Cutting-Edge Technology for a Cognitive Load Performance Assessment System

An embedded cognitive load performance assessment system collects neurological and physiological data unobtrusively and seamlessly during training sessions, classroom engagements, or outdoor activities for contextual analysis of performance, cognitive loads and psychological assessments.

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For the modern information-intensive and demanding workloads, it is frequently necessary to have quantitative metrics for individual and collective engagement assessment in multiple tasks simultaneously. Usually personnel with higher cognitive abilities would have distinct advantages or abilities in real-life practical scenarios where safety-critical decisions need to be made within a short span of time, such as combat fields, first responders, or medical emergencies. With the advent of newer technologies and the ability to non-invasively monitor cognitive activities, there exists every possibility that our ability to identify and distinguish various levels of cognitive ability quantitatively with a high degree of confidence will be realized in the near future. Access to such technology in various practical settings such as classroom, training session, testing facility and other safety-critical situations, could deliver a significant leap in identifying competent leaders and high performers for real-life stressful activities including those associated with emergency, medical and other crisis.

Among various technologies that can non-invasively monitor brain signals and thus cognitive abilities, electroencephalography (EEG), magnetoencephalography (MEG) and functional magnetic resonance (fMRI) are prominent. Among all of these non-invasive sensing techniques, EEG and MEG have excellent temporal resolution, while MEG and fMRI have higher spatial resolution, as magnetic signals are less distorted by the skull, scalp and other fluids surrounding the cerebral cortex. MEG in particular primarily records activity of sulcus, in comparison to gyrus. On the other hand, fMRI is an indirect measurement of brain activities as it records increased blood flow in the cortex that represents increased brain activities. Both MEG and fMRI require highly sensitive magnetic sensors (such as SQUID) and a magnetically shielded room (MSR), and hence require relatively heavy components. MEG or fMRI sensors are rarely usable in the daily routines at home or outdoor settings. In contrast, EEG sensors are miniature and lightweight for convenient ambulatory wearing and continuous sensing while unobtrusive and convenient to the users. Such a system can be built with new cutting-edge embedded technology consisting of an onboard microcontroller with dedicated input and output ports with specific functionalities within a larger system and would operate within specified real-time computing constraints.

We conceptualize a performance assessment system that is comprised of an EEG and other co-sensed data and compactly contains an embedded system platform, which can be routinely worn for long periods, and collects, stores and wirelessly communicates such biometric (neurological and physiological) information in an autonomous fashion. The system would incorporate ultra-low-power embedded technology, smart wireless communication and power management algorithms for extended battery life yet powerful processing capabilities. The onboard real-time computing ability comes with high capacity storage capabilities and ubiquitous connectivity for data extraction, analysis and assessment.

System Description

The system is comprised of embedded hardware nodes wirelessly communicating with each other and the central communication unit (CCU). A number of embedded wearable hardware nodes would need to be located at various strategic locations on the user's body, which are wirelessly communicating among themselves through a body area network (BAN) and transmitting their data to a CCU within a personal area network (PAN).

The two major elements of the each wearable performance assessment node in the system are the embedded wearable hardware and the data collection sensors. The embedded wearable hardware platform gathers the sensor data and stores it locally. Once each node is configured in the network, its data is communicated to the CCU for post processing, storage and re-transmission to a remote computing system as required. A system block diagram designed to perform assessment of cognitive loads of multiple individuals in a group setting is shown in Figure 1.

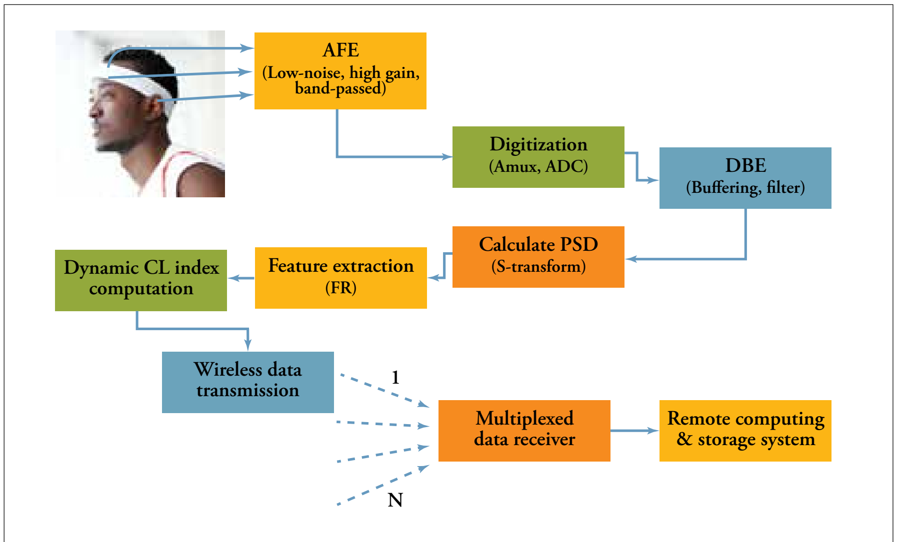

Figure 1. A block diagram depicting various elements of the system and corresponding computational functionalities.

