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Publisher's version / Version de l'éditeur:
https://doi.org/10.1109/TBME.2010.2090880
IEEE Transactions on Biomedical Engineering, 58, 3, pp. 750-754, 2011-03

Towards Brain First-Aid: A Diagnostic Device for Conscious Awareness

Ryan C. N. D'Arcy*, Sujoy Ghosh Hajra, *Member, IEEE*, Careesa Liu, *Member, IEEE*, Lauren D. Sculthorpe, and Donald F. Weaver

***Abstract*—When the brain is damaged, evaluating an individual's level of awareness can be a major diagnostic challenge (Is he or she in there?). Existing tests typically rely on behavioral indicators, which are incorrect in as many as one out of every two cases. The current paper presents a diagnostic device that addresses this problem. The technology circumvents behavioral limitations through noninvasive brain wave measurements (electroencephalography, or EEG). Unlike traditional EEG, the device is designed for point-of-care use by incorporating a portable, user-friendly, and stable design. It uses a novel software algorithm that automates subject stimulation, data acquisition/analysis, and the reporting of results. The test provides indicators for five identifiable levels of neural processing: sensation, perception, attention, memory, and language. The results are provided as rapidly obtained diagnostic, reliability, validity, and prognostic scores. The device can be applied to a wide variety of patients across a host of different environments. The technology is designed to be wireless-enabled for remote monitoring and assessment capabilities. In essence, the device is developed to scan for conscious awareness in order to optimize subsequent patient care.**

***Index Terms*—Health monitoring, neuroscience, point-of-care diagnostics, sensor technologies utilization, wireless reporting and assessment.**

I. Introduction

WHILE diagnostic imaging methods, such as computerized tomography (CT) and magnetic resonance imaging (MRI), have long been employed to determine the extent of structural insults to the brain, clinical testing for the functional integrity of the brain has traditionally been left to the domain of tests that rely on behavioral responses (verbal or motor). These tests are typically designed for awake, alert patients who are capable of providing such responses. Brain injury, however, commonly induces altered states of consciousness, unconsciousness, and/or paralysis—making standard testing impossible. This is all too often the case for a host of brain disorders and diseases (e.g., traumatic brain injury, stroke, Alzheimer's disease, Parkinson's disease, autism, etc.).

For many years, the "gold standard" for testing conscious awareness has been the Glasgow Coma Scale (GCS). First reported more than 35 years ago [1], this and other long-standing clinical tools rely on the capacity for voluntary movement. Reliance on behavioral responses fundamentally limits these diagnostic tests [2], and estimates of misdiagnosis using such methods are as high as 43% [3]. The prevalence of such misdiagnoses leaves basic questions about a patient's level of functioning unanswered. Cases like Terri Schiavo and Rom Houben—in which level of conscious awareness was hotly debated—represent real-world examples of the problem. Unfortunately, the problem exists across levels of conscious awareness, from locked-in (fully alert, but cannot respond), minimally conscious, vegetative, coma, to brain death [2]. The human, family, medical, ethical, and legal implications of misdiagnosis are significant.

Advances in functional brain imaging technologies are providing a more objective, physiological solution [4]–[7]. Functional MRI (fMRI) is one popular neuroimaging method for such work, but requires large and expensive instrumentation. As such, fMRI cannot realistically provide portable, point-of-care diagnosis. Tests like the GCS are pervasive in medicine due to three key features—they are practical, easy to implement, and the results can be rapidly communicated [1].

It has been suggested that electroencephalography (EEG) may be the neuroimaging method that is best suited to point-of-care consciousness assessment [2]. Event-related potentials (ERPs), derivatives of the EEG obtained by signal averaging, can even be used to obtain indices of specific stages of sensory and cognitive information processing. Indeed, more than a decade of comprehensive research in this [8]–[11] and other labs [12]–[16] has demonstrated the diagnostic power of several ERPs in assessing cognitive function in behaviorally unresponsive patients. The current letter presents a novel brain wave technology that executes this kind of ERP-based test rapidly and provides a diagnostic measure that blends the clinical features of the GCS with the physiological measurement of conscious awareness. An overview of the scientific and technical features is presented next. Additional detail can be found in the US provisional patent application for the Halifax Consciousness Scan (HCS).

