure. Using a microphone we look for characteristic background sounds like the humming of an air condition or sound of machinery. The light conditions analysis is based on the fact that different locations tend to have different characteristic light conditions, in particular the ratios of infrared, visible and UV light. Similar differences between locations can be found for temperature and humidity. An atmospheric pressure sensor provides information about altitude changes when going up or down between building levels.

Environment State Component (ES). What is happening in the user's environment is probably the most complex context component. Keeping in mind the limited resources of a wearable we will restrict our definition to two broad, low level types of information: (1) physical properties of the environment and (2) general level of activity. For the recognition we will concentrate on two cheap channels that are also used for extended location detection: ambient sound and light intensity. Background ambient sound is an important indication of the activity around the user. Sounds from sources like an overhead projector, coffee machine or the 'cocktail party effect' of many people in a room speaking, can be an excellent indication of what is happening around the user. Light conditions, in particular intensity changes not accompanied by the user's movement, can provide important clues.

User Activity Component (UA). Our approach to monitoring the user's activities is based on the importance of human posture and gesture. Most situations and activities can be characterized by a specific body position and/or limbs motion pattern. A person presenting a talk is likely to be standing up, possibly slowly walking back and forth, and gesticulating. To detect postures and motions we rely on a network of motion sensors (3 axis accelerometers, gyroscopes and/or electronic compass) distributed over the user's body. Each sensor provides us with information about the orientation and movement of the corresponding body part.

User State Component (US). Knowing whether the user is stressed, relaxed, etc. is useful to a wearable system in many ways. While reliable detection of physical and emotional state of a human is a difficult task, it has been demonstrated by several researchers [11,12] that cues can be derived from basic physiological parameters that can be easily measured. Our user state analysis is based on 3 such parameters: galvanic skin response (GSR), pulse and blood oxygen saturation.

Table 1. Overview of sensors needed for the proposed logical context components

Observable(s)	**Needed for**				**Device**	**Power**	**Size**	**BW**
	EL	ES	UA	US		[mW][d]	[mm^2 x mm]	Byte/s
light IR	x	x			BPW 34 FS	-	25.4 x 1.2	10-20
light visible	x	x			SFH 3410	0.3	9.2 x 1.1	10-20
light UV	x	x			SFH 530	0.2	67.2 x 8.8	10-20
magnetic 2-axis	x		x		HMC 1002	25.8	132 x 2.6	10-20
acc. 2-axis	x		x		ADXL202E	2	25 x 2	200-400
rotation 1-axis	x		x		ENC-03J [a]	15	126 x 4.3	100-200
humidity, temp	x	x			AH31 [b]	2	81.6 x 3.5	1-2
atmospheric pressure, temp	x	x			MS5534 [c]	3.3	81.0 x 4.7	1-2
GSR				x	-	-		10-20
pulse, oxygen sat.				x	-	3.3	375 x 2	1-2

[a] Murata, [b] Sensirion, [c] Intersema, [d]Continuous operation

3 Wearable Design Considerations

In a wearable system different sensors need to be placed in different locations to best acquire the desired signals. Once the placement has been fixed two system architecture issues remain to be resolved: (1) communication/computation tradeoffs resulting from the possibility of equipping the sensors with processing devices and (2) the network architecture and transmission technology. Both issues are determined by the same criteria: system power consumption and user comfort.

Sensor Placement Constraints. The placement of the sensors is dictated by a tradeoff between two considerations: the quality of the signal received in a particular location and ergonomic concerns as described for example in [13].

The pulse and GSR sensors need to be placed in contact with the skin. In addition the GSR sensors have been found to produce good results on fingers, palms and feet only. A good choice is to put the GSR electrodes as rings on the fingers and the pulse sensor on the wrist.

The inertial navigation sensors should be placed in a location which follows as closely as possible the motion of the body's center of gravity and remains uninfluenced by the motion of individual body parts. A good choice is the middle of the lower back.

Environmental sensors need to be placed in a location where they are least likely to be obstructed during typical activities. Possible locations are head or upper torso.

Ideally, to provide a detailed description of the user's posture and body motion at least one 3 axis accelerometer should be placed on each side of every relevant joint. In practice, placing one sensor on selected, relevant body parts should be sufficient for most purposes. This includes the upper and lower legs and arms, shoulders, and the torso (e.g. chest). Since the head's orientation and movements

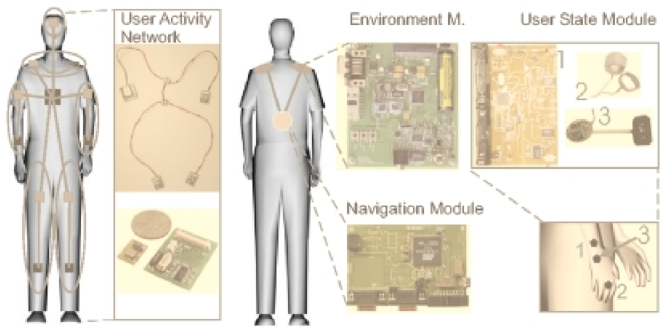

Fig. 2. Module placement and pictures of the WearNET hardware

indicate the user's focus of attention an electronic compass should be placed on the head.

