A Smart Wearable Sensor Assisting in Mental Health

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ABSTRACT
The stress and poor sleep quality of a person may be used as two of several components for predicting the onset of mental health problems, in particular depression. Ergonomic smart sensors that can determine the heart rate variations related to stress and the variability of sleep may provide unique insights to the coping behavior of stressed people. Rather than relying on wearable computers, a single smart miniature sensor that is worn 24/7 should perform the complex embedded recognition tasks while meeting difficult battery life, wireless communications and ergonomic constraints. The development and testing of such a smart sensor is described focusing on implementation within a distributed intelligence based architecture. The manner in which the user's heart rate and the user's physical motion is used to measure stress and sleep quality is explained.

Author Keywords
Wearable ECG sensor, heart rate variability, depression.

ACM Classification Keywords
C.5.7Wearable Computers.

General Terms
Algorithms, Design, Experimentation, Human Factors.

INTRODUCTION
This work relates to a heartbeat and activity monitoring sensor developed within the EU research project OPTIMI (Online Predictive Tools for Intervention in Mental Illness). The project's aim is to provide on-line predictive tools for the early identification and intervention of a mental illness in particular depression following the inadequate coping with day to day stress. Power spectrum analysis of heart beat, and in particular the heart rate variability (HRV) is a non-invasive method for identifying the activity of the autonomic nervous system (ANS) and its control functions.

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The variations in heart rate (HRV) are detectable using power spectral analysis of the HR and the power spectrum may be divided into low and high frequency powers (LF and HF). When a person is subject to mental stress it is known that most people react with an increase in their sympathetic response and a reduction in parasympathetic response. Associated with these reactions is a frequently reported increase in low frequency (LF, centered around 0.1 Hz) heart rate variability, a decrease in high frequency (HF, 0.15–0.4 Hz) power, and/or an increase in the LF/HF ratio. HRV measurements have been shown to be related to stress occurring during acute laboratory psychological and cognitive stressors such as mental arithmetic as well as real-life acute stressors such as college examinations, earthquakes and even day-to-day hassles [1]. Therefore HRV measurements should allow us to identify the stress levels of a subject in real life on a 24/7 basis.

Insomnia (i.e. problems to fall asleep or to maintain sleep or non-restorative sleep) is independently associated with psychopathological conditions [2], most notably depressive disorders and the evidence clearly indicates that insomnia is a predictor for depression. Depressed patients frequently suffer from disturbances of sleep continuity including an increased latency to fall asleep, an increased frequency of nocturnal awakenings and early morning awakenings, often associated with physical movement. Furthermore, specific sleep architecture alterations are evident in depression, namely a reduction of slow wave sleep, a shortened REM latency and an increased REM density. Sleep detection, using movement sensing of the sleeping person, has a relatively long history. Webster [3] introduced the first computerized scoring algorithm. Cole [4] reported an optimal precision of sleep detection of 88%.

Heart rate is reduced in NREM sleep and higher during REM phases and in association with arousal events during sleep. Recent studies [5], [6], have found clear correlations between heart-rate variability and sleep depth: Low frequency and LF/HF were significantly lower during non-rapid eye movement (NREM) than REM, and were lower in stages 3 and 4 than in stages 1 and 2. Therefore by sensing the movement of a sleeping person and combining these with measures of their HRV, it has been shown to be possible to generate better estimates of sleep quality for use in mental health prediction [6].

In summary an ECG plus motion sensor, that can recognize HRV and motion activities, is being developed and this paper reports on the success to date.

THE ECG SENSOR

In many wearable ECG sensor applications, data from the sensor is streamed to a signal processing computer such as a wearable PDA. This approach can result in a 90% wastage of the available sensor battery energy in wireless communications and sensors that are worn 24/7 would require frequent recharging. Instead significant energy conservation can be achieved by making the sensor itself do the signal processing using highly optimized code. When this data is communicated wirelessly not only is their little energy spent on communications but in addition raw data privacy and data security are enhanced. Only one time during the day will the user be invited to update their daily diary hosted on a Home PC and download the sensor data.

ECG Hardware

The ECG hardware is based on the nRF24LE1 from Nordic. This micro-controller was chosen despite its limited processing capability, based on its very low cost, very small footprint, suitable ADC and flash EEPROM resources and the integration of a 2.4Ghz RF transceiver. The nRF24LE1 is combined with an Analog Devices ADXL325 three axis accelerometer to detect physical motion of the user. The heart beat is detected with two electrodes placed across the chest.

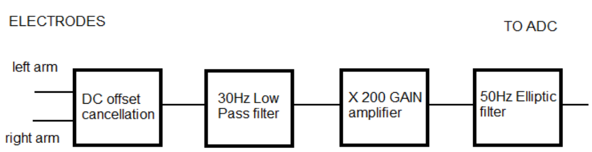

Figure 1, ECG Front end signal conditioning stage

The front end comprises an instrumentation amplifier (INA321) and support amplifiers (OPA336) for electrode offset compensation, the main amplification stage set at between 200 and 300, and an 8th order elliptic filter (MAX7407) used to remove 50/60Hz noise. The heart beat and accelerometer signals are digitized at 12 bit resolution using the on chip ADC.

