UNOBTRUSIVE DATA RETRIEVAL FOR PROVIDING INDIVIDUAL ASSISTANCE IN AAL ENVIRONMENTS

Carsten Rachuy[1], Sandra Budde[2] and Kerstin Schill[1]
[1]*Kognitive Neuroinformatik, Universität Bremen, Bremen, Germany*
[2]*Cognitive Systems, Universität Bremen, Bremen, Germany*

Keywords: Ambient assisted living, Wearable computing.

Abstract: We present a prototype for a wearable device that measures physiological data in an unobtrusive way. The aim is to utilize changes in these physiological patterns to infer about the user's affective state which is used as a evidential source of contextual information for recognizing activities of daily living (ADL) in an ambient assisted living (AAL) environment. We describe the device, compare it to a commercial stationary solution and give an outlook on possible scenarios for its application.

SCIENCE AND TECHNOLOGY PUBLICATIONS

1 INTRODUCTION

Current statistics on changes in age groups in Germany show a major increase in the ratio between elderly people and the following younger generation. While in 2008 the number of people below 20 approximately equals the number of people over the age of 65, forecasts show that in the year 2060 the share of people over the age of 65 will be approximately twice as high as the share of people under 20 (see (Plötzsch, 2009), p. 16.). As aging is always a process that affects the capabilities of the human body and impairs the general performance regarding physical as well as mental capabilities, the need of age-adequate and context-dependent assistance increases. Assistance in this context is focused to AAL environments where AAL denotes the principle of providing assistance not through defined tools like wheelchairs, walkers or other devices but by incorporating the assisting devices into the environment: the environment itself both recognizes the need for assistance and provides it in an adequate way. As the main goal of such environments is to support a life independent from the support of caregivers as long as possible, such environments mostly provide assistance in order to perform ADLs on one's own. Assistance on these can either be provided in a static way by e.g. structural changes in the environment namely wheelchair rams, rails, panic buttons and stair lift or in a more flexible way by adapting it to the varying condition over the course of the day. In the latter case, assistance is provided on the basis of dynamic contextual data which is situation-dependent and varies during the course of the day. For instance physiological measurements can be used to infer a person's actual affective state (Calvo and D'Mello, 2010). In this paper, we present a device that is able to measure physiological signals in an unobtrusive way and show that its data is reliable enough to infer the user's affective state.

2 PREVIOUS AND RELATED WORK

There exist various approaches to measure physiological data and to use these measurements to infer about the state of the user. Regarding the hardware there are numerous devices which are mostly developed for clinical use and are therefore most often stationary or semi-mobile but also some wearable devices are available. In the line of stationary devices Thought Technology[1] offers sensor units which are mainly used for monitoring, biofeedback or rehabilitation purposes. An example for a mobile device is the Telcomed MiniClinic[2] which resembles a wristwatch and is eligible for measuring heart rate, electrocardiogram, heart rhythm regularity, respiratory rate and body temperature. Advantages of stationary devices are - being situated in the medical domain - their high reliability and accuracy. The downside is

[1]http://www.thoughttechnology.com

[2]http://www.telcomed.ie/wristwatch.html (verified Mai 4, 2010)

Rachuy C., Budde S. and Schill K..
UNOBTRUSIVE DATA RETRIEVAL FOR PROVIDING INDIVIDUAL ASSISTANCE IN AAL ENVIRONMENTS.
DOI: 10.5220/0003137705170520
In *Proceedings of the International Conference on Health Informatics* (HEALTHINF-2011), pages 517-520
ISBN: 978-989-8425-34-8
Copyright © 2011 SCITEPRESS (Science and Technology Publications, Lda.)

- in the stationary case - that they are not suitable for monitoring over a longer duration of time when performing activities of daily living. In the wearable case problems arise from proprietary software which makes working with the raw data complicated.

There also exist some approaches on how to use physiological data in order to adapt the behavior of an assistance system. In (Fischer et al., 2008) the π^2, a multi-sensoric hardware platform was developed using a fuzzy-logic-based control unit designed for providing assistance for people suffering from incontinence. Based on the collected data the fuzzy-controller computes an estimation on the remaining time until the next urination and provides appropriate feedback and/or warnings to the user.

In the work performed by (Poh et al., 2010) a wearable device was developed which was used to measure electrodermal activity (EDA) and evaluated certain patterns during common activities as cycling, studying and watching a movie.

