Reconfigurable Architecture of Neuro-physiological Sensors for Mobile Health System

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***Abstract*— Reconfigurability in a Body Sensor Network (BSN) increases the scalability and heterogeneous potential of the sensor network to provide efficient patient-specific monitoring. Therefore, in this work, a key question is addressed: how to design a BSN with inherited modularity and scalability? To answer this question, we have designed integrated wearable "Smart Sensor Nodes" (SSN) consisting of EEG and piezo-resistive sensors to measure brain and heart-rate signals, respectively, at real-life settings. The modularity in EEG sensing is introduced by using a novel analog front end that can measure brain signals without using the conventional Driven-Right-Leg (DRL) circuit. The reconfigurability in the network is realized by connecting SSNs to a Command Control Node (CCN) using a five-pin digital Inter-Integrated Circuit (I^2C) bus interface at 100 kbps bus-speed. The CCN synchronizes the attached SSNs every second, aggregates data from the SSNs and wirelessly sends the data via a Bluetooth transceiver at a baud rate of 115.2 kbps. The network is scalable to any SSN attached with or detached from the bus. This allows reconfigurability and hardware node upgrade without the redesign of the entire system. We have functionally validated few custom-designed SSNs (three EEG SSNs and one heart rate variability SSN) against the commercially available EEG and pulse oximeter. The proposed reconfigurable architecture promises a scalable BSN in mobile health (mHealth) that can be connected to any neuro-physiological sensor for data acquisition in the practical settings.**

Keywords—Body sensor network, Electroencephalogram, I^2C bus, Reconfigurable architecture, and Modular sensors

I. INTRODUCTION

There is a copious amount of research on designing wireless Electroencephalography(EEG) systems using custom-fabricated ICs and commercial-off-the-shelf components [1,2]. Most of the existing wearable sensor network systems [3-6] have fixed hardware architecture with a constant number of channels due to the requirement of a Driven-Right-Leg (DRL) circuit. For routine patient monitoring, point-of-care scenarios and Brain-Computer Interface (BCI) applications like cognitive load assessment, there may be a need to monitor only a few specific lobes of the brain [7]. But, irrespective of the need of the application, with the existing EEG systems, a subject has to wear the entire uncomfortable headset/harness which makes the data acquisition process time-consuming, obtrusive and inconvenient for the subjects. This becomes challenging especially for subjects with development delays, in-class monitoring, and emergency care situations. In this study, we address the need of a modular "DRL-less" EEG device by developing a reconfigurable EEG system which can be configured during deployment as per the demand of the application. Such system can enable scalable Body Sensor Network (BSN), to collect multimodal neuro-physiological signals through a wired or wireless network in the vicinity of the body [8].

The conventional wall-powered EEG systems use the DRL circuit in their design which mitigates the common mode interference from the subject during data acquisition. The DRL circuit design substantially depends upon the number of channels to be used and needs to be modified in case of inclusion of any new channel, thus prohibits modularization in the EEG system. We have developed an Analog Front End (AFE) that eliminates the need for DRL circuitry while maintaining a comparable signal quality of the EEG (similar to as reported in [9-10]). This DRL-less AFE design allows sensor level modularization in BSNs. Even though most of the literature on reconfigurable body worn sensors provides system level reconfigurability [11- 13], few reconfigurable networks on data layer exist for physiological signals. For example, a small cuboid-shaped device with substantial computing power that offers wireless connectivity and plug-and-play components called 'GumPack' has reconfiguration capability [14]. Multiple modular architectures for wireless sensor nodes [15,16], and wearable Reconfigurable Fabric (RFab) [17] have also been reported.

In this study, we propose a reconfigurable architecture with an arbitrary number of sensor nodes that can communicate in a modular fashion to a central node along with other physiological sensor nodes leading to a scalable BSN of wearable sensors. Some of the key features of the proposed architecture in comparsion with existing designs are:

- *Flexibility* to deploy sensors at any desired place.
- *Modularity* in the system which allows connecting multiple physiological sensors on the same shared digital bus.
- With *distributed intelligence* in the SSNs, events of interest (EOI) information can be sent rather than the raw data which helps in reducing the overall payload requirement.

II. PROPOSED SYSTEM ARCHITECTURE

The proposed reconfigurable architecture of integrated sensor network consists of Smart Sensor Nodes (SSN) that replaces the traditional "non-intelligent" sensors while the

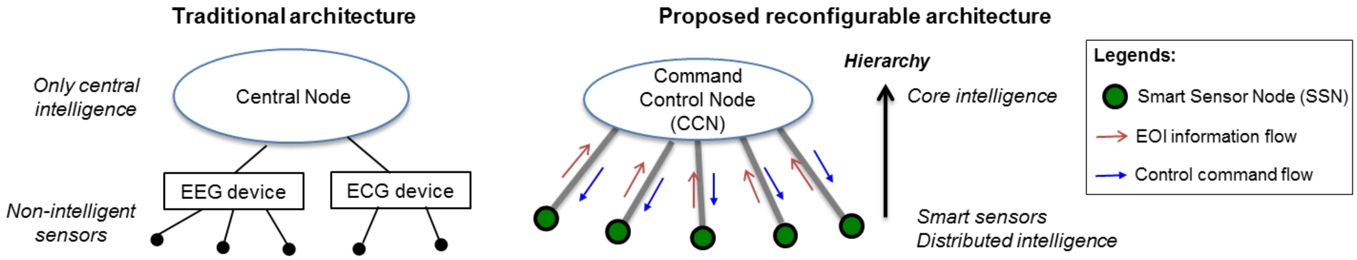


Figure 1. Concept of the proposed scalable BSN system compared to the conventional BSN for neuro-physiological signal monitoring. (EOI- events of interest)

