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Affective Wearables

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Abstract

An "affective wearable" is a wearable system equipped with sensors and tools which enables recognition of its wearer's affective patterns. Affective patterns include expressions of emotion such as a joyful smile, an angry gesture, a strained voice or a change in autonomic nervous system activity such as accelerated heart rate or increasing skin conductivity. This paper describes new applications of affective wearables, and presents a prototype which gathers physiological signals and their annotations from its wearer. Results of preliminary experiments of its performance are reported for a user wearing four different sensors and engaging in several natural activities.

1 Introduction: Why affective wearables?

One of the distinguishing features of wearable computers, as opposed to merely portable computers, is that they can be in physical contact with you in a long-term intimate way. A wearable may hang on your belt like an old pocket calculator, or it may take the form of clothing or jewelry, residing in your shoes, hat, gloves, eyeglasses, ring, or other accessories, providing a variety of kinds of physical contact beyond the traditional paradigm of fingertips touching only a keyboard and a mouse. In particular, when equipped with special sensors and tools from signal processing and pattern recognition, a wearable computer can potentially learn to recognize physical and physiological patterns—especially those which correspond to affective states—such as when you are fearful, stressed, relaxed, or happily engaged in a task.

Sensing physiological patterns is not a new thing; ambulatory medical devices have been under development for years, helping people with various medical complications, to monitor heart rate, blood pressure, and more. Affective wearables overlap with medical wearables in that both may sense physiological signals. In particular, both may be concerned with sensing signals that indicate stress or anxiety [?], an application of interest not just for people suffering from anxiety attacks or other medical conditions, but also for healthy people who are interested in staying healthy. Affective states of depression, anxiety, and chronic anger have been shown to impede the work of the immune system, slowing down healing and making people more vulnerable to viral infections [?]. Wearables provide a means of monitoring stress and other conditions outside the confines of a medical facility, gathering data as the wearer goes about his or her daily activities. Of course, none of the data collection or analysis implies that a user will choose to change his behavior or lifestyle, but it can help a wearer make informed decisions, and can be shared with a physician, if the wearer desires, for help in treating chronic problems like back pain and migraine headaches which can be stress related.

There is a movement in computer science toward developing systems that *learn* what their users want, and that try to model their user's interests and respond in a more adaptive way. However, a natural way that people express what they want, especially whether they like or dislike something, is through affective expression. They may speak with a pleased or distressed voice. They may smile or frown. They may gesture, nod, slump, or otherwise indicate that they feel good or bad about something. A big problem is that current computers are oblivious to most of these affective expressions. They ask us to click on menus to indicate whether we like something or not, or they watch what we type, both of which are not the most natural way for us to communicate. This is especially true of affective communication. In contrast to the keyboard and mouse, a wearable offers many other forms of interface, including physical contact with the wearer's skin, and other opportunities to sense how a person gestures, walks, and moves. Wearables have an unprecedented opportunity to "get to know" a person.

One of the problems in giving a computer the ability to recognize affective patterns is that emotion theorists still do not understand what emotions are and how they are communicated. One of the big problems in emotion theory is determining what physiological patterns accompany each emotion [?]. In some individuals, an increase in temperature and blood pressure might co-occur with anger. An acceleration in heart rate and pupillary dilation might indicate the person likes what he is looking at. However, almost all of the studies trying to determine which responses occur with which emotions have been done on artificially elicited emotions in a lab setting, where there is good reason to believe that people might not feel the emotions in the same way as when they are more naturally elicited. This problem has held back progress in emotion understanding. A wearable allows a tremendous opportunity to learn about affective patterns in natural situations. Affective wearables provide a perfect opportunity to bring powerful computational methods to bear on testing emotion theories.

2 Applications of affective wearables

There are dozens of applications of affective computing in addition to the medical and health applications mentioned above [?].). For example, emotions are known to provide a keen index into human memory; therefore, a computer that pays attention to your affective state will be better at understanding what you are likely to recall on your own, and what is of interest to you. This is potentially very useful in helping people deal with information overload. For example, instead of a system recording *everything* you hear, see, or click on, the system might learn to record (or play back) just those places where you were interested. Or, it might play back just those places in a lecture that you missed, perhaps because your mind wandered or you were bored. Augmenting a system like Steve Mann's WearCam [?] with affective sensing and pattern recognition could help it learn when to "remember" the video it collects, as opposed to always relying on the user to tell it what to remember or forget. Of course the user can still direct what the system does; that function does not go away. The goal is simply to begin to automate those functions that the user typically applies, especially when they are predictable with affective information.

