Pervasive Embedded Real Time Monitoring of EEG & SpO2

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***Abstract* — Recent research has underscored the potential role of analysis of EEG signals as indicators of cognitive decline. In addition, we have also seen the emergence of embedded systems that are capable of analyzing biological signals in real time to track a number of physiological variables and make accurate conclusions about the individual's physiological status and health. This paper presents the design of an embedded system which is capable of tracking relevant bio-signals from the person in real time and facilitating a dependable decision making process that provides alerts for potential brain activity changes. The design focuses around the use of sensors and a processing element. It incorporates the use of electroencephalography (EEG) and oxygen saturation (SpO2) signals. As an early proof-of-concept, our system collects data from the sensors, performs initial processing and provides the framework to compute significant physiological variables.**

Keywords: cognitive decline, embedded monitoring, EEG and SpO2

I. INTRODUCTION

Recent research on mildly demented AD patients revealed slowing of the EEG, that is higher theta power, less beta power and lower peak frequency, were linked to cognitive decline on the cognitive test [1]. Similar results were confirmed by [2] using change in Global Deterioration Scale (GDS) score as an indicator of cognitive decline in subjects with subjective memory complaints. Increases in theta power, slowing of mean frequency and changes in coherence among regions were observed at baseline in subjects who declined after 7-9 years follow-up. Cross-sectional studies in elderly with different levels of cognitive impairment have also reported correlations between EEG spectral parameters, i.e. higher theta activity during rest and lower alpha activity during memory activation and decreased GDS scores.

This research on cognitive decline underscores the need for advanced *embedded monitoring systems* that are robust, secure, relatively non-invasive for use in a number environments, e.g. at home, in a residential facility, or hospital. Our vision of such trustworthy, pervasive health technologies is depicted in Figure 1, which shows the conceptual framework and *core architecture.*

The proposed architecture is intended to represent the key design philosophy of our system, which includes:

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- A multi-sensor network consisting of cost-effective wearable sensors, room-mounted sensors, or other types of sensors that gather heterogeneous data
- Signal and data processing module to provide immediate feedback to caregivers and patients, and also determine what information to transmit or draw from remote decision-support systems.
- Secure, private, and trustworthy networking capabilities that leverage novel distributed security and privacy algorithms and hardware for low-cost sensors on powerful networks.
- Remote intelligence/decision-support that interfaces to relevant information for decision and control.

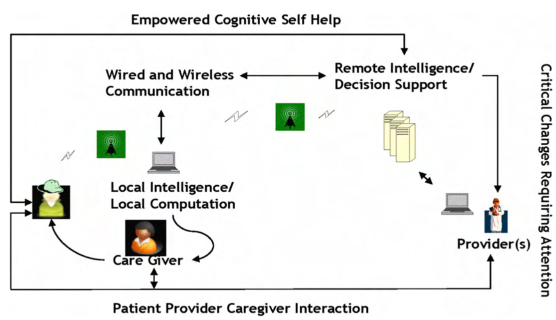

Figure 1: Core Architecture

The result of applying our core architecture to monitoring and management of cognitive decline are low-cost, highly trustworthy systems that can be easy adapted to the needs of individual users. While in this paper we focus on sensors and systems for detecting symptoms of cognitive decline, the discussed embedded monitoring architecture has the potential for use in a number of environments.

II. BACKGROUND

Unlike the painfully obvious losses seen in Alzheimer's disease and other forms of dementia, subtler changes in cognitive functions such as memory, attention, perceptual and motor skills, language and problem solving are common, in the elderly but not universal. In addition, some older adults exhibit "mild cognitive impairment" yet not enough to merit a diagnosis of dementia. Age related cognitive decline usually occurs gradually. Sudden cognitive decline is not a part of

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normal aging. When people develop an illness such as Alzheimer's disease, mental deterioration usually happens quickly. In contrast, cognitive performance in elderly adults normally remains stable over many years, with only slight declines in short-term memory and reaction times.

Studies of healthy older adults have found a wide range of prevalence of cognitive decline, from less than 10 percent to more than 40 percent of those aged 60 or older, with incidence increasing with age. The broad range may reflect, in part, a lack of consensus about how age-related cognitive decline should be defined, measured and described [3]. Two technologies which have proven effective in monitoring brain activity is pulse oximetry and electroencephalography [4][5].

Pulse Oximetry. One benefit of pulse oximetry is that oxygen saturation (SpO_2) can be measured noninvasively. This is important because studies have shown that cerebral oxygen desaturation is associated with cognitive decline [6]. Another added benefit of most pulse oximetry systems is the ability to calculate the heart rate from the same signals used to calculate oxygen saturation levels in the individual. Abnormalities in the heart rate can be monitored and incorporated in the final decision making process, thus eliminating the need for an additional sensor.