traditional "non-reconfigurable" central nodes are replaced with a reconfigurable Command Control Node (CCN). SSNs process the sensed data locally to identify events of interest information and send it to the CCN using a digital Inter-Integrated Circuit (I^2C) topology [18]. In this proof-of-concept prototype, we have custom-designed three EEG SSNs and one heart rate variability (HRV) monitoring SSN to communicate with the CCN in real-time. The network can also seamlessly incorporate SSNs for other physiological sensors such as ECG, breathing pattern, pulse oximetry, and body temperature. Fig. 1 shows the comparison of the proposed system and the traditional neuro-physiological monitoring BSN. In the traditional architecture, sensing nodes (EEG/ ECG as depicted in the Fig. 1) are non-intelligent and continuously send the raw physiological signal to the central node. The central node is the only intelligent unit, which can process the data on it or can send it to a paired device using wired/wireless communication. On the other hand, in the proposed architecture the sensing nodes i.e, SSNs are intelligent in order to partially process the locally available data to compute and transmit EOI information to the control node i.e, CCN. The control node can broadcast commands to synchronize the sampling instances of the sensor nodes, further process the aggregated EOIs and data of the sensor nodes, and transmit them to a paired device to a hierarchical level (e.g., cloud). The following sections discuss the hardware and software co-design of SSN and CCN. Further, results of the comparison of the prototype with commercial systems are also mentioned.

III. Hardware System Design

The hardware for both SSN and CCN is custom-designed in-house using an Allegro PCB designer (Cadence Design Systems Inc., CA, USA) and fabricated through a commercial PCB foundry (OSHPark.com).

A. SSN for EEG monitoring

EEG signals at scalp are roughly less than 100 µV that necessitates extremely low-noise differential mode amplification and high input impedance amplifier. The "DRL-less" AFE of referential montage based EEG SSN consists of a high common-mode rejection ratio (CMRR) instrumentation amp followed by filtering stages (active notch filter with -28 dB attenuation at f_c=60 Hz and band-pass filter for f_c=47.5 Hz) and operational amplifier which leads to the overall differential gain, A_v=604 for frequencies 0.16 – 47.5 Hz. In comparison to the other similar analog designs [19-20], the proposed design has a sharp notch filter which reduces any power-line interferences that may affect the neural recording in the real-life settings. We have used a commercial disposable pre-gelled electrode (GS-26, Bio-Medical Instruments, MI, USA) that can be placed on the scalp and can be directly snapped on to the SSN for EEG data collection. Compared with the conventional EEG, the designed sensing nodes do not need any long leads to connect to the electrodes leading to a robust signal sensing. The sensed brain signals are digitized (on the node itself) at f_s=512 sps using a 12-bit SAR core ADC of an ultra-low power 16-bit MSP430F5528 microcontroller (Texas Instruments, Texas, US). The sampled ADC data triggers the DMA controller, which places the result in a mutex software buffer of size 1024 bytes using an Interrupt Service Routine (ISR). The data is sent to the CCN using I^2C bus topology at 100 kbps baud rate, explained in detail in Section 4. EEG SSNs can also be used for the ECG measurement after gain modification in the AFE.

The general block diagram of the SSN as shown in Fig. 2 consists of a sensor (EEG/ Heart rate), signal conditioning circuit and a microcontroller with an I^2C interface. The designed four-layer PCB for EEG SSN has a diameter of 32.7 mm compared to a US quarter of diameter 24.3 mm. For referential EEG sensing, a dedicated reference node is designed along with the virtual ground node that can be snapped on the electrodes at the mastoid. Both nodes do not have any active instrumentation.

B. SSN for HRV monitoring

The Heart Rate Variability (HRV) SSN measures the heart rate of the subject using an ultra-thin piezo-resistive sensor FSR402 (Interlink Electronics Inc., CA, and USA). The sensor is attached on the side of the neck to sense pulse on the carotid artery. The sensed signal is filtered with a low-pass filter, f_c=30 Hz and digitized using a 12-bit ADC in the MSP430F5528 microcontroller at f_s=20 sps. This smart node counts the number of pulses obtained in 10 s and multiply with six to calculate the heart rate information. This EOI is sent in response to a request by the CCN via an I^2C bus. The two-layer PCB for this SSN has a dimension of 35mm x 33 mm.

C. CCN

CCN aggregates data from different SSNs and transmits it wirelessly to a paired smart phone, PC or laptop. A four-layer PCB is designed for the CCN with a dimension of 49.7 mm x 33.7 mm. Compared with the SSN, it does not have any signal conditioning circuit. Fig. 3 depicts the general block diagram, in which a TI microcontroller MSP430F5659 is used to share command control and data flow information with the SSNs.

Apart from the I^2C interface and 16-bit timer inside the microcontroller, CCN has an RN-42 Bluetooth module (Roving Networks, CA, USA) which allows the UART communication in a serial port profile (SPP) mode for wireless data transfer at 115.2 kbps.