Suppose for example that you let the WearCam roll in a continuously learning mode while playing with a cute little child. It might notice that you always save the shots when the child makes you laugh, or smile. By detecting these events, it could become smarter about automatically saving these kinds of photos in the future. Moreover, by labeling the photos with these affective events, you can later ask the system to retrieve data by its affective qualities, "Computer, please show us the funny images." Of course the wearer should be free to communicate with the system at all times, which includes sometimes overriding what the system has learned. But, if the wearable learns continuously, by watching what the wearer chooses, it should help reduce some of the users workload and enable the wearer to offload repetitive tasks.

We have built a prototype of an affective WearCam, based on the wearable described in the next section 1. This prototype includes a small camera worn as a pendant around the wearer's neck, together with skin conductivity sensors and pattern recognition software. The camera continuously records and buffers images in a rotating buffer, deleting the oldest images as the buffer fills. Simultaneously, the system uses small electrodes to sense skin conductivity in the wearer's skin, either across two fingers or across the arch of the foot. Pattern recognition software has been trained to recognize the wearer's "startle response," a skin conductivity pattern that occurs when the wearer feels startled by a surprising event. Unlike many affective signals, the human startle response is fairly robust and easy to detect. With a matched filter and threshold detector, the startle pattern in the wearer's skin conductance signal is detected in real time. The skin conductivity response occurs with a typical latency of three seconds after the startling event. When the pattern is detected, the images leading up to the startle event are extracted from the buffer. The buffer can be set to hold arbitrary amounts of imagery, typically in the range of 5 seconds to 3 minutes of data. When the startle is detected, the images extracted from the buffer can then be saved into a more permanent

Figure 1: The StartleCam system, consisting of a wearable computer (lower left), electrodes to measure skin conductance (center left) and the digital camera (center right). Photo courtesy of Frank Dabek

memory for your later perusal, or automatically sent back to a remote location to be analyzed by a "safety net" [?], community of friends or family with whom you felt secure, to see if the event warranted any action on your behalf.

The StartleCam is an example where analysis of a wearer's affective patterns triggers actions in real time. In the future, a "fear detector" might also trigger a wearable camera to save a wide-angle view of the environment, and with a global positioning system attachment, the wearer's position, viewpoint, and fear state could all be transmitted using the wireless modem.

The applications extend beyond safety to many other domains. In an augmented reality role-playing game, a fear detector might change the wearer's appearance to other players, perhaps applying a "cloak" or updating an avatar's expression. Alternatively, a noted reduction in fear might be recognized, and the player rewarded for overcoming his fear, with bonus points for courage.