Electroencephalogram (EEG). For many years, EEG has been used extensively to monitor brain activity [5]. One difficulty with EEG is that only trained clinicians are able to interpret EEG waveforms. On the other hand, quantitative electroencephalography (qEEG) takes the EEG signal and transforms them into bands using a Fast Fourier Transform. This provides a mechanism where decision can be automated.

III. System Design and Implementation

The system design involves the use of sensors to detect various events and produce data which are collected and analyzed by the processing element.

A. Hardware Description

The prototype hardware architecture consists of a set of sensors and corresponding hardware modules for reading, collecting, and processing the sensed data.

Oxygen Saturation Module. Oxygen saturation measures the percentage of hemoglobin binding sites in the bloodstream occupied by oxygen. The device used to perform the calculation is called a pulse oximeter. It relies on the light absorption characteristics of saturation hemoglobin to give an indication of oxygen saturation. The OEM III module from Nonin with its Puresat® Signal Processing technique is used as it is ideal in motion and low perfusion environments. This approach provides more reliable readings over simple microcontroller based pulse oximetry solutions. The sensor is capable of providing a 4-beat average heart rate value and a 4-beat average SpO_2 value.

Electroencephalography (EEG) Electrodes. EEG refers to the measurement of the electrical activity produced by the brain. It is recorded using multiple electrodes placed on the scalp. Electrode locations and names are specified by the 'International 10-20' system ensuring consistency in the naming convention. In most clinical applications, 19 recording electrodes along with 2 reference electrodes are used. However, for purposes of this research, only 4 electrodes are used for monitoring abnormal activity. These 4 electrodes are FP1, FP2, C4 and O1. The EEG is typically described in terms of rhythmic activity. This rhythmic activity is divided into bands by frequency Delta (1 – 3 Hz), Theta (4 – 7 Hz), Alpha (8 – 12 Hz), Beta (13 – 24 Hz), and Gamma (24 – 70 Hz).

To develop and test this system we utilized EEG signals generated by an EEG simulator (Grass Techonologies, Model EEGSIM). The same stored signal is replayed with a period of 60 seconds. Several models of the EEG simulator are available with each storing an EEG signal corresponding to different types of EEG waveforms. The simulator that we used for this research simulates the EEG of a person who suffered a seizure. For comparison purposes, a sample of non-seizure EEG signals was analyzed. This data set was taken from a visual attention experiment described by [7].

Microcontroller. The information from the sensors is collected and processed by a processor – a microcontroller is used in our design. The MSP430FG4618 from the MSP430 line of microcontrollers from Texas Instruments is chosen. The important peripherals included in the microcontroller are the Analog to Digital Converter (ADC) and the Serial Communication Interface. A hardware board with this microcontroller is used for the prototype development.

B. System Operation

The sequence of operations carried out by the system can be explained as follows. First, the signals from the sensors are collected, namely the oxygen saturation module and EEG electrodes. An initial data processing (if required) is carried out in the pre-processing stage. This is followed by a sequence of operations performed by the microcontroller, the final result of which is the computation and display of the various physiological metrics. The preprocessed signals are sampled by the ADC integrated within the microcontroller. The monitoring of sensor signals can be either event triggered or continuous. While the prototype implementation employs continuous monitoring, an event triggered monitoring scheme can be easily established with minor software modifications to the microcontroller. In the latter scenario, the trigger to begin monitoring is a software-based detection of an abnormality in the sensed data. For example, an abnormal heart rate or oxygen saturation value (which is anything below/above the baseline value for that person) can be used as a trigger for entering the monitoring mode.

For the EEG electrodes, the preprocessing stage involves amplification and level-shifting. Typical EEG voltages are of the order of micro volts and the simulator generates voltages typically in the range of 5- 50uV with a peak of 500uV. This voltage is too low to be detected by on-chip ADCs. Hence, the signals are amplified by a factor of 2000 using a high impedance differential amplifier. EEG signals have a negative

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voltage level which is translated to a digital 0. To overcome that, a dc-level shifter is used to add a known DC voltage to the EEG signals before sampling them.

The data values from the oxygen saturation sensor are available in digital format through the serial interface and hence, no pre-processing is required. The frequencies of interest from the EEG signals lie in the 0-70 Hz range. The signals are sampled at a frequency of 500 Hz which is high enough to avoid aliasing. Oversampling can also be done to increase accuracy. Once the signals are sampled, the EEG signals are digitally band-pass filtered to extract rhythmic activity in the different bands as per the classification described in Section III.A. The bands of interest in the detection of cognitive decline are the delta and theta bands. The EEG used here is known to have abnormality on account of seizures. Seizures are known to have spikes in the delta band. Thus, the abnormality in the EEG signal along with oxygen saturation and heart beat information helps us compute a signature or health indicator of cognitive decline.