Another approach was the work performed in the SHARE-it project[3] where aim was to infer affect on the basis of physiological measurements and to model the impact of affective states on the user's cognitive performance. These findings were used to both adapt the level of driving-assistance of an autonomous wheelchair to the current user's needs and to modify the complexity of displayed visual information with the aim to reduce the amount of needed cognitive information processing in situations where the user's attention had to be focused on the navigation tasks.

3 HARDWARE DEVELOPMENT

The hardware consists of two components. These are a commercial heart rate detection belt which is normally used during exercise and which is distributed by Suunto[4] and a device which was manufactured by LIGHTRONIC[5] based on specification by the University of Bremen (see Figure 1).

It has the dimensions of 3.5 cm x 4.0 cm x 1.5 cm and is worn using a wristband. It incorporates an integrated bluetooth module for wireless communication and a Li-Ion-Accumulator serving as power source which has a lifetime of approximately 4 to 5 hours for continuous monitoring and sending. The device provides a number of sensors to measure different types of data namely skin conductance (SC), ambient temperature, skin temperature and both orientation and acceleration information along the x-, y- and z-axes. Additional focus has been set to keep the design as close to normal clothing therefore being as obtrusive as a watch in terms of pressure and movement constraints.

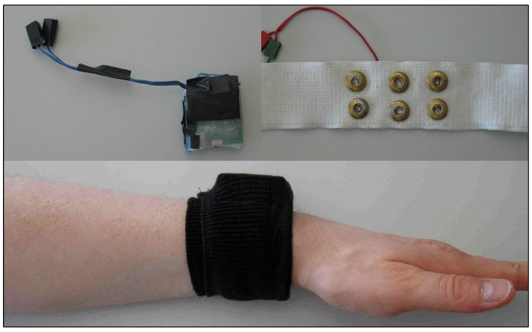

Figure 1: Top left: sensor module. Top right: skin conductance sensors. Bottom: combined device when worn.

4 EVALUATION

The device was evaluated during experiments in order to test the reliability and stability of the measurements by comparing it to the measurements of a commercial medical device and to investigate the correlations between stimuli and induced affective states. The experiment consists of two phases: during the first we focused on inducing affective responses, during the second on inducing stress.

The first phase of the experiment follows a method which is developed by (Bradley et al., 2001) and uses 72 stimuli from the international affective picture system (IAPS) (Lang et al., 2008) which is an international valid and trusted method for inducing emotions. The second phase of the experiment focuses on inducing stress by presenting 25 mathematical tasks which are a subset from the arithmetic tasks presented by (Kellogg et al., 1999) and increasing time pressure during solving these tasks. The participants for this experiment were healthy volunteers, mostly students in the age from 20 to 40.

In both phases, *heart rate* (HR), *skin conductance* (SC), and *skin temperature* (Temp) were measured using the developed device and the commercial Thought Technology system. In addition, during the first experiment, participants were asked to do Self-Assessment Manikin (SAM) ratings (Bradley and Lang, 1994) with respect to the induced emotion.

In the first phase, each stimuli presentation begins with the display of a preparation slide and at the same time the recording of the physiological data is started. After three seconds, the affective stimulus is presented to the subject for six seconds. Sub-

[3] http://www.ist-shareit.eu/shareit

[4] http://www.suunto.com

[5] http://www.budelmann-elektronik.com

SCIENCE AND TECHNOLOGY PUBLICATIONS

sequently, the physiological data is collected for two more seconds. After this, the rating procedure follows in which the subject rates the pleasure dimension and the arousal dimension of the induced emotion.

In the second phase, the timing behavior of the task presentation is triggered by the participants performance during the very first task of each task block. These tasks are presented as long as the participant needs to solve them. The answer is entered into the system by the advisor. After this, each task of a certain difficulty level is presented for a slightly shorter time as the participant needed or was given respectively for the preceding task of the same time. To depict this time limit, a progress bar is displayed which illustrates the time spent for this task as well as the time left. After the time has run out, the task is no longer displayed and the participant has to give his solution to the task.

5 RESULTS

To analyze the physiological data which is recorded during the experiments, we extract and compute attributes as arithmetic mean, standard deviation, first-forward-difference, pearson correlation coefficient and spearman's rank correlation coefficient.

5.1 Comparison with Medical Device

The correlation between the signals recorded from the sensor device (heart rate and skin conductance) and the values collected using the Though Technology medical system was checked by normalizing both data and calculating the mean square difference. The mean square percental difference between the sensors for the heart rate measurements is 6%, the mean square percental difference for the skin conductance and skin resistance is 13%.

