SLEEPIC
Developments for a Wearable On-line Sleep and Wake Discrimination System

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Abstract: The design of wearable systems comes with constraints in computational and power resources. We describe the development of customized hardware for the wearable discrimination of human sleep and wake based on cardio-respiratory signals. The device was designed for efficient and low-power computation of Fast Fourier Transforms and artificial neural networks required for the on-line classification. We discuss methods for reducing computational load and consequently power requirements. The SleePic prototype was tested for autonomy and comfort on eight healthy subjects. SleePic showed an energetic autonomy of more than 36 hours. The SleePic device will require further integration for increased comfort and improved user interaction.

1 INTRODUCTION

Monitoring sleep and wake behavior of subjects at home allows the early detection of sleep troubles and disorders, and can reduce health care costs (Colten and Altevogt, 2006). Home monitoring of sleep/wake behavior imposes particular challenges, namely that necessary sensors, electronics and intelligent signal processing algorithms require integration into a comfortable, wearable device.

The most common physiological signal used for sleep discrimination in clinical sleep monitoring is the recording of brain activity with an electroencephalogram (EEG) (Ogilvie, 2001). Unfortunately, EEG cannot be easily recorded with a wearable system. Alternatively, actigraphs are often used for long term sleep studies (Sadeh, 2002). Actigraphy is a passive measure of sleep/wake behavior. The actigraphy wristbands are small, lightweight, low-power, and therefore easy to wear over several days. However, actigraphy algorithms often incorrectly classify low activity tasks (e.g. reading or watching television) as sleep because the measured behavioral quiescence is not unique to sleep (Sadeh, 2002; de Souza et al., 2003). In previous studies we showed that sleep / wake classification is possible with frequency-domain features of cardio-respiratory signals using a single-layer, feed-forward artificial neural network (ANN) (Karlen et al., 2008; Karlen et al., 2009).

Comfort and wearability imposes constraints on the design of devices. For instance, micro-controllers are preferred to the high-performance 32-bit application processors from the standpoint of power consumption (i.e. compared <0.1 W for micro-controllers to 1-2 W for application processors used in smart phones). However, micro-controllers are limited by the computational resources they provide, as well as being less flexible by not running operating systems and rich data formats. These constraints therefore impose particular challenges in the design of accompanying digital signal processing (DSP) algorithms to have low computational complexity.

We have developed a wearable hardware system called *SleePic* (derived from *Sleep* discrimination with a *Programmable interface controller*).

The SleePic implements the preprocessing and ANN classification principles previously suggested in (Karlen et al., 2009). We describe the research and development of the wearable hardware design of SleePic and present methods to minimize the power

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consumption of the classification algorithm to be embedded in wearable systems. We also describe validation experiments with data obtained from eight users wearing SleePic for 36 hours.

2 HARDWARE REQUIREMENTS

For the development of the wearable sleep / wake discrimination system, we formulated a series of design criteria that were based on general recommendations for a wearable bio-medical device (Martin et al., 2000; Scheffler and Hirt, 2004) and the classification algorithm described in (Karlen et al., 2009). The system was expected to:

- Be *wearable*. From sensors to user feedback, we wanted to integrate all elements of the device into a wearable system. This implies low size and low weight. It is desirable that the wearable system is comfortable and does not display any cables or wires.
- Be *autonomous*: The system is expected to have power autonomy for at least 24 hours. After usage, easy recharge is a plus.
- Record *cardio-respiratory* data. The algorithm in (Karlen et al., 2009) processes electrocardiogram (ECG) and respiratory (RSP) signals for classification.
- Be able to *execute the classification algorithm on-line*. The processing resources on the system need to cope with the signal processing and classification in minimal time without excessive energy consumption.
- Give *feedback to the user*. The system needs an interface to communicate with the wearer. The feedback method has to adhere to the energy restrictions.

To our knowledge, there exist no systems on the market that comply with all these design criteria. Therefore, to embed the classification algorithm developed in (Karlen et al., 2009) into a wearable demonstrator, we built our own prototype. To keep development cost low, we relied on commercially available sensors and components for prototyping. Missing functionality, such as user interface and computational resources for on-line classification, were added by designing custom extension modules.