Fig. 4 represents the fully assembled boards of three EEG SSNs, one heart rate SSN and a CCN used in this study for network integration. The I^2C connectors on each board are connected with a flat ribbon cable of six strands (pitch 0.05″).

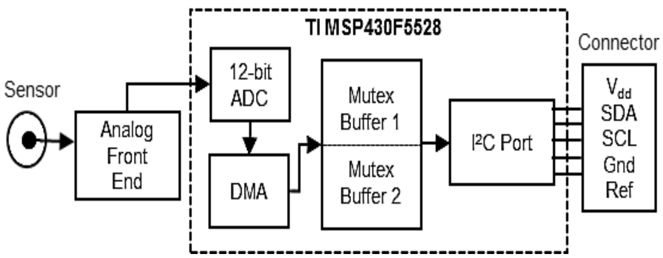


Figure 2. Block diagram of the designed SSNs. Sensor could be any of the EEG or piezoresistive sensors (with appropriate AFE).

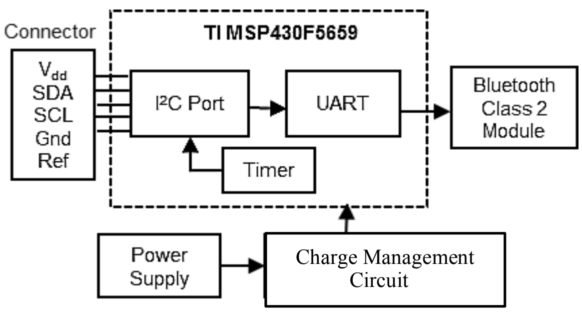


Figure 3. Block diagram of the custom-designed CCN. RN-42 Bluetooth is used for the wireless data transfer.

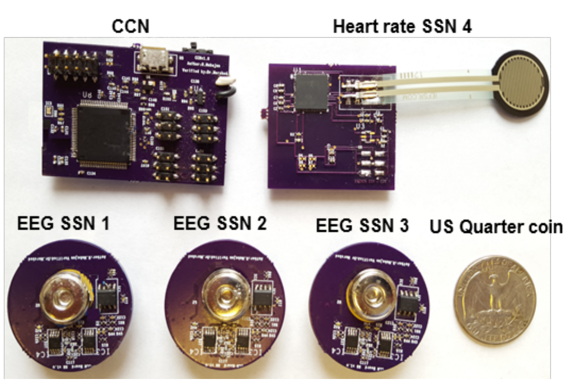


Figure 4. Prototype boards for EEG SSN, heart rate monitoring SSN and CCN. (Size compared with a US quarter coin).

IV. Software Design

The firmware is developed in Code Composer Studio 6.1 software which is an integrated development environment (IDE) that supports TI's microcontroller. The main components of the proposed architecture are SSN and CCN which communicate serially using the I^2C protocol. Though SPI protocol can provide higher speed communication compared to I^2C, this study employs latter because of its capability of in-band addressing needed for a multi-SSN BSN system.

The four wire I^2C communication which allows connecting multiple sensors on the same shared digital bus is initiated by the master (CCN) with the slaves(SSNs). Each SSN connected to the bus is software addressable by a unique address and connected with the bus with its Serial Data Line (SDA) and Serial Clock Line (SCL) pulled up with 4.7 kΩ resistors. We have used a standard seven-bit addressing system and the bus speed of 100 kbps, but it can be upgraded to the fast-mode speed of 400 kbps.

A. SSN architecture

The main objective of SSN is to sample the neuro-physiological data and transmit it to the CCN when requested. On power reset, SSN waits till it receives a broadcast command from the CCN to start the timer triggered 12-bit ADC in the microcontroller. A timer is initialized to trigger at 1.9 ms (for EEG SSN) or 50 ms (for Heart rate SSN) to start the ADC. Every time a SSN receives the broadcast command, it resets the timer (refer Rx ISR of Fig. 5). This helps in synchronizing all the attached SSNs on the bus.

In order to reduce the power consumption and increase the throughput of an I^2C module, a Direct Memory Access (DMA) controller is used to move the ADC conversion results to the random-access memory. The DMA controller saves the ADC conversion results in a mutex buffer 1 or 2 (1024 bytes) depending upon whichever buffer is empty (refer to DMA ISR of Fig. 5). Whenever CCN requests data, SSN enters Tx ISR (Fig. 5), checks if any of the buffers is full or not and responds accordingly. If none of the buffers is full, SSN sends an arbitrarily fixed digit (e.g., 0x33h), which indicates the CCN that the data is not ready yet. CCN stops the communication with this slave and requests data from the next slave in a round-robin fashion. Fig. 5 represents the ISRs addressed by the SSN for receive, transmit and DMA controller interrupts. As mentioned before, each SSN is configured as a slave in the network and is identified by a unique address known to the CCN.

SSNs are intelligent to pre-process the data before sending it to the CCN. For EEG, algorithms like real-time artifact removal, feature extraction, etc. can be implemented on the node itself. Thus, instead of sending raw data continuously, SSNs can send the important EOI information and can thereby significantly reduce the payload requirement of the network. For instance, instead of transmitting EEG data from a SSN to CCN (a typical data payload 512B/s for each channel), EEG rhythmic band powers (δ, θ, low-α, high-α, and β) can be computed at SSN (data payload of 50B/s for a 100ms refresh rate) that will reduce the data payload by one order of magnitude. Similarly, HRV SSN can compute HRV in real-time and transmit only HRV information at a much slower rate (e.g., 1 sps).