5.2 Reaction on IAPS Stimulus Material

One major point is inferring from the physiological signals to the emotional state and the stress level. For that reason we analyzed the sensor output in conjunction with the ratings the subjects gave according to the IAPS pictures. The pearson and spearman's correlation coefficient for the preprocessed values are displayed in Figure 2. The four blocks correspond to the different correlation coefficients (pearson / spearman's) and the different ratings (valence / arousal). Depicted are the correlation coefficients for each subject. We have a sample size of $N = 72$ (72 images). The tables for pearson and spearman's are capped at

Sub	Cor	Aff	HR	SC	HR1st +	-	SC1st +	-
1	Pe	Val	0.06	0.19	0.01	0.10	0.03	0.13	0.28	0.06
2	Pe	Val	0.21	0.05	0.01	0.06	0.00	0.09	0.01	0.08
3	Pe	Val	0.19	0.10	0.10	0.08	0.10	0.01	0.01	0.00
4	Pe	Val	0.29	0.15	0.17	0.14	0.14	0.05	0.06	0.01
5	Pe	Val	0.08	0.11	0.01	0.00	0.01	0.01	0.05	0.01
1	Sp	Val	0.01	0.21	0.00	0.06	0.06	0.24	0.24	0.25
2	Sp	Val	0.18	0.06	0.08	0.00	0.05	0.03	0.06	0.01
3	Sp	Val	0.19	0.12	0.04	0.11	0.02	0.06	0.09	0.06
4	Sp	Val	0.26	0.14	0.03	0.13	0.02	0.08	0.07	0.05
5	Sp	Val	0.17	0.12	0.27	0.16	0.17	0.12	0.16	0.11
1	Pe	Ar	0.02	0.00	0.08	0.01	0.09	0.04	0.12	0.02
2	Pe	Ar	0.22	0.08	0.01	0.09	0.03	0.08	0.06	0.08
3	Pe	Ar	0.26	0.18	0.21	0.20	0.20	0.15	0.11	0.16
4	Pe	Ar	0.03	0.09	0.10	0.02	0.11	0.13	0.07	0.13
5	Pe	Ar	0.05	0.02	0.24	0.20	0.25	0.33	0.10	0.32
1	Sp	Ar	0.07	0.15	0.13	0.06	0.18	0.17	0.18	0.18
2	Sp	Ar	0.24	0.08	0.02	0.05	0.14	0.06	0.04	0.06
3	Sp	Ar	0.26	0.14	0.16	0.22	0.18	0.11	0.03	0.13
4	Sp	Ar	0.03	0.11	0.09	0.18	0.00	0.18	0.13	0.18
5	Sp	Ar	0.00	0.14	0.03	0.09	0.10	0.17	0.01	0.16

Figure 2: Correlation coefficients for IAPS test.

$N = 30$ or $N = 60$. Due to the fact that for increasing N the thresholds are decreasing too we can safely work with a threshold for a $N_{table} < N_{experiment}$. For $\alpha = 0.05$ we get $t_{pearson} = 0.195$ and $t_{spearman's} = 0.214$. If a value exceeds these thresholds, the zero hypothesis (which states "there is no correlation") is proven wrong and the correlation is considered being significant. Applied to the physiological data it means that if we find a correlation coefficient which exceeds these thresholds, a significant correlation exists between the valence / arousal and the appropriate physiological measurement. All cases in which this is the case have been marked with a red square. As we can see we have a number of significant correlations, both from the pearson as well as from the spearman's test. This indicates that a significant correlation exists between the rated arousal and valence values and the physiological measurements.

5.3 Reaction on Mathematical Stimulus Material

As the difficulty of the mathematical tasks was increasing while the time for each task was decreasing, the stress level for the subjects gradually increased during the experiment. The pearson and spearman's correlation coefficient for the preprocessed values are displayed in Figure 3. The four blocks correspond to the different correlation coefficients (pearson / spearman's) and the task difficulty. Depicted are the correlation coefficients for each subject. We have a sample size of $N = 25$ (25 mathematical tasks). For $\alpha = 0.05$ we get $t_{pearson} = 0.323$ and $t_{spearman's} = 0.337$. Just like in the IAPS case, if a value exceeds these thresholds, the zero hypothesis (which states "there is no correlation") is proven wrong and the correlation is considered being significant. Applied to the physiological data it means that if we find a correlation coefficient which exceeds these thresholds, a significant