3 SLEEPIC DESCRIPTION

The SleePic sleep / wake discrimination system is composed of three modules (Figure 1):

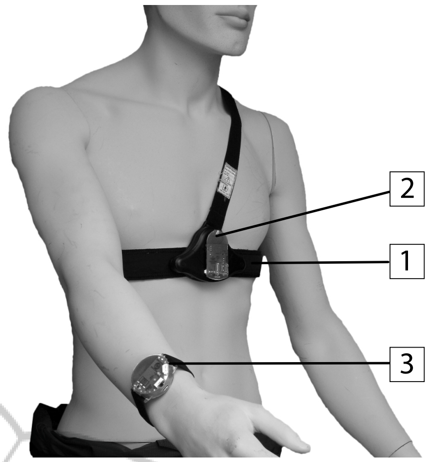

Figure 1: A subject wearing the complete SleePic sleep / wake detection system. 1) Equivital^{TM} Sensor Belt; 2) SleePic Core extension module; and 3) SleePic Watch for user interaction.

1. The *SleePic Sensor module* is worn around the chest.
2. The *SleePic Core processing module* is responsible for all signal preprocessing and classification. The module connects directly to the SleePic Sensor module.
3. The *SleePic Watch* is worn on the wrist. The SleePic Watch is responsible for remote sensing and user feedback. It communicates wirelessly with the SleePic Core.

3.1 Wearable Sensor Module

Sensors integrated into textiles appeared on the market only recently. The technology is not yet established and expensive. The Equivital^{TM} physiological monitoring system (Hidalgo Ltd, UK) has been chosen as sensor module for this system development. It offers a good compromise between cost, wearability and real time sensor access. It offers high integration of sensors and textile electrodes in a single belt worn across the upper chest area, which facilitates the correct wearing and use of the system by inexperienced users. Equivital^{TM} can operate continuously for up to 48 hours with the integrated, rechargeable Lithium-Ion battery (760 mAh). However, there is a lack of user feedback possibilities, and options for computing the classification algorithm on-line are also missing. Equivital^{TM} is composed of two units:

1. A washable sensor belt which integrates 3 textile dry electrodes for 2-lead ECG recordings and a piezo-resistive strain gauge to measure RSP. The sensor belt weights 94 grams (size M).

2. A Sensor Electronics Module (SEM) that can be attached to the sensor belt with five connective clips. The SEM measures 3-axis acceleration (ACC), temperature and features a real time clock (RTC). The SEM also embeds a vibrating actuator. The SEM weights 75 grams including the battery.

3.2 SleePic Core Processing Module

The SleePic Core (Figure 2) is a printed circuit board (PCB) that plugs to the SEM. It was designed for receiving the raw sensor data from the Wearable Sensor module and the SleePic Watch , the processing of the sensor signals, executing the classification task, and the coordination of the tasks between all three SleePic modules.

The SleePic Core is composed of a processing unit, a power unit, storage unit and a communication unit. The processing unit is the central element on the SleePic Core and contains the 40 MIPS dsPIC33256GP710 micro-controller (Microchip Technology Inc., USA). This programmable interface controller has a 16-bit architecture, 32 kB RAM, 256 kB program memory and DSP functionality. It has been chosen because of the presence of multiply-and-accumulate (MAC) and a barrel shifter functionality which simplifies the Fast Fourier Transformation (FFT) and ANN calculation. At time of development, it was the largest available microcontroller from the dsPIC33 series. The relatively high amount of RAM was required for the FFT preprocessing. The communication unit contains a UART port for the communication with the SEM, another UART port to communicate with a PC over a USB converter and an SPI port for the NRF02L wireless chip (Nordic Semiconductor ASA, Norway) to communicate with the SleePic Watch module. For saving energy, each of the units can be disabled when not needed by the micro-controller, including itself. The dimensions of the SleePic Core module are 65 mm$\times$35 mm$\times$8 mm, and weights 8 grams without battery.