Computation and Communication Considerations. In a simplest architecture the raw data generated by each sensor would be sent directly to a central module. However, a distributed approach has several advantages. For one it is often more power efficient to perform parts of the feature extraction locally than to transmit large amounts of raw data. In addition to power considerations, higher data rates require more cumbersome transmission systems (more, thicker wires, more EM smog, larger transceivers). Finally by combining data from physically adjacent and logically related sensors the overall number of long links crossing clothing and body parts boundaries can be reduced. Further improvements can be obtained by combining such sensors into modules sharing computing resources.
A detailed discussion of the communication/computation tradeoffs that has determined the WearNET architecture is beyond the scope of this paper. The approximate bandwidths of the raw sensor data can be found in Table 1. As will be shown in section 5 useful features require filtering, spectral analysis and simple statistical parametrization. In particular for the acceleration and sound sensor performing such operations locally has proven advantageous. For the acceleration sensor network a hierarchical topology following the body anatomy is necessary.

4 System Architecture and Implementation

This section outlines the architecture of the WearNET system and describes a first prototype which has been implemented and tested in our Lab. The architecture layout and the hardware of the implemented subsystems can be seen in Figure 2.
Based on the consideration described in the previous paragraphs we have partitioned our sensor architecture into four subsystems: Navigation Module (NM), Environmental Module (EM), User Activity Network (UAN) and User State

Module (USM). The first two are used in combination to derive the Extended Location and Environment State. The latter two are user oriented and taken together provide the User Activity and the User State (see Figure 1).

Navigation Module (NM). The NM contains the GPS and the inertial navigation sensors (acceleration, gyroscope and magnetic field sensors) to provide the physical location part of the extended location context component. In addition, it contains a processor fast enough to perform all computation necessary for position tracking. Because of the availability of a CPU the module also serves as a central coordination and evaluation unit of the WearNET system.

In the implemented system which is based on the devices listed in Table 1 the accelerometer and the gyroscope signals are all sampled with 200 Hz, the magnetic field sensor signal with 50 Hz, and the GPS receiver with 1 Hz. The system is equipped with a 32 Bit RISC ATMEL AT91M55800A micro controller.

Environment Module (EM). The sensors of the EM measure UV, IR and visible light, magnetic field, temperature, atmospheric pressure, humidity and sound. The module is based on an ultra low power mixed signal processor that takes care of the analog to digital conversion, sensor control and basic features extraction. The latter includes the processing of the light sensor data and some simple sound preprocessing.

The implemented module provides 10 analog and digital micro sensors delivering 15 sensor signal channels connected to a TI's 16bit MSP430F149 micro controller and 512 kByte of SRAM for data logging. All analog sensor signals except the magnetic sensors are processed by a non-inverting amplifier and a subsequent unity gain sallen-key low pass filter. From the visible light sensor two sensor channels with different amplification factors are derived increasing the combined dynamic range.

User Activity Network (UAN). This is a multistage network of motion sensors with a hierarchy that reflects the anatomy of the human body. It is divided into subnetworks assigned to body parts that form a logical unit. It provides data on the relative motion and orientation of the corresponding body part. Individual subnetworks are assigned to each limb, head, and torso. The actual placement of the sensors can vary according to the application. Each subnetwork is a bus with a dedicated master. The masters of all subnetworks form a higher level bus in which they are slaves to a central master node. This two-layered hierarchical approach provides a logical separation of the sensor information increasing the amount of local processing and reducing the computational load on the central master.

Each sensor node contains two perpendicularly aligned dual-axis accelerometers (ADXL202E) connected to a TI MSP430149 mixed signal controller for preprocessing and communication with the other nodes. The sensors measure both dynamic and static accelerations up to ± 2 g. The nodes within the network are interconnected using a two wire I2C bus with an additional third wire used as a common synchronization clock.

User State Module (USM). The module combines the GSR sensor with the pulse and oxygen saturation sensors and an ultra low power micro controller.