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS

Sub	Cor	Aff	HR	SC	HR1st	+	-	SC1st	+	-
1	Pe	Ar	0.40	0.85	0.29	0.23	0.35	0.32	0.06	0.10
2	Pe	Ar	0.58	0.83	0.40	0.14	0.15	0.50	0.03	0.32
3	Pe	Ar	0.09	0.99	0.21	0.16	0.29	0.64	0.13	0.56
4	Pe	Ar	0.17	0.02	0.36	0.01	0.04	0.35	0.33	0.22
5	Pe	Ar	0.00	0.72	0.07	0.00	0.16	0.46	0.29	0.11
1	Sp	Ar	0.34	0.80	0.19	0.21	0.10	0.25	0.03	0.16
2	Sp	Ar	0.56	0.85	0.27	0.21	0.21	0.46	0.19	0.39
3	Sp	Ar	0.00	0.99	0.15	0.31	0.35	0.61	0.03	0.54
4	Sp	Ar	0.21	0.01	0.17	0.16	0.36	0.35	0.27	0.24
5	Sp	Ar	0.24	0.74	0.05	0.24	0.35	0.53	0.33	0.06

Figure 3: Correlation coefficients for mathematical tasks.

correlation exists between the difficulty of the task and the appropriate physiological measurement. All situations in which this is the case have been marked with a red square. As we can see we have a number of significant correlations, both from the pearson as well as from the spearman's test. This indicates that a significant correlation exists between the task difficulty the experienced physiological reaction of the subject.

6 CONCLUSIONS

We presented a prototypical development of a wearable device which can be used for measuring physiological data and showed that inferring from these measurements to the affective state of the user is possible for scenarios utilizing standardized affect-inducing techniques. Analysis of the data and comparison between the subjects showed that measured physiological responses are highly individual for different subjects, even in standardized experimental settings. An even higher impact of these inter-individual response characteristics to affective stimuli on the collected data can be expected when these measurements are taken in non-standardized scenarios - e.g. while performing activities of daily living in a home environment.

7 OUTLOOK

Further development and evaluation has to be performed regarding two aspects. The first is to evaluate to which degree physiological signals - as responses to standardized stimulus material - are comparable with those recorded in real world scenarios. It has to be investigated whether inference mechanisms based on the former setting can be transferred and applied to the latter. The second is to perform a thorough analysis on the recorded physiological patterns and evaluate whether channel-dependent, non-ambiguous signal characteristics can be found which could then be used as discriminating features for improving the inference algorithm.

ACKNOWLEDGEMENTS

The presented work is funded by the project I3-[SharC], R1-[ImageSpace], and A5-[ActionSpace] in the Transregional Collaborative Research Center SFB/TR 8 Spatial Cognition. The support by the German Research Foundation (DFG) is gratefully acknowledged.

REFERENCES

Bradley, M. M., Codispoti, M., Cuthbert, B. N., and Lang, P. J. (2001). Emotion and motivation I: Defensive and appetitive reactions in picture processing. *Emotion*, 1(3):276–298.

Bradley, M. M. and Lang, P. J. (1994). Measuring emotion: The self-assessment manikin and the semantic differential. *Journal of Behavioral Therapy and Experimental Psychiatry*, 25:49–49.

Calvo, R. A. and D'Mello, S. (2010). Affect detection: An interdisciplinary review of models, methods and their applications. *IEEE Transactions on Affective Computing*, 1(1):18–37.

Fischer, C., Sancho-Pradel, D., and Schill, K. (2008). Towards a Multisensory-based Automation of Urinary Incontinence Behavioural Treatment. In *AI IN ELDERCARE: NEW SOLUTIONS TO OLD PROBLEMS: PAPERS FROM THE AAAI FALL SYMPOSIUM*, Arlington, Virginia.

Kellogg, J. S., Hopko, D. R., and Ashcraft, M. H. (1999). The effects of time pressure on arithmetic performance. *Journal of Anxiety Disorders*, 13(6):591–600.

Lang, P. J., Bradley, M. M., and Cuthbert, B. N. (2008). International affective picture system (IAPS): Affective ratings of pictures and instruction manual. Technical Report A-8, University of Florida, Gainesville, FL.

Plötzsch, O. (2009). *Bevölkerung Deutschlands bis 2060 - 12. koordinierte Bevölkerungsvorausberechnung*. Statistisches Bundesamt, Wiesbaden.

Poh, M.-Z., Swenson, N. C., and Picard, R. W. (2010). A wearable sensor for unobtrusive, long-term assessment of electrodermal activity. *IEEE Trans Biomed Eng*, 57(5):1243–52.