3.3 SleePic Watch Module

The SleePic Watch module is used for the SleePic user interaction (Figure 2). The module is placed on the wrist to be highly visible to the user. The user interaction unit is composed of 5 LED's in the colors of green, orange, red. A button provides the user possibilities for feedback. The sensor unit contains a 3-axis accelerometer (Freescale Semiconductor, USA) and a photo-diode to measure ambient light. The data from

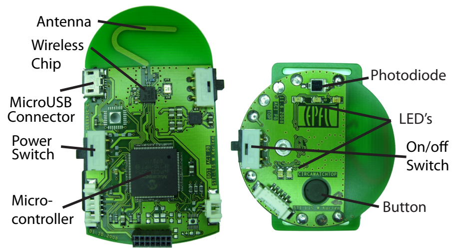

Figure 2: Bottom view of the *SleepPic Core* processing module (left). Top view of the *SleePic Watch* module prototype (right).

these sensors were not evaluated in this study. The communication unit is composed of a USB-UART converter which allows data exchange and recharging via microUSB The diameter of the SleePic Watch module is 41 mm and the height 10 mm. A fully assembled SleePic Watch weights 28 grams.

4 EXPERIMENTS

A series of recordings were conducted to test the SleePic device and to obtain sleep / wake data in real-life situations. Following informed consent, eight (two female and six male) volunteers in the age between 24 and 30 years wore the SleePic system. The subjects were in good health and reported no cardio-respiratory disease or any sleep disorders. The subjects came to the laboratory in the evening and were instructed about the experiment procedure and how to wear the device. The subjects wore the SleePic device for a minimum of 36 hours that included two nights. They were allowed to remove the belt during heavy sport or when showering. During the experiment, the subjects performed a randomly scheduled reaction task using the button on the SleePic Watch. The subjects were asked to sleep at home. After the recording, the subjects returned the SleePic recording system to the laboratory, were debriefed, and filled out a questionnaire about the usability and comfort of the system. Because of the ambulatory nature of the experiment, the subjects were expected to move freely and perform normal daily activities. Therefore, we did not consider the possibility of recording EEG signals for reference. Instead, the subjects had to maintain a logbook by indicating the system-off times, their sleep times, and particular events related to the system that may happen during the experiment. Additionally, a technician installed an infra-red video camera in the bedroom to record the sleep behavior during bedtime. After the study, the technician analyzed the logbook entries and video recordings and labeled the wake / sleep periods of the subjects.

5 RESULTS & DISCUSSION

Using the SleePic system, 250 hours of valid recordings were obtained and 37 % of which were labeled by the technician as sleep. Classification and user adaptation experiments involved the cardio-respiratory and activity data obtained. These experiments were designed to assess the sleep/wake prediction performance and are not described in details in this paper.

5.1 User Acceptance

From the post-study questionnaire, we were able to evaluate the subjects' acceptance of the SleePic prototype. Interestingly, the female subjects felt the wearable device comfortable enough, whereas the male subjects either could not decide (50 %) or were not comfortable with it (50 %). The male participants argued that they could not get used to the belt because of it was either too tight or too big. The SleePic system was most disturbing when the subjects were lying face down. An integration of the SleePic Core extension module into the Sensor module would reduce the overall size of the system worn on the chest and decrease disturbance when lying on it. All subjects found the light vibration that accompanied the reaction task helpful and not as disturbing. The subjects also agreed with the frequency of the reaction time tasks. Wearing the device was influencing the daily activities of the subjects only slightly (60 %) or not at all (40 %). Compared to the perceived decrease in comfort from an actigraphy device, the users did not have a visible advantage from the device in this study. Additional experiments with a device displaying on-line sleep/wake schedules are required. For this, a low-power liquid crystal display might be added to the SleePic Watch. We also plan to demonstrate improved comfort by embedding the SleePic Core module into the body of the Sensor module.