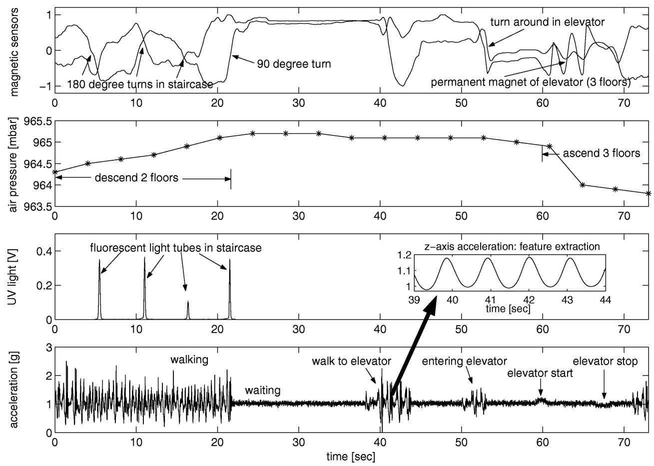

Fig. 3. Experiment 1: path in a building. The readings of key sensors used for tracking.

It requires only a simple mixed signal processor for the analog digital conversion, control, and basic preprocessing and features extraction.
In our implementation we use a PIC16LF877 mixed signal controller, a photoplethysmography pulse and oxygen saturation sensor from SPO MEDICAL and a custom built GSR sensor. The GSR sensor consists of two Ag/AgCl electrodes placed on the middle segment of the first and the middle finger, on the side of the palm. In the subsequent analog filter section the signal is amplified and separated into its two components: the tonic baseline level and the short term phasic response [14] using a high-pass filter with a cut-off frequency of 0.05 Hz. Additional filters are needed to suppress aliasing effects of the following A/D converter stage. All filters are multiple feedback (MFB) second order filters.

5 Experiments

To verify that our sensor selection and the system implementation can provide information required for complex context recognition we have acquired data for selected wearable scenarios. Two such scenarios are summarized below.

Complex Path in a Building. In the first experiment the person wearing the WearNET walks two levels down a staircase, waits for 20 seconds, and continues walking a few steps to an elevator. He then takes the elevator three floors up. The raw outputs of the following sensors are displayed in Figure 3: x- and y-axis of the magnetic field sensors, atmospheric pressure sensor and UV sensor of the EM, and the axis of an UAN accelerometer parallel to the upper leg (z-axis). As can be seen the atmospheric pressure difference between levels can be detected. The staircase consists of two sections per level so that the person has to turn around 180 degrees twice every level. This can be clearly seen in the change of the magnetic field sensor data. The user passes underneath four fluorescent

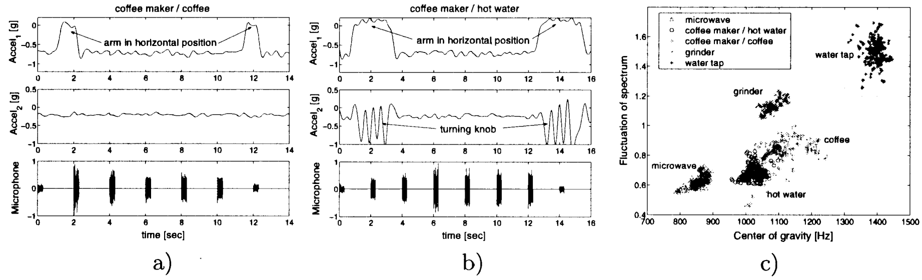

Fig. 4. Experiment 2: in the kitchenette. Figure a) and b) show the acceleration measured on the wrist (top: parallel, middle: perpendicular to the arm) and the sound intensity (bottom) when getting coffee (Fig. a) and hot water (Fig. b) from the coffee maker. Figure c) shows the simple features extracted from the spectrum of the sounds of different kitchen appliances.

light tubes located at every floor and in between which explains the UV peaks. The accelerometer can detect walking motion as well as the movement of the elevator. To recognize the walking motion we look at the changes of the angle between the upper leg and the axis which is perpendicular to the ground. This angle can be calculated from the low pass filtered acceleration signal. As shown in the insert of the acceleration graph in Figure 3 the change of orientation of the upper leg associated with walking produces a characteristic periodic signal.

In the Kitchenette. In the second scenario the user walks through the hall towards a kitchenette containing electrical appliances and a sink with a water tap. The appliances include a coffee maker (which can also be used as a hot water dispenser), a coffee grinder, and a microwave. This far the scenario is similar to the previous one and can be recognized as described above. Next the user activates one of the appliances.