Applications of affective wearables extend to other forms

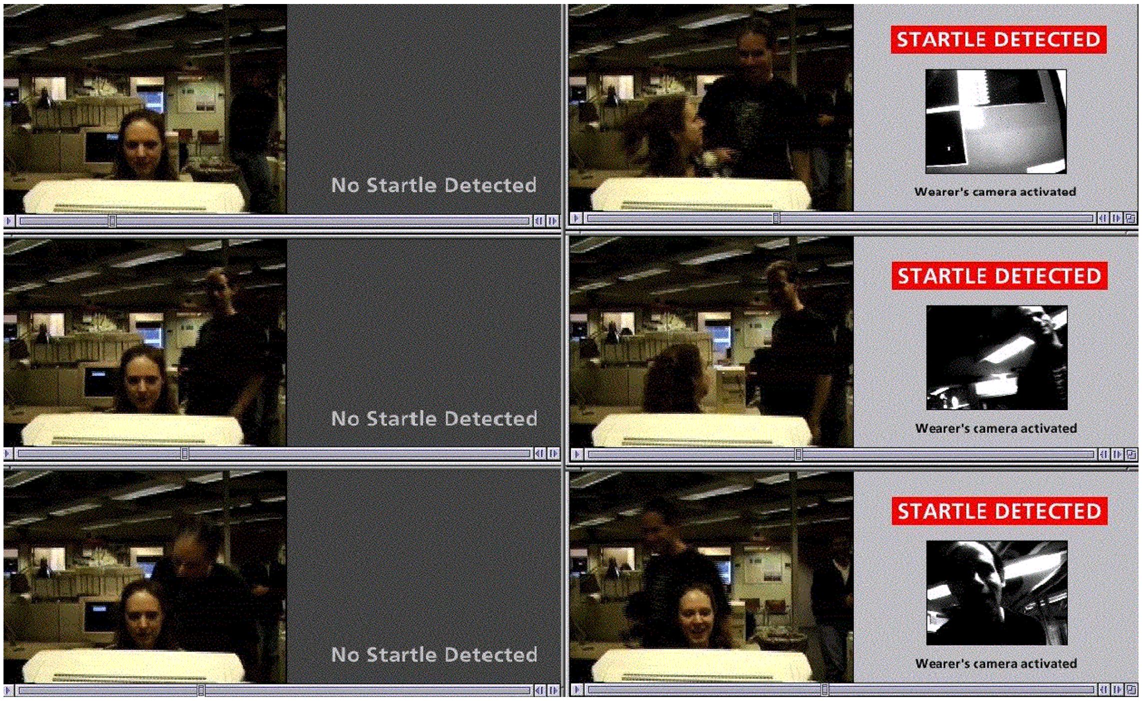

Figure 2: A series of images taken from an MPEG movie showing the StartleCam in operation. The images to the left in each column show the wearer of the StartleCam being surprised by a person sneaking up from behind. The images to the right in each column show the images captured by the wearable camera when the system is activated by the detection of a startle pattern in the skin conductance response (Images courtesy of Jennifer Healey and Jonathan Klein).

of information management beyond image and video. An intelligent web browser responding to the wearer's degree of interest could elaborate on objects or topics that the wearer found interesting, until it detected the interest fading. An affective assistant agent could intelligently filter your e-mail or schedule, taking into account your emotional state or degree of activity.

The relationship between long-term affective state or "mood" and musical preferences can lead to other personal technology applications. Music is perhaps the most popular and socially-accepted form of mood manipulation. Although it is usually impossible to predict exactly which piece of music somebody would most like to hear, it is often not hard to pick what type of music they would prefer—a light piano sonata, an upbeat jazz improvisation, a soothing ballad—depending on what mood they are in. As wearable computers gain in their capacity to store and play music, to sense the wearer's mood, and to analyze feedback from the listener, they have the opportunity to learn patterns between the wearer's mood, environment, and musical preferences. The ultimate in a musical suggestion system, or "affective CD player" would be one that not only took into account your musical tastes, but also your present conditions – environmental and mood-related.

The possibilities are diverse – a wearer who jogs with her wearable computer might like it to surprise her sometimes with uplifting music when her wearable detects muscle fatigue and she starts to slow down. Another wearer might want the system to choose to play his favorite soft relaxing music whenever his stress indicators hit their highest levels. He might also want the computer to evaluate its own success in helping him relax, by verifying that, after some time, he did achieve a lower stress level. If the wearer's stress level increased with the music, or with a suggestion of music, then the computer might politely try another option later.

The whole problem of building *systems which adapt to you* is an important domain for affective wearables. Many times technology only increases stress, making users feel stupid when they do not know how to operate the technology, or making them actually become stupid when they rely on it in a way that causes their own abilities to atrophy. Our goal is to give computers the ability to pay attention to how the wearer feels, and to use this information to better adapt to what its wearer wants.

We need to be careful in considering the role of wearables in augmenting vs. replacing our abilities. For example, we know when a human is highly aroused (as in a very shocking or surprising situation) that she is more likely to remember what is happening–the so-called "flashbulb memory[?]." If the human brain is recording with full resolution at these times, then the wearable imaging system may not need to record more than a snapshot, or it may wish to focus on a wide-angle view, to complement the data the person is likely to remember. In contrast, when the human is snoozing during a lecture, the wearable might want to kick in and record the parts the wearer is missing. A truly helpful system learns the wearer's preferences, and

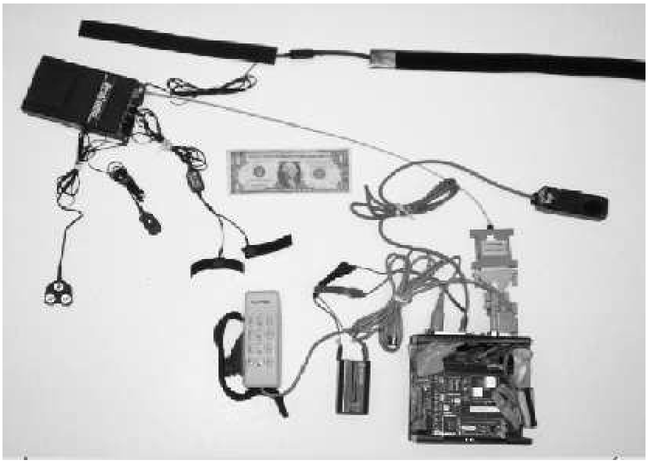

Figure 3: This affective wearable includes a ProComp sensing system (upper left corner) surrounded by four sensors, clockwise from top: respiration, galvanic skin response (GSR) (center, left), blood volume pressure (BVP), and electromyogram (EMG). This unit attaches to a PC104 standard based computer (lower right) which receives data from a Twiddler hand-held keyboard (lower left). and displays data with the Private Eye (far right, below respiration sensor.) The dollar bill is included to show scale. (Photograph by Jennifer Healey.)

tries to please the wearer by adapting accordingly.