5.2 Reducing Computational Load of Preprocessing

Although the dsPic micro-controller with the highest amount of RAM memory available was embedded in the SleePic Core, the RAM was not sufficient to calculate the FFT of ECG and RSP at the Sensor Module sampling rates. As the high frequency features were not needed for the classification, it was reasonable to reduce the sampling rate accordingly. We therefore sub-sampled the ECG from 256 Hz to 51.2 Hz and maintained the RSP at the recording sampling rate of the Equivital^{TM} (25.6 Hz). For an efficient calculation of the FFT on the dsPic micro-controller, the sliding window size had to contain power of two sampling points for each window. The use of a window size of 40 seconds was suggested (Karlen et al., 2009). For our sampling rate, this window size resulted in 1024 (RSP) and 2048 (ECG) samples. The window fitted the available RAM, but left only little space for other variables. Therefore, the processing load was further reduced by decreasing the window size for the FFT preprocessing. However, by the nature of the FFT, with an increase in time resolution, the resolution of the frequency output decreases. The reduction of the window from 40 to the next possible size of 20 seconds resulted in a frequency resolution shift from 0.0122 Hz to 0.025 Hz. This change could result in a change in classification accuracy which had to be investigated.

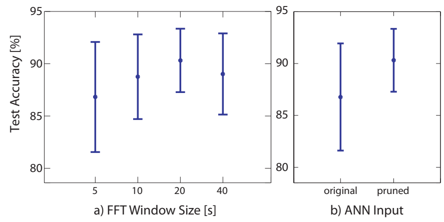

Figure 3: a) Performance analysis for different sliding window sizes (5, 10, 20 and 40 seconds) for the FFT preprocessing. b) Performance comparison when the entire feature set (original) or the reduced feature set (pruned) is used as input of the ANN. The bullets represent the mean over all trials and subjects, the bars cover the standard deviation.

We conducted an off-line experiment using data from (Karlen et al., 2008) and compared the classification accuracies depending of the size of the windows. Figure 3a shows the test results when the FFT was calculated on a window size of 5, 10, 20 and 40 seconds respectively. Smaller sliding windows than 5 seconds were not meaningful because all useful frequencies contained in the original physiological signal would lie in one frequency band. Larger windows could not be computed with the dsPic micro-controller and were not considered. Although the accuracies for the different window sizes were not significantly different (Figure 3a), we observed a positive trend toward the 20-second segments. This was expressed with the highest mean performance, minimal standard deviation and the highest total accuracy. It was therefore reasonable to use a 20-second window instead of the 40-seconds suggested in (Karlen et al., 2009) for the FFT computation on the SleePic device.

5.3 Network Inputs

We analyzed the input network weights of the single layer ANNs obtained from the previous experiment where the entire frequency spectrum served as input. We observed that the weights of the neural inputs with the higher frequencies of the ECG and RSP spectrum did show a very weak activation and variation compared to the weights of the low frequencies. Based on physiological reasons and because the simple structure of the ANN, we hypothesized that the low activation and variation in the domain above 3 Hz is linked to a reduced importance of these features for the classification. Therefore we designed a different network topology that only used the most relevant input weights. In our particular case (single-layered network), all input features $i \in 1,\dots,N$ were considered as relevant when the mean weight over all training runs 1 to M was larger than the median standard deviation of all layer weights of all runs, as follows

$$S(w_i) = \begin{cases} 1 & mean(\vec{w}_i) \\ & > median(std(\vec{w}_{1,\dots,N})) \\ 0 & \text{otherwise,} \end{cases} \qquad (1)$$

where $\vec{w}_i = (w_i^1,\dots,w_i^M)$ and S is the selection function. The resulting pruned network input numbers and the pruning frequencies for each signal are shown in Table 1. The input size of the pruned network was reduced to 8.3 % of its original size.

We compared the performance of the reduced networks with the networks using all frequency inputs. Figure 3b shows the accuracy for the original and pruned network inputs when the experiments from (Karlen et al., 2008) were repeated. We observed that the accuracies showed no statistical difference, but revealed a tendency for a higher median and better worst performance for the pruned input. The positive effects in accuracy of the pruned ANNs can be attributed to the reduction of the search space and therefore to the reduction of over-fitting due to the increased noise on the higher-frequency inputs. A smaller input feature set did accelerate the training and the network computation, and also reduced the required amount of training input vectors (curse of dimensionality). It was therefore reasonable to use the pruned network for the SleePic implementation.

Using DSP functionality, 202’742 instruction cycles were necessary to compute a single classification. If the device is running at the maximum speed of 40 MIPS, the required processing time is about 10 ms.