Due to the fact that the RF end of the microcontroller consumes a large proportion of the power, the RF stage is seldom switched on during normal operation. However every 5 seconds, the RF stage is switched on for 20 milliseconds and the device listens for a command packet from the users Home PC. In the event one is received the sensor begins an authentication handshake and subsequent interchange of relevant data.

As the device is to be worn continuously three very important design constraints have been demanded:-

- The battery life must be as long as possible
- The device must be small and hermetically sealed to survive swimming and bathing
- The device must therefore be non contact charged

The device is powered by a 20mAh lithium polymer battery with the intention being to last ideally 72 hours between charge times. Besides reducing any unnecessary usage of the RF stage, as previously mentioned, the design includes several energy saving methods.

For example the ADXL325 device has been chosen for its wider G range and very low cost however it is slightly more power hungry than other devices available. Additionally the ECG front end amplifiers use a significant power and together they can consume up to 2.5mA. To reduce power the whole analogue section power is controlled by an FET transistor and is switched off when not in use. When the FET is switched on and the amplifier is allowed to stabilize, there is still the option to switch on and off the fast acting MAX7407 filter in order to save power. Allowing for switch on times delay, this saves about 50% of the power compared to leaving them on at all times i.e. saving roughly 1.25mA on average.

In order to save power through software methods, the signal processing tasks are managed depending on time and observed activity. That is, by using the local timer and sleep function, the sensor will set to conduct ECG measurement between around 10% and up to 70% of the time, depending on the ECG signal quality. The aim is to obtain one clean stress measurement every 10 minutes. Since ideally a clean measurement can be achieved in 2 minutes of signal processing of sequential heart beats, this can save 60% of power usage.

Ergonomic Constraints

The current sensor is still in prototype and is 50% larger than the planned final sensor that will be deployed in large scale trials in 2011.

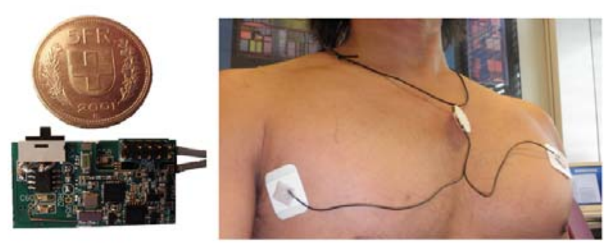

Figure 2, The ECG sensor prototype (Left) and final usage worn as a necklace on a person's chest (Right).

During the planned trials volunteers will be asked to wear the sensors 24/7 and this means that they may bathe, swim, or do sports while wearing the sensor. This means that the sensor must be hermetically sealed to avoid any ingress of moisture or dirt. The hermetic sealing requirement implies that the sensor must have a contactless charging method and that the sensor is totally encapsulated.

To achieve this, the sensor incorporates a LiPo battery charging circuit as well as the rectification stage for an inductive voltage power input. The microcontroller, powered by the battery, is able to sense when the rectified inductive input voltage rises above the input threshold required by the charging circuit. When this occurs the microcontroller goes into a deep sleep effectively switching itself off and appearing as a tiny load shunt across the battery. This allows the charging circuit to charge the LiPo battery without any interference, until the battery voltage has reached the fully charged level. The inductive loop coil which is driven at 10KHz by a standard off the shelf inductive power supply, is built into the sensor.

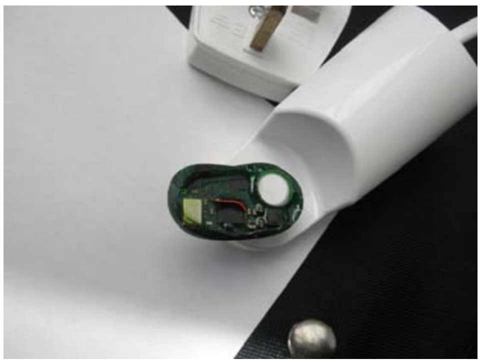

Figure 3, An OPTIMI sensor in encapsulation and on inductive charge.

Figure 3 shows a device under inductive charge. The electronics is sealed within a two part epoxy resin (ALH Systems Ltd., U.K.) that has been chosen to provide maximum water resistance, maintain hardness to over 80 degrees C., and above all to be extremely toxic and irritant free when worn against the skin. Further the color and molding of the resin is chosen to create a device that could be worn as a fashionable accessory.

SIGNALPROCESSING

The ECG sensor will perform two different signal processing and feature estimation tasks. First it will perform a time domain and power spectral analysis of the heart rate beat to beat (RR) interval. Secondly it will detect the user's posture and identify specific movements of interest.