The recognition of what the user is doing is based on two signals: the acceleration readings from the arm used to activate and stop the appliance and the sound made by the active appliance. The acceleration is measured at the wrist of the right hand by one of the the UAN modules. The sound is sampled for 0.3 sec every 2 sec at 10 kHz by the EM microphone. The combination of the activation motion, followed by an increase in sound intensity lasting until the deactivation motion (see Figure 4a) and 4b)) combined with the knowledge that the user is in the kitchenette is a reliable indication the user has activated one of the appliances. To find out which appliance was used the sound analysis only has to distinguish between the characteristic sounds of these appliances. Figure 4c) shows the distribution of two simple features extracted from the spectra of the these sounds: the center of gravity and the spectrum-fluctuation[1]. It can be seen

[1] Spectrum-fluctuation is defined as $\frac{\mu(A(f))}{\sigma(A(f))}$, where μ is the mean and σ the standard deviation of the amplitude spectrum $A(f)$.

that all sounds except for those of making coffee and getting hot water (which both come from the same appliance) can be clearly separated. However, making coffee and getting hot water lead to different acceleration signals. To get a coffee the user presses a start button, waits until the cup is filled and then presses the stop button. For hot water he needs to turn the hot water knob of the machine to the open position and then back to the close position when the cup is full. Both, pressing the button and turning the knob are associated with the arm coming into nearly horizontal position leading to the low pass filtered signal from the sensor axis parallel to the arm going from about -1g at around 0g (Figure 4a) and 4b) top). As can be seen in Figure 4b) in the middle, each turn of the knob also changes the orientation of the axis perpendicular to the arm from horizontal to vertical and back.

6 Conclusion and Outlook

We have described a design of a distributed multi-sensor system for context aware wearables. By introducing an intermediate context component level we were able to find a good compromise between efficiency and versatility of the design. Through an analysis of sensor placement constraints together with the computational and communication complexity of the individual sensor channels we were able to optimize the system for the wearable environment. Using a first prototype implemented in our lab we have shown how a combination of fairly generic, vague features from different context components can add up to complex, specific context information.

Future work needs to target an automatic derivation of such information through standard algorithms like HMMs or neural networks for a wide range of situations and an analysis of achievable recognition rates. To this end further research is also necessary on modeling the relation between the different sensor channels and different context components leading to reliable extraction of well separable features. In addition the hardware platform needs to be miniaturized and integrated into conventional clothing in a truly unobtrusive way.

References

1. D. Abowd, A.K. Dey, R. Orr, and J. Brotherton. Context-awareness n wearable and ubiquitous computing. *Virtual Reality*, 3(3):200–211,1998.
2. T. Starner. The challenges of wearable computing. *IEEE Micro*, 21(4):44–52, 2001.
3. G. Chen and D. Kotz. A survey of context-aware mobile computing research. Technical report, Dept. of Computer Science, Dartmouth College, Nov 2000.
4. B. Clarkson, K. Mase, and A. Pentland. Recognizing user context via wearable sensors. In *Proc. of the 4th Int'l Symposium on Wearable Computers*, October 2000.
5. R. Picard and J. Healey. Affective wearables. In *Proc. of the 1st Int'l Symposium on Wearable Computers*, pages 90–97, October 1997.

6. J. Healey, J. Seger, and R. Picard. Quantifying driver stress: Developing a system for collecting and processing bio-metric signals in natural situations. In *Proc. of the Rocky Mountian Bio-Engineering Symposium*, April 1999.
7. H.-W. Gellersen, A. Schmidt, and M. Beigl. Adding some smartness to devices and everyday things. In *IEEE Workshop on Mobile Comp. Systems and Applications*, 2000.
8. A. Schmidt, K.A. Aidoo, A. Takaluoma, U. Tuomela, K. Van Laerhoven, and W. Van de Velde. Advanced interaction in context. In *Int'l Symposium on Handheld and Ubiquitous Computing (HUC 99)*, pages 89–101, September 1999.
9. G.Q. Maguire Jr, M.T. Smith, and H.W.P. Beadle. Smartbadge: A wearable computer and communication system. In *Proc.of the 6th Int'l Workshop on Hardware/Software Co-Design (CODES/CASHE'98)*, pages 89–101, March 1998.
10. A.K. Dey and G.D Abowd. Towards a better understanding of context and context-awareness. Technical Report GITGVU -99-22, Georgia Tech, 1999.
11. J. Healey. *Wearable and Automotive Systems for the Recognition of Affect from Physiology.* PhD thesis, MIT, May 2000.
12. J.T. Cacioppo and L.G. Tassinary. Inferring psychological significance from physiological signals. American Psychologist, 45(1):16–28, January 1990.
13. F. Gemperle, C. Kasabach, J. Stivoric, M. Bauer, and R. Martin. Design for wearability. In *Proc. of the 2nd Int'l Symposium on Wearable Computers*, October 1998.
14. W. Boucsein. *Electrodermal Activity.* Plenum Press, New York, NY, 1992.