IV. EVALUATION AND RESULTS

Real-time collection of sensor signals: The system is capable of collecting the signals in real-time in a synchronous manner. Figure 2 depicts the data sampled and collected by the microcontroller. The first four waveforms depict the signals from the four EEG electrodes- *FP1, FP2, C4 and O1*- as analog voltages while the last waveform indicates the oxygen saturation value as a percentage. The samples were collected for a period of 1 minute. The ability to collect the samples synchronously provides the foundation for further processing and shows that an embedded design approach using EEG and other sensors is indeed, a feasible and viable solution to detecting cognitive decline.

***Extraction of Frequency Bands**:* Figure 3 depicts the frequency band information which was extracted from the FP1 EEG electrode. Five (5) different bands are depicted here. The developed system permits the real time extraction of all frequency bands for dynamic analysis of brain activity. It is possible to do the same band information extraction with the signals from other electrodes, but it is not shown here. As mentioned in Section III.B, the EEG simulator generates the signals for a patient who suffered a seizure, which is characterized by spikes in the delta region. The spikes can be seen clearly in the first waveform in Figure 3 (see data around sample 15,000) and can be automatically extracted.

Closing the Loop. Different types of real time analyses of the extracted waveforms can be done using the proposed system. Three metrics are discussed here: *theta-relative power, alpha-theta ratio, and coherence.*

All three of these metrics are affected by the absolute theta power, which generally increases in patients with seizures. The theta-relative power and the alpha-theta ratio of the EEG signals are typical metrics used for biofeedback. The theta-relative power is the ratio of average power in the theta band to the total power in alpha and theta bands. The alpha-theta ratio is the ratio of the average power in the alpha band to the average power in the theta band, which can be computed from the area under the power spectral density curve.

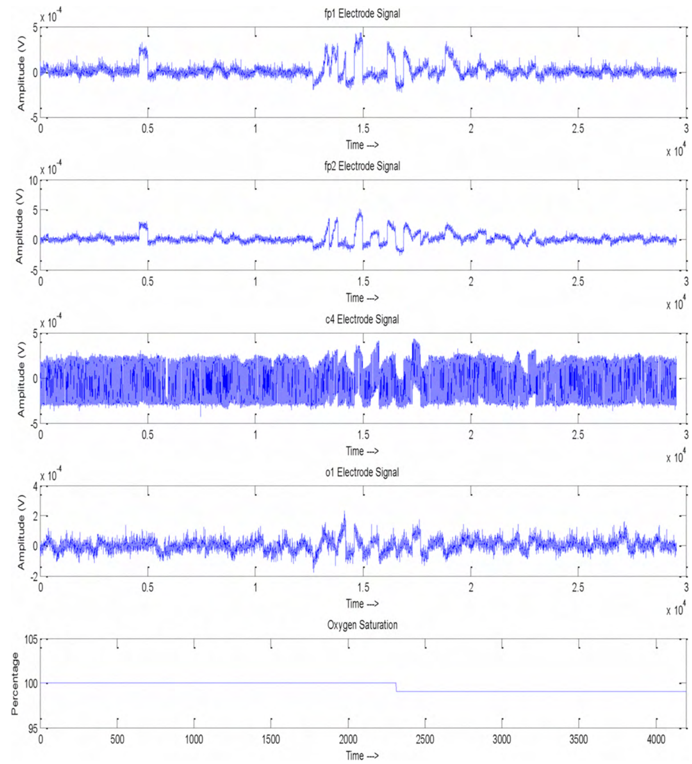

Figure 2: EEG Signals with Oxygen Saturation

Another important analysis of EEG bands is the analysis of the functional connectivity between hemispheres and within hemispheres – *coherence*. Coherence, $C_{xy}(f)$, between two waveforms can be defined as the following expression:

$$C_{xy}(f) = |P_{xy}(f)|^2 / P_{xx}(f)\, P_{yy}(f) \qquad (1)$$

Where, $P_{xy}(f)$ is the cross-power spectral density of x and y; $P_{xx}(f)$ and $P_{yy}(f)$ are the power spectral densities of x and y, respectively. Coherence values range from 0 to 1. As an example, the coherence was calculated for the alpha frequency band in the FP1 and FP2 electrodes. The coherence across the alpha band is generally used for studies pertaining to cognitive decline though it can be computed for the other bands as well.