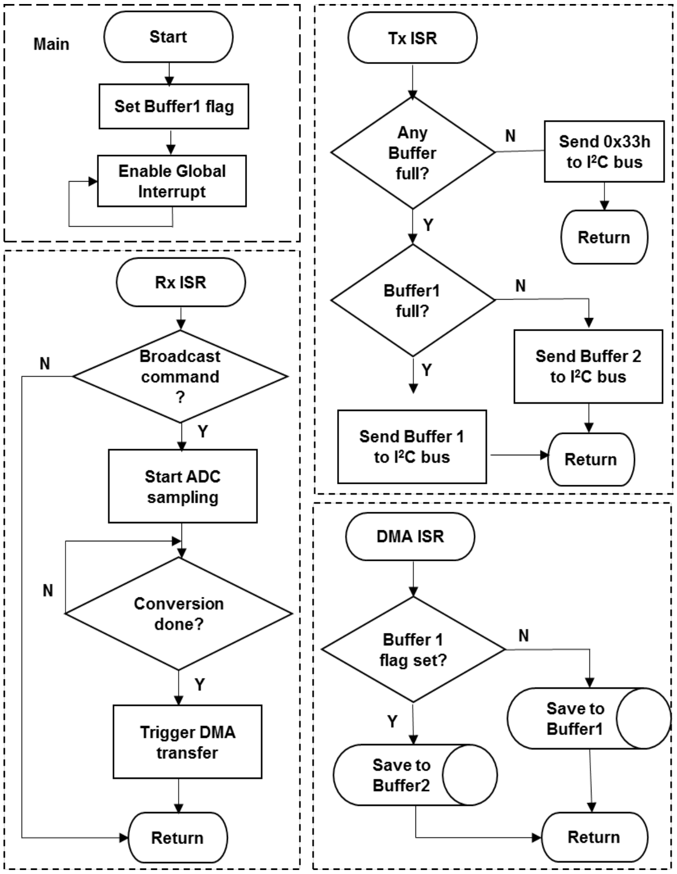


Figure 5. Firmware flowchart of SSNs in the proposed reconfigurable architecture.

B. CCN Architecture

CCN is the master of I^2C network so it generates the SCL whenever a communication is required with the SSN. On power reset, CCN sends the broadcast command to all the attached SSNs on the bus to start sampling the signals with inbuilt ADC. The broadcast command is timer-triggered and is sent every 1 s, which synchronizes the existing SSNs on the bus. After sending the broadcast command, CCN requests 1024 bytes data from each SSN in a polling mechanism and send it to UART at a baud rate of 115.2 kbps. SSN takes ~80 ms to send 1024 bytes of data on the I^2C bus and it takes ~ 88ms to send this data on UART. Fig. 6 depicts the flowchart of the communication protocol for CCN. The proposed architecture is fully-adaptive to any new SSN introduced in the network, allowing reconfigurability at the time of deployment.

In order to avoid the data loss, we select the sampling time of the sensors such that

$$T_{sample} \geq \sum_{N} T_{frame} \qquad (1)$$

where N is the number of homogenous sensors in the network and $T_{frame} = (T_{clkbus} \times x)$; x is the number of bits in the packet required to send the data and T_{clkbus} is clock period of the I^2C bus. With this, assuming a sampling frequency of 512sps for each SSN with 12-bit ADC, six homogenous SSNs can be used at 100 kbps, if all raw data is transmitted simultaneously.

With heterogeneous sensors for heart rate monitoring, pulse oximeter, body temperature measurement, etc. the sampling rate requirement is very low compared to the EEG and ECG SSNs (preferable 256, 512 sps or even higher). So more SSNs can be introduced to the network by configuring the buffer size and sampling rate. From a hardware point of view, using a 7-bit addressing system, maximum 112 SSNs (out of 128 addresses 16 are reserved by the I^2C manufacturer) can be connected to the bus. However, taking into consideration I^2C specifications for bus capacitance of 400 pF (for 100 kbps speed) we can connect at the most 39 SSNs (C_b=10 pF each) with one master (C_b=10 pF) in the network. This provides access to enough sensor nodes for typical BSN applications.