The wearable hardware node components are shown in Figure 2. Without a solid hardware platform to process and accurately capture the sensor data, the performance assessment algorithm will produce imprecise results and, hence, lead to errors in data analysis. Therefore, keys for the embedded platform in each node are:

- Concurrent processing of multiple physiological data while keeping power consumption low to enable data collection over many hours
- Real-time processing algorithm to compute the key metrics, packaging of multimodal data with timestamps

The main processing is performed by a high-performance, low-power 32-bit ARM-based microcontroller. The processor includes onboard analog-to-digital converters (ADCs) with 16-bit resolution and at least one synchronous serial module, commonly Serial Peripheral Interconnect (SPI) for connection to various outside peripherals.

The system includes additional interfaces (analog & digital) to accommodate other sensors. In addition, the system incorporates a wireless (Bluetooth low energy) module for communication with other sensor systems, remote units and the CCU. The data storage capabilities allow the embedded system to store the collected sensor data locally and transmit the data wirelessly with a smart algorithm when the computation constraint is less and power consumption is lowered. Figure 3 shows some early prototypes of such embedded wearable hardware platforms.

The main support system is power management. As with most battery-powered consumer devices, each node must perform under a wide range of rough environments. Factors such as temperature have significant effect on battery endurance. Power for recharging batteries is not always available or convenient.

The sensor node packaging must be designed to minimally affect the user and ensure that performance is not altered by outside disturbances. The shape of the housing is a key factor to overall performance and is designed to not interfere with garments worn over it. The optimal form factor for such a device is a disc shape (low aspect cylinder) with soft transition edges (fillets) from the sides to the top. Figure 4 shows an example of the sensor node unit mounted to the hand.

The CCU is responsible for collecting the individual sensor node data, storing it, and communicating the data to a remote computing system. The remote computing system records the wirelessly transmitted data, and computes individual or collective physiological states in real time or at a later time with contextual and time markers from the data. Transmission of computed data (such as cognitive load) instead of raw EEG data drastically reduces data-load and allows co-monitoring of many users with a simple wireless receiving unit.

The system is comprised of a number of sensors to capture physiological conditions. These sensors include transducers from EEG sensors, 3-axis orientation sensor, 3-axis gyroscope and 3-axis compass (e.g., MEMS-based ICs), heart rate variability (HRV) or Electrocardiogram (ECG) measurement, humidity sensor and temperature sensors. The low amplitude EEG signals must be conditioned carefully to remove noise and artifacts, then sufficiently amplified (70 - 80 dB) before digitization. The filtration of EEG data must have a second or higher order band-pass filter with range of 0.5 to 100 Hz. A notch filter at 60 Hz allows reduction of utility line noise—the most severe noise of the system. A sigma-delta ADC samples the amplified and biased analog data with low-quantization noise.

Among various onboard processing capabilities, the requirement to include an onboard real-time artifact removal algorithm is critical for EEG data processing. Useful metrics, such as cognitive load index (CLi), are computed from the processed data with the following expression:

$$CLi = \frac{P_\alpha^R}{P_\alpha^M} \times \frac{P_\beta^M}{P_\beta^R}$$

where P_α^b denotes the power spectral density (PSD) within the brain rhythms α (where α is α or β, two rhythms with frequency range of 8 to 13 Hz and 13 to 25 Hz, respectively), and b represents baseline relaxed state (R) or monitor stage (M).

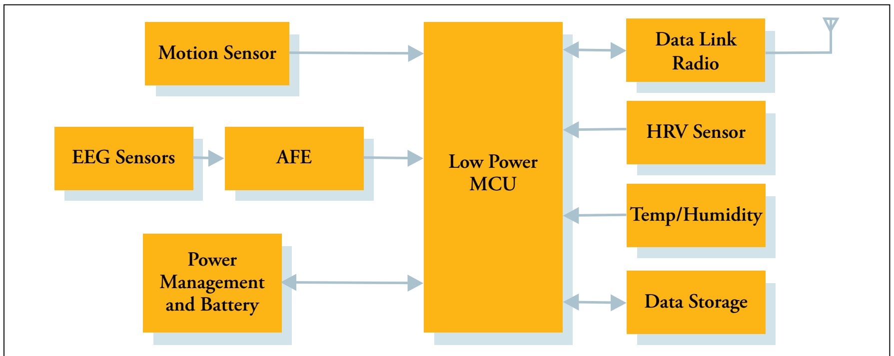

Figure 2. The cognitive load assessment embedded hardware block diagram.