3 Prototype of an Affective Wearable Computer

Ideally, an affective wearable would be able to sense and recognize patterns corresponding to underlying affective states, and respond intelligently based upon what it has sensed. We know of no computers that can do all of this yet; there are many difficult problems which need to be solved first. However, we have a prototype that achieves part of these goals, which we will now describe. The rest of this paper will focus on the results we have achieved so far in our efforts to develop the sensing and annotation aspects of an affective wearable computer. (The pattern recognition aspects are also important; these will be presented in a forthcoming publication.)

The current version we have built of an affective wearable is an augmentation of Starner's design [1] [?] using the PC 104 board standard and the Private Eye display, shown in Figure 3. Attached to this is a medically approved biomonitoring system made by Thought Technologies, which has the ability to simultaneously monitor respiration, skin conductivity (GSR), temperature, blood volume pressure (BVP), heart rate (from BVP), and EMG (electromyogram, for muscular electrical activity). All of these can be sensed painlessly from the surface of the skin. Future versions of the system, already under development, include audio and video inputs and displays, wireless links to the Internet, and wireless localized sensors.

Current functionality includes the monitoring of four sensors by a linux based operating system. The input from the four sensors can be displayed on a text-based screen such as the Private Eye with an option for concurrent user annotation. The annotations are automatically time-stamped by the system and stored in a separate log file. In the near future, we hope to add a third log file recording the user's location at periodic intervals using GPS for outdoors, and a system of fixed infrared location broadcasting stations for inside our lab.

The four biometric sensors can be sampled at up to 20 samples per second by the linux based ProComp system which allows an hour of data to be stored uncompressed in 1.125 MB as four-byte floating point numbers. A Sierra Wireless data modem attached to the wearable unit allows time-stamped data to be transmitted wirelessly to remote networks.

A difficult challenge of affective computing research is to determine which features of the sensor information should be considered salient, both to reduce the amount of data that is stored and transmitted, and to improve the analysis of the data. For example, it could be that a user is interested in monitoring her relative stress level over an extended period of time. Salient features for measuring stress could include the slope of the skin conductivity, average heart rate, average respiration rate or a combination of these and other signals. This data could easily be assessed and stored at a much lower saving rate (e.g., once per minute). At the end of a day or week, the user could view her daily stress profile. With intelligent annotation from the user—comments such as "begin work," "end work," "begin lunch," "end lunch," "met with supervisor," "begin driving," and so forth—the stress profile could be sorted by activity and presented to the user in a format which communicates the relative levels of stress.

4 Challenges of Ambulatory Affect Sensing

A wearable computer with bio-metric sensors, in constant contact with its user, offers an opportunity to obtain unprecedented amounts of physical and physiological data about a single user. This advantage also presents many challenges. To use the data effectively in learning algorithms, and to interpret the results, the data must be accurately labeled. We are in the early stages of developing ways to record the physical and psychological events of the wearer's life without interrupting their normal activities. Currently, an automatically time stamped notes file allows the user to annotate data from the sensor screen. Adding an audio recording device or video camera would improve the users ability to annotate data after the fact, but would make the annotation cumbersome. We propose to add two sensors to the system to improve annotation: a foot pressure sensor to indicate ambulatory movement and an audio detector that would detect if the wearer was making any vocal sounds (speech, sneezing, etc.) The latter could record and analyze the audio if privacy was not an issue, or if privacy was an issue, it would not record voice, but only use features of the sound signal to prompt the user for annotations, e.g. computer detects the presence of speech and prompts the user "Did you just talk to someone?" to

[1] http://wearables.www.media.mit.edu/projects/wearables/ has up-to-date information as well as a picture of this system.

which the wearer could respond "Yes, my boss."

It is important to annotate the physical activities of the user because such physical activities can overwhelm the physiological effect of psychological events. Even under "ideal" laboratory conditions, with a resting subject responding to a directed stimulus, scientists have yet to find reliably discernible features of physiological signals for affect detection. In a natural environment where weather, diet, and physical activity are present, the patterns corresponding to particular affective states are at a much greater risk of being obscured. We must identify and account for these confounding variables.

In psychological studies by Lang [?] and Winton, Putnam and Krauss [?], subjects were monitored while looking at a series of photographs which were supposed to elicit an emotional response. These studies showed that heart rate variability was an indication of valence (whether or not the person found the photograph pleasant) and that the ratio of skin conductance to heart rate variability was an indicator of arousal. However, the greatest changes in skin conductance and heart rate in their study were 0.6 micro-Siemens, and 8 beats per minute respectively, in the ten second period after viewing the slides. These results are significant for a resting subject under controlled laboratory conditions, but we have found that such results can be overwhelmed by physical activity in an ambulatory subject.