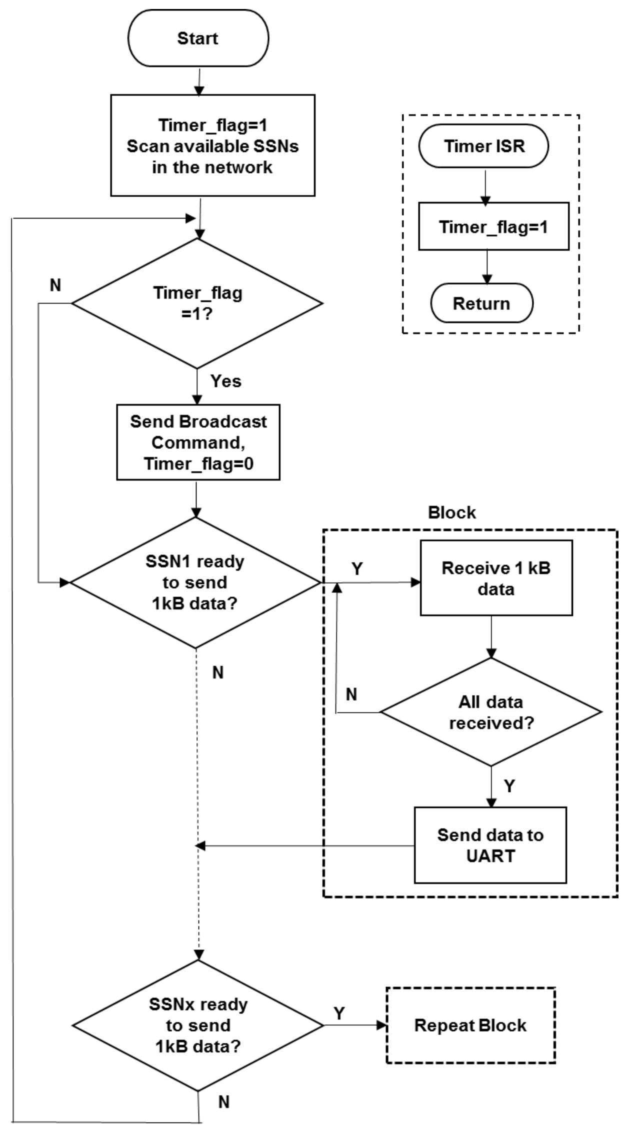


Figure 6. Flowchart of the CCN communication with SSNs (via an I^2C digital bus at a speed of 100 kbps) in a round-robin fashion.

V. System Prototyping And Testing

The designed prototypes were verified in the lab-settings and the actual recorded neuro-physiological signals were also validated against the commercially available systems. For EEG validation, signals from a consumer-grade Emotiv EPOC [3] were compared with the simultaneously recorded data with EEG SSN. EPOC is considered as the best low-cost EEG in terms of usability [21]. The HRV SSN's data was compared against a commercial finger pulse oximeter CMS-50D (Accu-Med Systems Inc., OH, USA). The sections below discuss in detail the methods and signal analysis techniques used for the system validation.

A. Real-time data collection with prototypes and EPOC

For EEG data collection in the office-settings, designed modular EEG SSNs were deployed on the frontal lobe of the subjects. The reference and the ground nodes were placed on the left and right mastoid respectively. Subjects were asked to perform multiple activities like close eyes, open eyes and walk, etc. while the data was recorded continuously in the laptop in real-time in non-clinical settings.

To compare the EEG signals with Emotiv EPOC, one of the EEG SSN was placed side by side on the AF3 location. EPOC is a 14-channel, DRL based EEG which filters the brain signals using inbuilt analog filters (bandwidth 0.2–45 Hz) and then samples them with a 16-bit ADC at f_s=128 sps. It uses wet-electrodes which are soaked in the saline solution. In comparison with configuring EEG SSNs, the bulky EPOC needs a lot of preparation time and also has pre-defined fix locations on the scalp. To compare the signals in the frequency domain, power spectral density (PSD) was computed using the Welch method in MATLAB (MathWorks, MA, USA).

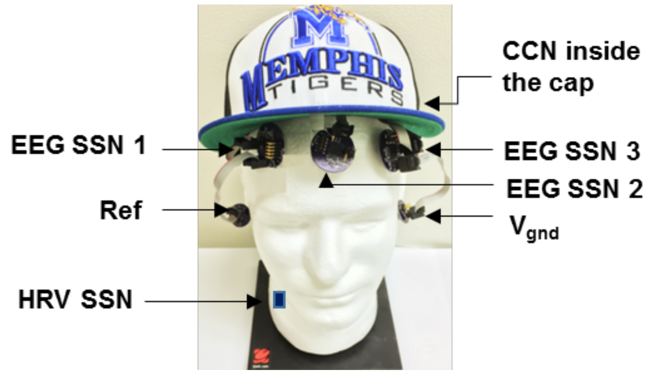
For collecting heart rate information, the HRV SSN was attached to the side of the neck, while the CMS-50D pulse oximeter was placed on the index finger simultaneously. The heart rate computed by the HRV SSN was comparable to the commercial sensor (±2) with multiple subjects. Fig. 7 (a) represents the way the designed SSNs were deployed on the subject in practical settings. Note that the location of SSNs is not fixed and can be changed as and when required.

B. Graphical user interface (GUI)

To receive the real-time data from the Bluetooth via a serial port, a GUI was designed in the MATLAB. Software handshaking in the GUI was enabled in order to avoid any data loss. CCN sends 1025 byte data at a time to the paired device in which one byte represents the SSN i.d and the rest 1024 bytes indicates the neurological/ physiological data. The GUI counts the number and sequence of the packets received and display on the command window, in the case of any discrepancy.

C. Institutional Review Board approval

This study was approved by the University of Memphis, Memphis Institutional Review Board (IRB), Approval Number: 2289. The IRB committee evaluated the safety concerns associated with the deployment of SSNs/ CCN. They also reviewed the protocol for acquiring real-time neuro-physiological data from the human subjects.



(a)

(b)

Figure 7. (a) Photograph of three prototyped EEG SSNs and one HRV SSN deployed on a mannequin. (b) 14-channel Emotiv EPOC headset for comparison [3]. Note that SSNs can be placed at any location on the scalp in comparison with EPOC in which the sensor location is fixed.