The remote computing system records the wirelessly transmitted data as well as processing individual or collective physiological states in terms of CLi and other cognitive ability in real time or at a later time with contextual analysis. The time-stamped data packets are also co-analyzed with data fusion technique for a complete analysis of individual or collective cognitive performance.

Performance Assessment

The power consumption (P_{Total}) of the system can be divided into four classes:

$$P_{Total} = P_{AFE} + P_{Digitization} + P_{DBE} + P_{St/Trans}$$

where P_{AFE} is the power consumption of the analog front end, $P_{Digitization}$ is for the ISR (interrupt service routine) along with ADC and analog multiplexor, P_{DBE} is the power consumed by the microcontroller-based digital back end, and $P_{St/Trans}$ is the power consumption related to the storage element (micro SD card) or wirelessly transmitted data. The power consumption of the system is approximately 10 mW, which allows each node in the performance assessment system to operate for extended periods of time before needing to be recharged.

Among the system components, the EEG sensor requires about 70 to 80 dB gain with low-noise amplifier (such as an instrument amplifier). The EEG sensor also requires signals to be filtered for low (0.5 Hz) and high (100 Hz) frequencies using second or higher order active filters. In addition, power line interferences are removed with a high order notch filter. For stability reasons and continuous periodic sampling, the analog front end might be required to be continuously in active mode. If the time required for the signals to become stable is T_{Samp}, and the sampling period is $T_{AnaTran}$, then the analog front end can only be power cycled when the following constraint is met:

$$T_{Samp} > T_{AnaTran}$$

For EEG sampling at 256 samples per second, such a constraint will not be met, hence the analog front end must use the lowest power consuming circuitry and be left operating while the data is being collected. The $P_{Digitization}$ usually can be shut down between sampling. The required setup time, hold time and active time is usually in µs range—much smaller than T_{Samp}. This stage is optimized with switching to active and standby (or shut-off) modes even during data collection. The digital back end and storage/transmission sections can also be optimized with a similar approach using dynamic clocking and microcontroller low power modes.

The collected physiological data can be assessed for cognitive load calculation (from EEG and HRV data), attentiveness/drowsiness (from eye blinks, motion and orientation sensors with data fusion), and many other cognitive and psychological assessments for individual as well as collective performance. The use of multiple sensors with real-time clock synchronization allows the potential for automated contextual computation, unsupervised verification of events, and synchronization for team dynamics and workload assessment. The performance assessment system would operate autonomously without human intervention; hence, it would not increase the task load or add any additional burden to the instructor, while providing quantitative information seamlessly on the cognitive activities of individuals and collective performance metrics in real-life practical settings such as in classrooms, training sessions, or other stressful, safety-critical activities.

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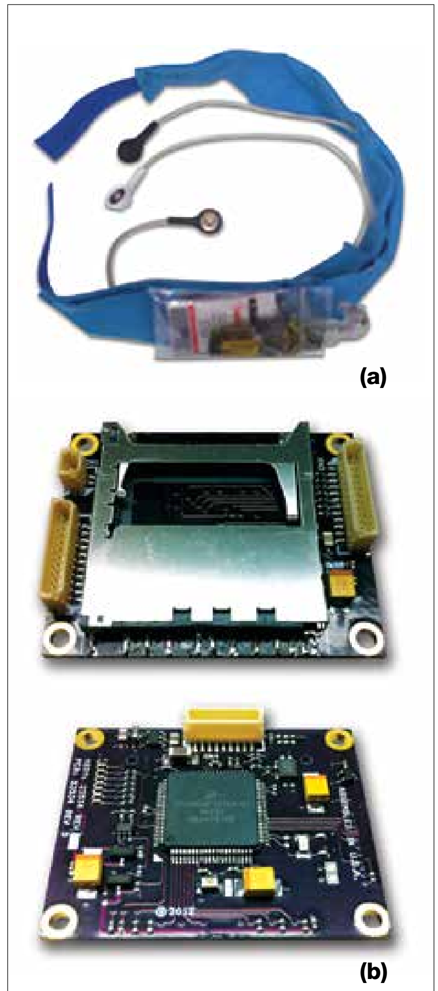

Figure 3. Various prototypes of the embedded wearable hardware platforms including ambulatory EEG device (a) and onboard data logger (b).

Figure 4. The small nature of the embedded wearable sensor node allows for a variety of mounting options.