We conducted experiments in the laboratory to show that the physical activity of ambulatory subjects is an important confounding variable to detecting emotional responses from bio-sensors. Five different subjects were run through the ambulatory bio-sensing task, the results of which are reported in Table 1. The experimental protocol involved subjects wearing the bio-sensors from the FlexComp system while performing a series of ambulatory tasks. The subjects were first shown how to attach the bio-sensors. All subjects wore a respiration sensor, a BVP sensor, and a GSR sensor on the hand and another one on the arch of the foot. They were then asked to perform the following tasks: sit in a chair for one minute, resting quietly, stand up and sit down twice, walk around the room for one minute, sit in a chair normally for two minutes, stand up and walk around the room for one minute, sit normally for another minute, jog in place for one minute, then sit for a minute and finally the subjects were asked to cough as if they had a cold twice. An experimenter was in the room with the subjects at all times during the experiment to instruct the subjects to perform the activities. Subjects sometimes had questions during the experiment, and talking was noted in the experimental record. The rest times between the activities sometimes varied, due to questions, so the beginning of the tasks were marked by the experimenter with a specially designed mouse equipped with a sensor which would make a spike in the recording data when depressed.

The data for this experiment was saved at 16 samples per second using the FlexComp with a resolution of 0.01 micro-Siemens. Changes in the skin conductivity (GSR) were measured from a resting state to an active state. The changes were calculated as the difference between the baseline measurement, taken at the time each task was begun, and the first significant local maximum. The heuristic used for determining the significant local maxima is that the difference between the local maximum and the preceding local minimum is greater than 0.5 micro-Siemens. If there was no significant maximum, then the difference in the signal between the beginning and end of the activity was recorded. The heart rate was calculated from the peak-to-peak intervals and stored at 16 samples per second. To calculate the change in heart rate the average of the heart rate for 10 seconds before the task was subtracted from the average for the heart rate ten seconds following the task. An example of data from the experiments is shown in Figure 4.

Activity	Increase in HR (bpm)				
	S1	S2	S3	S4	S5
stand	16.0	15.8	19.7	22.0	15.2
walk	26.4	18.9	27.7	24.6	19.9
jog	68.2	60.8	74.0	80.9	87.4
cough	22.0	22.2	18.8	53.7	14.66
Activity	**GSR change for Hand (micro-Siemens)**				
	S1	S2	S3	S4	S5
stand	0.5	10.6	0.2	1.7	N/A
walk	2.0	14.3	0.8	2.8	N/A
jog	5.9	16.1	3.5	2.2	N/A
cough	5.4	11.0	2.1	2.7	N/A
Activity	**GSR change for Foot Arch (micro-Siemens)**				
	S1	S2	S3	S4	S5
stand	0.5	12.6	0.3	4.1	3.7
walk	1.5	10.4	1.7	6.9	3.4
jog	11.5	11.0	5.0	5.0	6.4
cough	6.9	9.9	2.4	5.9	3.2

Table 1: A wearer's activities can cause large changes in physiological signals. These changes need to be understood so that they can be taken into account by the system trying to recognize affect.

It is useful to have an accurate recording of the physical activity of the wearer and to understand how this affects the user's physiology and expression of affect. From this information we can attempt to decouple the psychological effects from the physical. For example, although the heart rate of the wearer changes drastically with inhalation and exhalation, the heart rate and respiration signals are highly correlated as shown in Figure 5. By recording respiration, we can state which heart rate changes are effected by this source and which changes must be attributed to other sources.

The selection of which signals to measure is another challenge for an affective wearable. There is evidence to believe that physiological signals including accelerated heart rate [?], raised blood pressure, increased skin conductivity, and constriction of the peripheral blood vessels [?] are associated with stress in humans and heart rate variability [?], pupillary dilation and right and left hemispheric activation in the brain [?] are associated with like/dislike. These states are particularly useful ones for interactions involving humans and computers, especially as computers try to understand and adapt better to their wearers.

We are experimenting to determine which physiological signals can be best monitored under ambulatory condi-

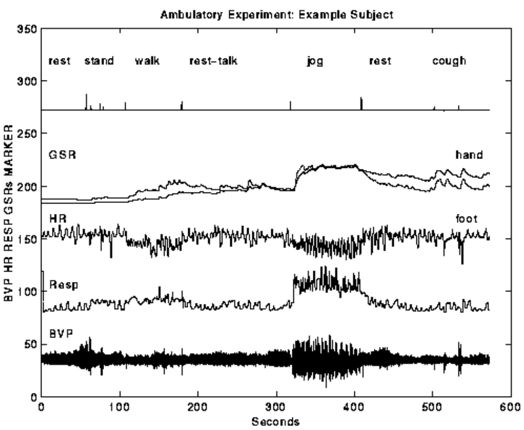

Figure 4: An example of data collected from the ambulatory experiment. Data is scaled and offset for showing the relationships between the signals.