5.4 Energy Consumption

For a wearable device it is important to keep energy consumption minimal. In the initially designed configuration, both energetically independent systems on chest and wrist achieved an energetic autonomy of 36 hours as required by the design criteria. Both systems could easily be recharged by connecting them to a PC.

Table 1: Properties of the input feature space for the ANN topology. The original features are all the frequency bins available from the FFT preprocessing, as used in (Karlen et al., 2008). The pruned features correspond to the features obtained by applying Equation 1.

	RSP	ECG	Total
	Frequencies [Hz]		
original	0-12.8	0-25.6	
pruned	0-1.4	0-2.25	
	ANN Input Size [number]		
original	257	513	770
pruned	28	46	74

5.4.1 SleePic Core and Sensor Module

The total average power consumption of 18.06 mW (6.02 mA @ 3 V) measured at room temperature lead to an autonomy of 36 hours. We observe that the major energy resources went to the dsPic and the wireless chip (NRF) in rx (receiving) mode. Compared to a standard micro-controller, the dsPic was relatively power hungry, because of the high clocking and the large RAM size. The power consumption was reduced by putting the dsPic into a very efficient idle mode (0.1 mA) at 93 % of the time.

In a future design, a significant decrease in energy consumption (50 %) could be achieved when the Recording Mode would be substituted by a single request for the 20-second sensor data packet instead of the continuous recording of the data stream. This was not possible with the Equivital^{TM} because it only allowed a single continuous output stream for the sensor values. The total consumption could further be decreased by 20 % by reducing the duty time of the wireless chip. This could be achieved by implementing an updated communication protocol that would not require a continuous powering of the wireless chip while waiting for a message from the SleePic Watch.

A more radical, but surely very energy efficient and power saving option would be the replacement of the dsPic micro-controller with a dedicated silicon chip for the recording, preprocessing and ANN calculation. However, these types of chips are very task dependent and their development expensive. Therefore we preferred the more flexible micro-controller solution for the prototyping.

5.4.2 SleePic Watch

The total average power consumption of 10.36 mW (2.8 mA @ 3.7 V) lead to an autonomy of 51 hours when using the 145 mAh Lithium-Polymer battery. The energy autonomy of the SleePic Watch could be increased in a next step by selecting a smaller and more energy efficient micro-controller that also offers a lower stand-by power consumption. The function of the SleePic Watch in our experiments was to attract attention from the users during the reaction task (LEDs) and provide an interface for responding (button). The peripheral location of the SleePic Watch required wireless transmission of data and an independent energy storage. The frequent wireless communication increases the power consumption of the SleePic Watch and Core. In future versions it is imaginable to replace the custom SleePic Watch with another, already existing pervasive device such as a smart phone or digital wristwatch.

6 CONCLUSIONS

We developed a SleePic prototype based on commercially available sensors and components. Missing functionality, such as user interface and computational resources for on-line classification, were added by custom designed extension modules. A DSP micro-controller was used to efficiently compute FFT for extracting the frequency features of the signals and to compute the ANN for classification. FFT and ANN were optimized for speed and lower power consumption. We used no liquid crystal display. To render the feedback information more meaningful to the user, it might be advantageous to integrate a liquid crystal display in a next step into the SleePic Watch.

Although cardio-respiratory signals were measured non-invasively with a wearable belt, it was more cumbersome to use than a wrist worn actigraphy device. It is therefore application-dependent whether a single actigraph device or a combined system like SleePic should be adopted. If, for example, the application is oriented toward sleep disorder diagnosis, the system with additional cardio-respiratory functionality offer a clear advantage, because current standards in sleep disorder diagnosis require the recording of these signals (Patel and Davidson, 2007).

The SleePic prototype demonstrated wearable sleep/wake classification that is less obtrusive than the EEG monitors currently used in sleep centers. We also showed how existing classification algorithms can be modified in order to comply with the narrow constraints given by wearable systems.

The SleePic prototype can be considered as a proof-of-concept for a new generation of health and wellness devices. It shows the feasibility of a wearable, on-line sleep/wake classifier using low-cost components. The minimal processing power requirements of the presented system opens new doors for the use of high-level algorithms required for context-awareness or automated diagnostics in point-of-care health care.

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