D. Power management and consumption

A LiPo battery of 800 mAh with the operating voltage set to 3.3 V is used as a power supply for the CCN. The battery can be charged with a micro-USB cable via a charge management circuit designed on the CCN using MCP73831 (Microchip Tech., AZ, USA). The experiments showed that most of the power is consumed by the Bluetooth module on the CCN (30 mA transmit mode) and microcontroller units on the SSN and CCN (290 µA at 1 MHz). The power consumption is optimized by switching to the lower clock speed of 32.768 KHz for the timers, reducing the CPU clock cycles by using DMA and by using ultra-lower power surface mount components. On an average, CCN consumes ~20 mW when connected with one EEG SSN which, therefore, allows continuous data collection up to six days. However, when connected with the HRV SSN, CCN only consumes ~ 8 mW.

E. Scalability and reconfigurability

All SSNs in the network are hardware-reconfigurable and Lego-like connectable which offers an ease of deployment. The total number of SSNs to be donned by the subject can be decided at the time of deployment. Also, a new SSN can be connected or an existing SSN can be removed at any time without any changes needed in the hardware. However, every time such change is done in the network, the system needs to restart which can be done by sliding the power on/off button on the CCN. The real-time EEG and heart rate variability data were collected from multiple subjects under various test conditions- different SSN locations, by connecting and disconnecting SSNs, and while subjects performing activities. Theoretically, up to 39 SSNs can be connected in the proposed network.

VI. Experimental Results

We have investigated the framework of the BSN in which four SSNs can be easily connected or disconnected at the time of deployment as per the need of the application. Each designed SSN was verified with a test signal for its expected time and frequency domain response. Fig. 8 represents the magnitude response of one of the representative EEG SSNs measured with the oscilloscope, which matches with the theoretical gain.

The I^2C paradigm was also verified for its expected clock frequency, rise time and data using a DSOX2024A digital oscilloscope (Agilent Tech., CA, USA). Fig. 9 depicts the communication protocol between CCN and SSN with respect to the SCL and SDA. From left to right, it represents a section of 1 kB received by the CCN from the SSN, followed by a broadcast command sent at 0x00 address for all the SSNs to synchronize their ADCs. After the broadcast, CCN receives 0x33h from the SSN indicating that the buffer on the SSN was not full. CCN thereby stops communication with this SSN and request data from the other SSN in the network.

In order to verify that there is no data loss in the communication, test input signals were applied to the EEG SSNs (SSN 1- sine wave V_{in} = 4mV at 20 Hz, SSN 2 - ramp wave V_{in} = 4mV at 10 Hz and SSN 3- sine wave V_{in} = 4mV at 20 Hz). The test signals were sampled at 512 sps on the SSN and were transmitted to the CCN via the I^2C bus. Fig. 10 shows a snapshot of the GUI representing the test signals received by the CCN through the Bluetooth. Note that these received test signals were amplified by the system gain of around 604. Also, it can be observed that the output is biased at 1.65V which is due to the virtual ground reference (mid rail of the supply) on the EEG SSN.

The actual heart beat and EEG signals were also acquired from various subjects by deploying the designed SSNs. Fig. 11 shows the output signal in response to the heart beat as measured by the piezo-resistive sensor for one of the subjects. The measured heart rate of 78 bpm was compared by the CMS-50D pulse oximeter which provided an average rate of 80 bpm. Considering that small duration sampling underestimates the measurement, this test validated the prototyped HRV SSN with a reasonable accuracy. The commercial pulse oximeter only provides the numerical value of the measured heart rate, so the time response of heart signals could not be compared in this study.

Fig. 12 depicts a 50 s EEG recording from a male subject with one EEG SSN placed on the AF3 location on the pre-frontal lobe. The subject was instructed to do three activities- close eyes, open eyes, and then walk in the lab, each activity for about 15 s. In the time response, an alpha rhythm can be observed during the eyes were closed and eye-blinks during the eyes were open [22]. Further, PSD was calculated for each activity and as expected a prominent alpha wave was observed between 10-13 Hz (see Fig. 13). Also, PSD for the walk session was noted higher than the other activities which were likely due to the frontalis and temporal muscle activity.

EEG signals were recorded (for ~100 s) from a subject sitting on a chair by placing the active and reference EEG SSNs next to the electrodes of the low-cost battery-powered Emotiv EPOC. For one-to-one comparison with the EPOC headset, signals from the proposed EEG SSNs were down-sampled at 128 sps. Signals from both devices were further digitally low-pass filtered from 1-40 Hz and notch filtered at 60 Hz in MATLAB. For the frequency domain comparison, normalized PSD estimate was computed using the Welch's method (Hamming window of length 512 over FFT length of 1024) in MATLAB. As shown in Fig. 14, the PSD plots for these devices were found comparable for most of the frequencies. Also, the time signals shown in Fig. 15 showed similar wave patterns both for the neural and the artifactual activities. These results validate the functionality of the designed EEG SSNs.