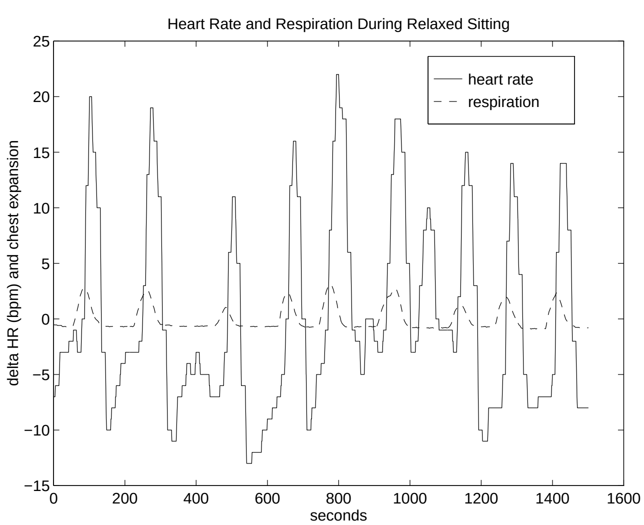

Figure 5: The heart rate and respiration signals from the ambulatory experiment, showing that although respiration has a large effect on heart rate, these effects are well correlated with the respiration signal and can be predicted.

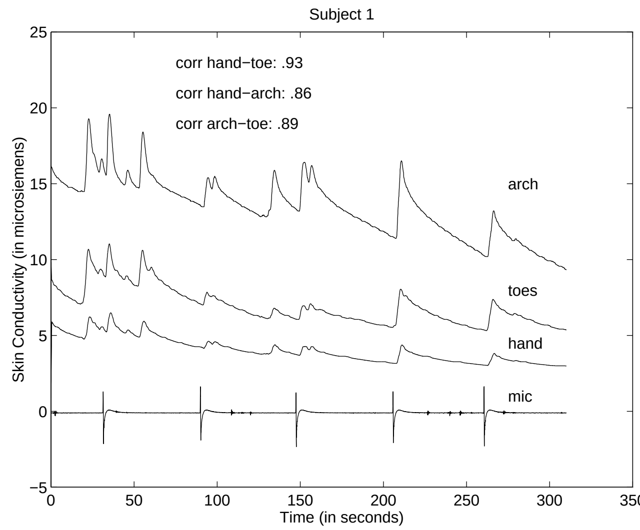

Figure 6: An example of data collected from the multiple startle experiment. This experiment was designed to test the correlation of the hand and the foot responses under extreme conditions.

tions to produce the most salient affective features, given the constraint that the sensors should be comfortable to wear. Such a system needs to be unobtrusive, lightweight, and easy to use. It should not require the user to make exceptions to her daily routine. Our goal is to create an affective wearable system that is comfortable and robust, able to extract and analyze complex features in both the time and frequency domain, and able to record annotations and context information, all for providing pleasantly useful services to its wearer.

The GSR sensor is one of the most robust wearable sensors because it is a bulk measurement and not very sensitive to exact placement of the sensor. Traditionally, this measurement is taken across the palm of the hand. However, the hand is one of the least ideal places for sensor placement. Ordinary activities such as washing your hands changes the baseline reading and repetitive motion of the fingers in activities like typing, creates a noise signal that confounds the signal. To alleviate this problem, we have explored the options of placing the electrodes on the toes, and measuring skin conductivity across the sole of the foot.

In this experiment, another five subjects were seated and startled with five white noise bursts while wearing skin conductivity sensors on three locations. The sensors were placed on the two middle sections of the first and second finger on the dominant hand, on the two middle sections of the first and second toes on the same foot, and on either end of the arch of the same foot. An electret microphone was used to record the startling tone burst as a reference. All skin conductivity data was sampled and saved at 16 samples per second with 0.01 micro-Siemens resolution. An example of the data recorded during these experiments is shown in Figure 6.