In order to measure the HRV the sensor must:-

- Detect the peak QRS curve in a valid heart beat
- Detect abnormal heart beats in order to reject data
- Record 128 valid heart beat RR intervals
- Perform time domain statistic analysis
- Perform frequency domain analysis
- Store and time stamp the data for later download

The RR-Interval measurement requires the accurate detection of the QRS complex in each ECG signal heartbeat [8]. Several methods provide high accuracy including the modified "So and Chan method" [9] as well as direct time-based cross-correlation methods. Among the methods studied, the "Pan Tomkins method" [10] provided particularly well suited to OPTIMI. Tests of the method against the MIT BIH Arrhythmia data base showed that it gave satisfactory results in about 96% of cases. It is also easy to implement on a simple, real time device.

To account for sharp signal distortions such as Ectopic PVCs and high levels of low frequency electrical noise that may look similar to heart beats the sensor implements a cross-correlation template matching filter as used by [11] to exclude these beats in the HR and HRV calculations and to detect the presence of these artefacts.

Every 10 minutes the sensor records a set of time domain statistics and frequency domain power spectrum analysis results. In the time domain these are the standard deviation of the NN or RR interval (SDNN) denoting heart variability in general and the pNN50 denoting the occurrence of high frequency variations.

In the frequency domain a DFT is applied to the RR intervals for 128 heart beats. In line with the work reported in [12] the RR interval data is re-sampled and samples falling between QRS complexes are computed by linear interpolation. After compensation for discontinuous signals in the time domain, using a Hann window on the re-sampled data, a 128 point DFT is applied and the squared magnitude of the result used. The area under the DFT for range of frequencies for the LF and HF bands is then calculated by simple summation.

Activity Measurement

The sensor, worn in a specific orientation on the chest, must detect and record three types of posture and motion:- If the person is lying down or not, If the person is engaged in strong physical activity, if the person is disturbed during sleep and moves slightly.

To identify if a person is lying down and not just bending over for a while, the vertical acceleration sensed by the accelerometer is filtered with a long time constant filter of 30 seconds. Only if this filtered value is between 0.3g and -0.3 g, is the person assumed to be lying down.

In order to detect a sleeping person's movements, the 3 instantaneous accelerometer values are compared against a 2 minute averaged version. This averaged version is used to define a sleeping reference point in 3D space. The distance between the two points is monitored and when this distance is greater than 0.2g, then this is classed as an awakening or sleep disruption.

In order to determine if the person is engaged in strong physical activity and in particular walking running or climbing stairs, we use the approach applied in [13]. It has been observed that walking and running can be distinguished from other activities on the basis of variability in the activity counts from the sensing actigraph.

Locomotor activities yield more consistent minute-to-minute counts than other more home and office activities which have more erratic movement patterns. Therefore the ECG sensor integrates the vertical acceleration signal, similar to a pedometer, and computes the coefficient of variation (CV) between 6 of 10 second epochs. If the CV is less than 0.1 or higher than 10.0 the activity is assumed to be home or office work. For all other values it is assumed the person is engaged in a strong physical activity.

RESULTS

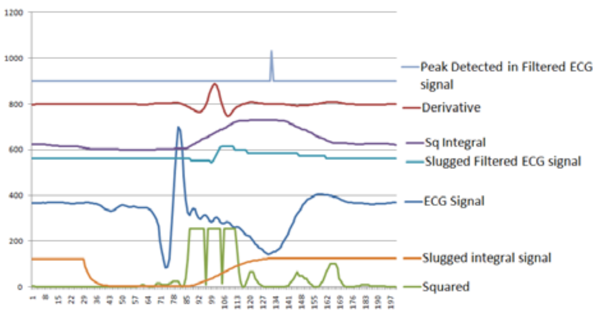

Figure 4, Pan Tomkins method, signals show ECG input, supporting signals and final QRS peak detection

The sensor samples at 360 Hz and sleeps for around 30% of this period. Figure 4 shows a debug output of the temporary variables used in the Pan Tomkins method. Thus far the sensor has been able to detect the RR interval and derive the HRV data required for stress and REM sleep prediction.

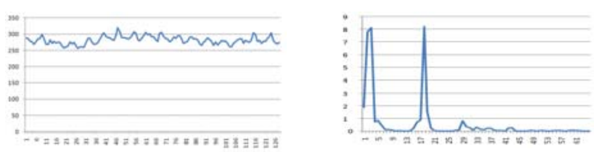

Figure 5, (left) RR data for 128 beats and (right) the PSD output calculated showing the energy at LF and HF.

The final computations take about 1 second to complete. Therefore there is no problem to record HRV data every 10 minutes and achieve a battery life of around 48 hours of continuous operation.

The activity recognition, though simple, is very effective providing the necessary recorded data to derive sleep scores during the night. The physical activity detection needs some improvement to detect all forms of strong activity other than those that are repetitive in form.

CONCLUSION

This work has demonstrated how existing know how in various fields may be effectively and optimally combined into a 24/7 wearable sensor performing tasks normally thought only possible with a secondary support computer. A single device is measuring and extracting the features necessary to identify the users stress levels as well as the basic information needed to compute sleep quality. Both are extremely relevant in mental health assessment. As far as is known this solution provides the first truly compact wearable design with long battery life and ergonomic any time any where usage for ubiquitous mental health monitoring. Following robustness improvements the sensor will be deployed on 300 trial subjects in 2011.

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