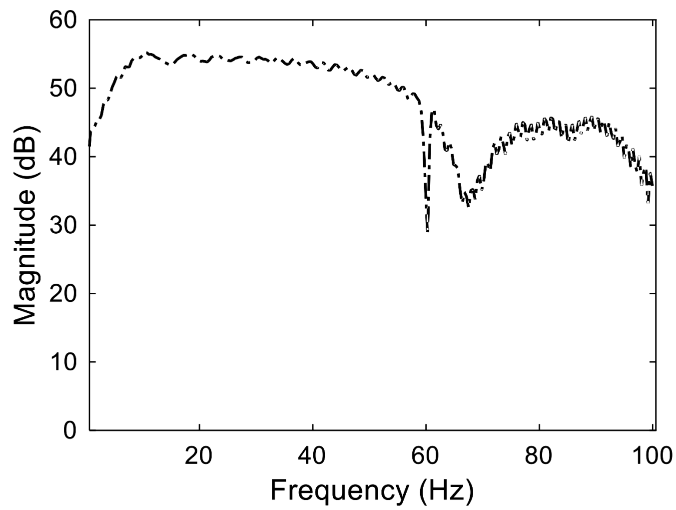


Figure 8. The observed magnitude response obtained for the given test input signal (V_{in} = 4mV) swept between 1-100 Hz frequencies. The sharp attenuation at 60 Hz is due to the notch filter in the AFE.

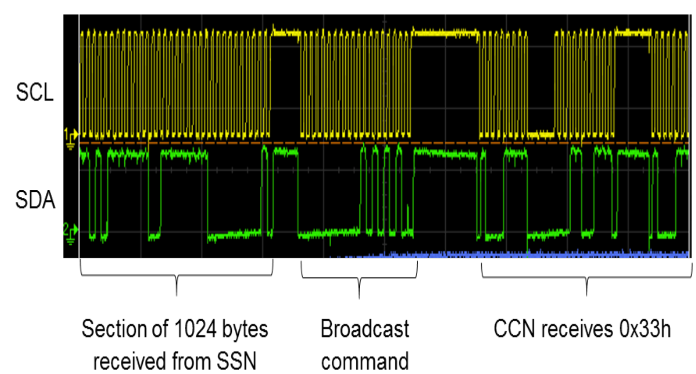


Figure 9. A snapshot of the oscilloscope display that shows the SDA and SCL signals of the I^2C bus during CCN communication with a SSN. The broadcast address is 0x00h and command is 0x33h.

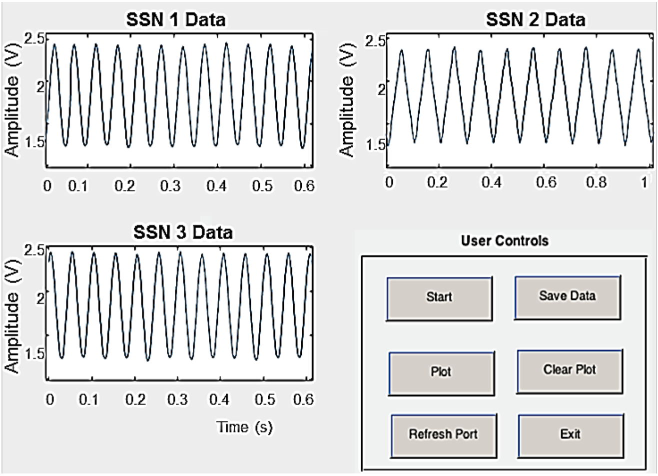


Figure 10. Snapshot of the GUI developed in MATLAB representing the output test signals acquired from the CCN when connected with three SSNs. The x-axis is in Time (s) for all SSNs.

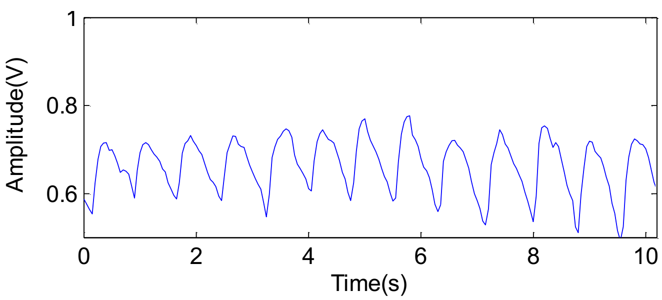


Figure 11. Heart beat signal of a subject obtained from the HRV SSN for 10 s depicting a heart rate of 78 bpm.

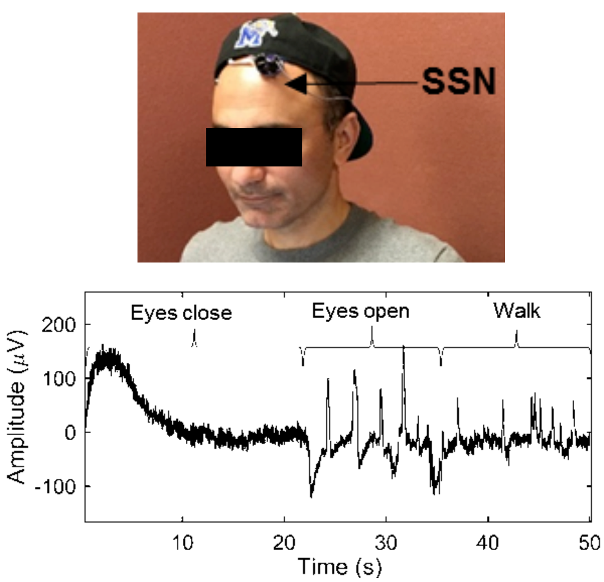


Figure 12. Real-time EEG data collected from one SSN placed at the AF3 location. The subject performed three continuous activities: eyes closed, eyes open, and walk, during the data acquisition period.