The startle experiment was designed to test the correlation of the hand and foot responses under extreme audio stimuli. The correlation coefficient was used to measure

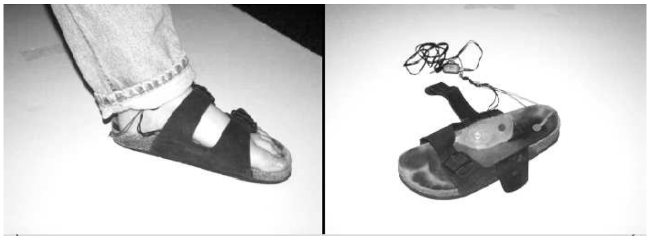

Figure 7: The shoe provides a convenient location for sensor placement. Here, a skin conductivity sensor is placed in the arch of the shoe and a pressure sensitive resistor is placed on the heel. Sensors look unobtrusive when worn. (Photograph by Fernando Padilla)

Activity	Correlation Coefficients for GSR				
	S1	S2	S3	S4	S5
hand-toes	.93	.90	.97	.53	.86
hand-arch	.86	.86	.99	.95	.81
arch-toes	.89	.96	.98	.57	.86

Table 2: The similarity between skin conductivity readings measured from the palm of the hand and the arch of the foot offers the possibility of placing sensors in the wearer's shoe instead of on the hand.

similarity between the signals taken from the three locations. The results of these correlations are reported in Table 2. In the natural sciences, the correlation coefficient is used in the Pearson correlation to test significance of traits, based on the number of data points. If we consider all samples of the signal data points for this test, all the results are extremely significant with $p>0.01$.

Strong correlations were found between the hand and foot responses in the ambulatory study with correlation coefficients of .90, .85, .83 and .88 for the first four subjects respectively. The fifth subject inadvertently detached the hand GSR during the experiment. From these results we concluded that the skin conductivity responses of the hand and the foot to a startle signal are highly correlated. Therefore, either placement of the sensor could be used to measure the GSR response for these subjects. Only one subject, subject four, showed an unusually smooth response from the toe sensor, as if the signal had been low pass filtered, resulting in poor correlations with the other signals. This could be due to sensor placement error or to a naturally sluggish sweat response along this pathway, indicating that different individuals may have different optimal sensor sites.

The blood volume pressure sensor uses photoplethysmography, a technique where an LED is used to "look" at the amount of blood flowing in the vessel. From this reading both the heart beat and constriction of the blood vessel can be determined. This sensor is sensitive to correct placement and motion artifacts; however, in a single-subject experiment we conducted driving through Boston at rush hour, where the wearer moved the hand with the sensors routinely to shift gears, adjust the radio, and turn the steering wheel, we found that although the signal was disturbed during motion, the signal re-stabilized after movements.

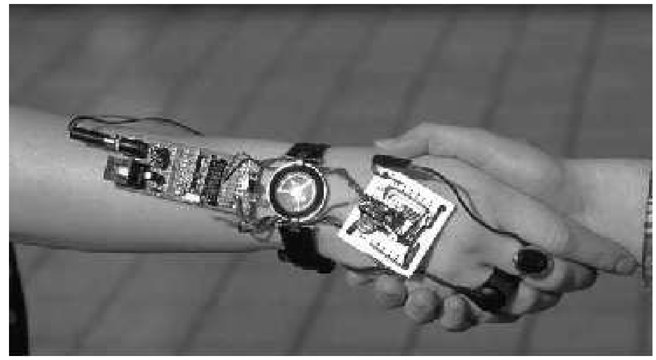

Figure 8: PIC chips on iRx boards can be used to sample data from sensors and transmit the digital signal using infrared. As these systems are shrunk into jewelry, shoes, and other wearables, they permit affective information to be wirelessly transmitted to a larger computer for analysis. (Photograph by Frank Dabek).

Hence, we think that motion artifacts can be compensated for. Nonetheless, the driver reported that the wires felt like they were in the way.

We are interested in moving sensors off the hands to sense what people are feeling during a variety of consumer tasks, such as diapering an infant. This is a particularly challenging task as it is important not to drag the wires through the dirty diaper, or let the infant grab them and pull them, or put them in his mouth. In other words, we are investigating options for moving the sensors off the hands.

Respiration is the easiest sensor to wear and tends to be the most immune from motion artifacts of the sensors investigated here. It uses a constrained Hall effect sensor to measure the expansion and contraction of the chest cavity. The confounding variables of this measurement mostly audio (e.g. talking, sneezing, coughing and sighing) all of which we hope to compensate for with the audio detector.

We have been investigating the optimal placement for the EMG sensor to detect stress. The greatest challenge of EMG placement is to find a muscle to which the EMG electrode pad will stick well and which is not involved in muscle motion. To solve the problem of affixing the sensors we are currently considering the use of new electrodes and glue designed by the Boston University Neuro-muscular Research Center which have been demonstrated to stay affixed through rigorous physical activity. To solve the problem of motion we may need to create sensors which detect motion and use this to correct the straight EMG reading. We are also developing alternative sensors for muscular movement using AMP piezo tape. These have the advantage of not requiring glues or gels.