Table 1 lists the alpha-theta ratio, theta relative power, and coherence values calculated across the alpha bands for some of the electrode signals for the simulated seizure EEG signals and for the non-seizure EEG signals. For example, the computed alpha-coherence for FP1 and FP2 is only 0.181, which indicates weak correlation between the alpha waves collected from the two electrodes. This may be due to significant difference in the activity in the left and right site of the brain. The purpose of showing these results is to demonstrate that the proposed system, while relatively simple, is powerful enough to collect real-time data and compute on-line metrics, which can be used as health indicators, e.g., cognitive decline of the subjects.

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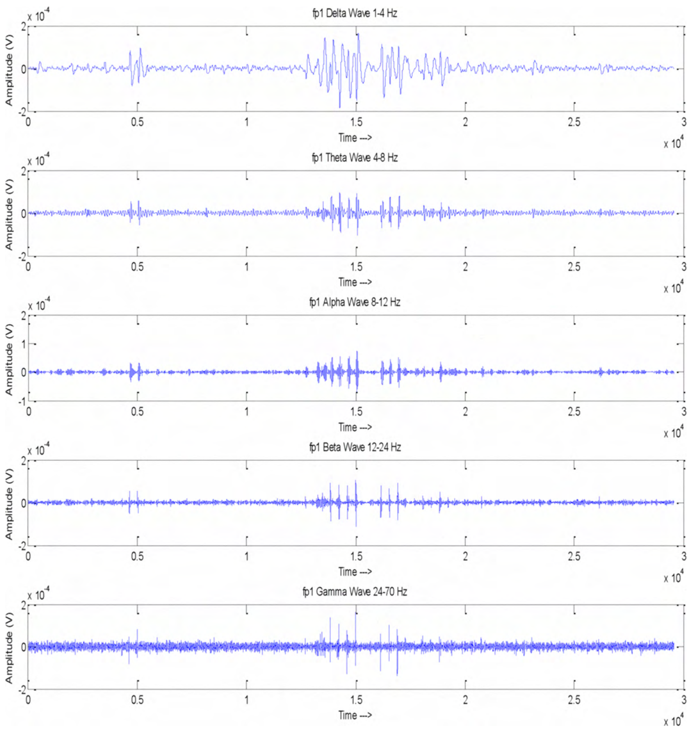

Figure 3: Delta, Theta, Alpha, Beta and Gamma Bands of FP1 Electrode

Table 1: Values of Computed Metrics

Metric	Simulated Seizure Value	Non-seizure Value
Alpha-Theta Ratio for FP1	0.393	1.3658
Alpha-Theta Ratio for FP2	0.40	1.3696
Theta Relative Power for FP1	0.7179	0.4227
Theta Relative Power for FP2	0.7094	0.4220
Alpha-Coherence for FP1, FP2	0.181	0.7637
Theta-Coherence for FP1, FP2	0.768	0.5662

V. DISCUSSION

Pulse Oximetry. While research suggests that oxygen desaturation is associated with cognitive decline, further work is required to expand these conclusions [6]. The technology described in this paper can be useful in alerting clinicians to hazardously low SpO_2 levels [8].

EEG. Studies have shown that power spectra from EEG signals can be correlated to cognitive decline in specific cognitive disorders [9]. One difficulty of qEEG analysis is the wide variety of methodological choices needed to develop a qEEG system. Since most of the research using EEG and qEEG has been done while the patient is resting, it is important to analyze EEG during an active state. Continuous qEEG monitoring would provide a simple and effective way to measure and analyze EEG signals during an active state.

Embedded Systems. The qEEG system described in this article is one part of an embedded monitoring system described in Figure 1. The physiologic data from the EEG and SpO_2 sensors would be sent to the clinician, the caregiver, and decision support algorithms to make the necessary clinical judgments. The benefit of such a system is that it would be faster than the traditional neuropsychological assessments used in [1][2]. In such embedded monitoring systems, qEEG analyses would allow clinicians to detect abnormalities related to specific cognitive disorders, compare significant differences in coherence, compare different activation states, and monitor the process of rather than the presence of cognitive decline.

VI. CONCLUSIONS AND FUTURE WORK

In this paper, we present an embedded system framework that is capable of collecting and analyzing data from sensors to calculate suitable metrics from which we can infer the physiological status of a person. Future work will focus on: (i) adding more sensors to monitor other human body responses, (ii) maintaining redundant sensors to account for reliable operation of the module, (iii) developing robust algorithms for analyzing various types of brain injuries and mental disorders, and (iv) adding support for the other features envisioned in the core architecture, for example wireless communication in a secure and trustworthy manner.

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