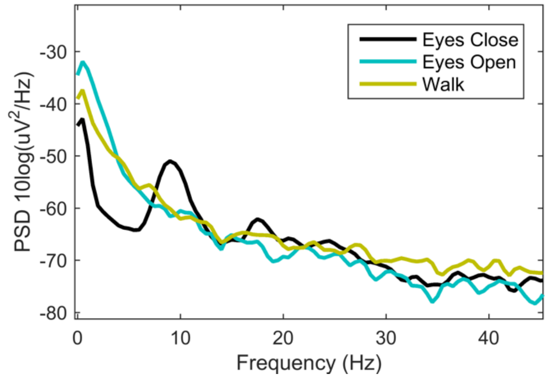


Figure 13. Power spectral density of the EEG recording for the three activities. As per expectation, alpha activity power increases for the session with the eyes closed as observed between 10-13 Hz.

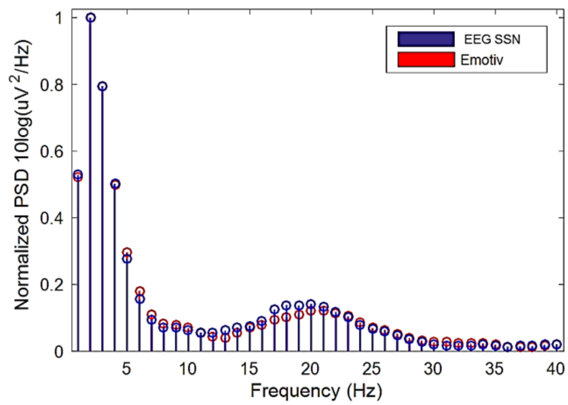


Figure 14. Normalized power spectral density of the simultaneously recorded EEG signals with Emotiv and an EEG SSN at the proximal AF3 location.

VII. Conclusions

We propose a scalable and reconfigurable BSN with modular sensors for neuro-physiological monitoring beyond clinical settings. The sensor network consists of smart sensing nodes (SSN) and a command control node (CCN). We have prototyped three single channel EEG SSNs and a single heart rate monitoring piezo-resistive HRV SSN, which collect signals in real-life settings and send it to the CCN using an I^2C protocol. The custom-designed "DRL-less" EEG SSN eliminates the need for the DRL circuit in the conventional EEG system which leads to a modular design. The ultra-low power TI microcontrollers on each SSN samples and processes the physiological signals at 512 sps (for EEG) and 20sps (for heart beat rate) before sending it to the CCN at a clock speed of 100 kbps. CCN with core intelligence synchronizes each SSN node, checks for any new SSN in the network periodically and interrogates SSN to collect event of interest information. CCN further transmits the meaningful information wirelessly via Bluetooth to a paired laptop/PDA at a baud rate of 115.2 kbps. The designed EEG and HRV SSNs are validated against the commercially available sensors. The temporal and frequency domain results show that the designed SSNs have a potential to be used for data collection in the non-clinical settings. The proposed BSN can also incorporate SSNs for ECG, body temperature measurement, pulse oximetry, etc. The proposed architecture of a scalable BSN is easily deployable for the mHealth system.

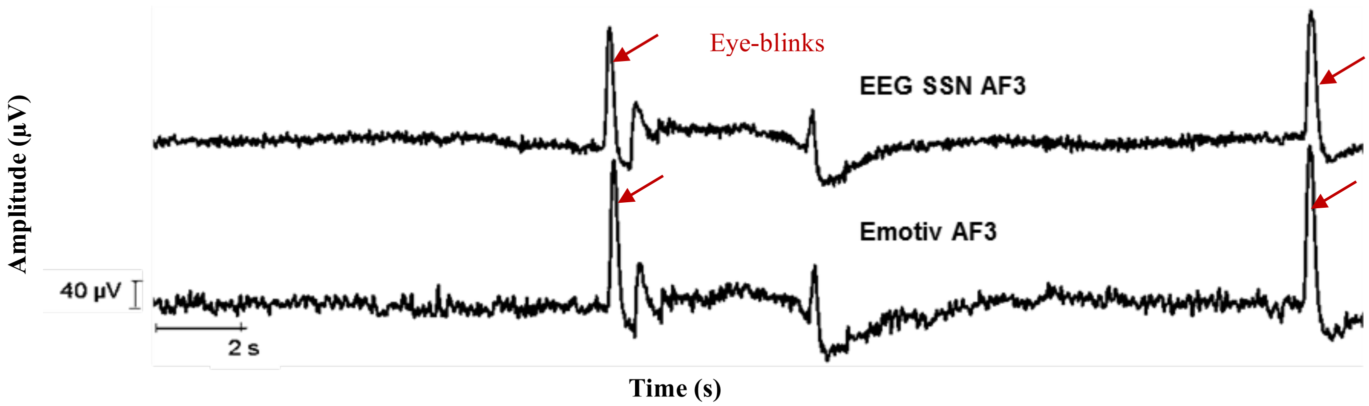


Figure 15. A section of the simulataneously recorded raw EEG time series from the AF3 location of a subject using Emotiv EPOC and EEG SSN. Red arrows repsresents eye-blinks by the subject during the recording.

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