We are in the process of creating a wireless interface for all of these sensors. There are two possibilities currently being investigated for wireless transmission of data from the sensors: infrared transmission, and constrained short wave FM transmission using the personal area network (PAN). We have currently designed working prototypes of analog sensors such as the skin conductance sensor shown in Figure 9 and the blood volume pressure sensor shown in Figure 10. These sensors are sampled using an

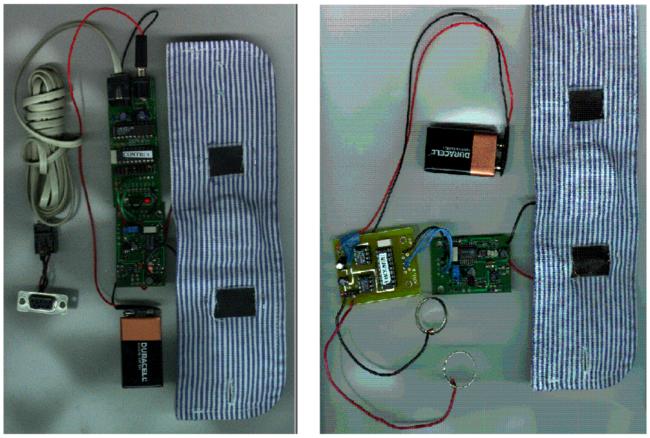

Figure 9: Skin conductance sensor attached to wireless Personal Area Network (PAN) device. The left figure shows the PAN transceiver which connects to the serial port of a computer and the right figure shows the analog skin conductance sensor with A/D converter. Both units are presently powered by 9 volt batteries and attached to the person using cuffs with conductive rubber electrodes. (Photograph by Jennifer Healey).

Figure 10: Analog BVP sensor in earring attachment for use with infrared or PAN A/D processing units (Photograph by Frank Dabek).

A/D converter chip. The digital bio-metric signal can then be transmitted either by the iRx PIC configuration or the PAN-CBPS system.

The PIC iRx infrared system allows line-of-sight transmission of data over short distances and does not interfere with electrical signals. It is ideally used in situations where there is little distance or obstruction between the sensing system and the target. Examples of situations in which this might be useful include transmission of data between two people who are in close physical proximity as shown in Figure 8 or between a person and a desktop computer. For example, a shoe sensor with an embedded iRx chip could transmit data to a receiver beneath the workstation.

The PAN system which uses short wave FM to transmit data beneath the surface of the skin [?] proves to be more useful in situations where the receiver and the sensor are not in direct line of site as would be the case for the bio-sensors and a wearable computer. In the system shown in Figure 9, a transceiver which attaches to the serial port of a computer interrogates a remote skin conductance sensor. The system attaches to the person's body using conductive rubber electrodes which require no gel. The wearer's body acts like a bus for the digital data [?]. By using a transceiver controlled interrogation scheme, this bus can be shared by up to fifteen sensors, with a shared rate of up to 2400 baud.

5 Technology, Interface, and Human factors issues

This work raises a variety of concerns on many fronts. One of these is the need for lightweight, efficiently-powered computation, which is comfortable to wear, i.e., that does not interfere with a person's ordinary comfort or activities. Another need is the development of robust sensors with reliable contact. Whether these are flexible rubberized electrodes attached with jewelry, or small sensors for temperature sewn into our garments, or stretchy fabric comprising parts of a sports bra, these interfaces need to provide accurate signal collection and be comfortable enough not to disturb their wearer.

One of the many interface concerns involves how to present affective information to the wearer and to those with whom the wearer wants it communicated. If you are willing to transmit your mood to your spouse 0at the end of the day, how should this information be presented? As a synthesized facial expression, modulated vocal announcement, or, encoded in something more subtle, such as a note announcing the arrival of fresh flowers at the local store which is on your way home? Of course, privacy is also a priority, since the good mood you are in might be great for your family to know about, but not something you want taken advantage of by a salesperson.

6 Conclusions

We have designed a prototype of an affective wearable computer and demonstrated many issues that need to be considered in the development of such systems. Bio-metric sensors need to be developed that are both accurate and robust to motion artifacts yet unobtrusive and comfortable to wear. Sensors that can allow the wearable to be aware of the users context (home or office), and level of physical activity (sitting, walking, coughing) need to be incorporated. Pattern recognition and analysis techniques for affect recognition which integrate this context information and which are able to operate in real time on a single user need to be developed. Such developments will enable many new future applications, some of which are described here. We also demonstrated one major step toward one of the information-overload management applications, the StartleCam, which has already been achieved with the current state of affective and wearable technology.

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