Manuscript received July 30, 2010; revised October 5, 2010; accepted October 26, 2010. Date of publication November 11, 2010; date of current version February 18, 2011. This work was supported by the National Research Council Canada. *Asterisk indicates corresponding author.*

*R. C. N. D'Arcy is with the Institute for Biodiagnostics (Atlantic), National Research Council Canada, Halifax, NS B3H 3A7, Canada, and also with the Departments of Radiology and Neuroscience, Dalhousie University, Halifax, NS B3H 4R2, Canada (e-mail: ryan.darcy@nrc-cnrc.gc.ca).

S. G. Hajra, C. Liu, and L. D. Sculthorpe are with the Institute for Biodiagnostics (Atlantic), National Research Council Canada, Halifax, NS B3H 3A7, Canada.

D. F. Weaver is with the School of Biomedical Engineering, Department of Medicine (Neurology), and the Department of Chemistry, Dalhousie University, Halifax, NS B3H 4R2, Canada, and also with the Queen Elizabeth II Health Center, Halifax, NS B3H 3A7, Canada.

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Digital Object Identifier 10.1109/TBME.2010.2090880

II. Methods

EEG measures the volume-conducted electrical currents produced by neural activity. The neural activity occurs in real time, on the order of milliseconds, therefore providing an online record of brain activity. From these data, it is possible to extract neural indicators of cognitive function (e.g., sensation, perception, attention, memory, and language). One of the most common methods relies on signal averaging to isolate ERPs. Clinical ERP applications have been shown to replace behavioral tests and successfully evaluate functional status in patients [8]–[11]. These studies demonstrated the general concept of decoupling the diagnosis of intact function from the limitations of behavior in brain-damaged patients.

The prior work did not, however, address the practical challenges in developing a point-of-care diagnostic device. At least five such challenges exist. *First*, the test should run on a portable, stable, and noise-resistant EEG device, which is easily integrated into a wide variety of environments (small and robust). *Second*, the test cannot be reliant on advanced expertise/training, but rather should be easy to administer, with no prior knowledge/training (similar to a home blood pressure monitor). *Third*, a spectrum of EEG-based cortical responses is needed (rather than assessing one specific brain function in isolation). These responses must be integrated into a rapid, meaningful clinical test. *Fourth*, the analysis software should incorporate a normative database so as to provide standardized test results. It should be noted that building and utilizing a normative database for comparison purposes requires that the procedure used for data acquisition be standardized (i.e., the stimulus sequence, EEG hardware, and analysis software must be held constant). And, *fifth*, the test should produce a range of results covering diagnosis, reliability, validity, and prognosis. The results should be easily interpreted and readily communicated using current IT capabilities (hand-held computer, wireless communications, etc.). Such a device, if made portable, could not only be used in hospitals and clinics, but also in a range of other settings (ambulances, arenas, nursing homes, home care, etc.). It could be easily integrated into the critical care cascade—the continuum of care from prehospital assistance to ICU discharge and rehabilitation [12].

A. HCS Device Design

Fig. 1 provides a schematic overview of the HCS. The EEG system is comprised of recording electrodes, a headset with earphones, an electrode interface, EEG data collection hardware (amplifiers and supporting electronics including ADC, microcontrollers, etc.), an impedance monitor, and a computer interface. The electrodes are configured in the headset to cover the anterior–posterior axis (three channels). Ground, reference, and ocular monitoring electrodes are also integrated into the device (four additional channels). Earphones provide auditory stimulation. The electrodes and earphones are embedded in the headset. They are designed for easy application yet high quality contact with the scalp. This is accomplished with the use of preamplifiers near the sensors, which present high effective input impedance allowing for the rejection of interference from

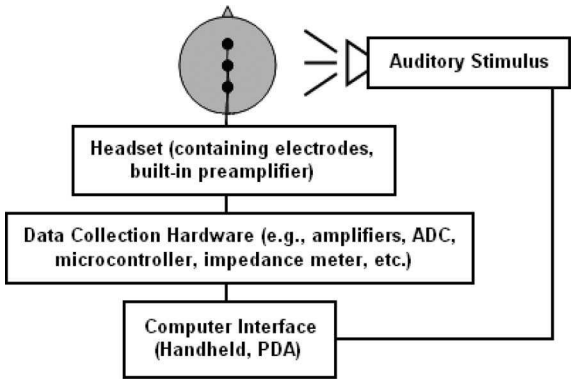

Fig. 1. Schematic overview of the HCS. The headset contains recording electrodes and built-in preamplifier. The data collection hardware amplifies and processes the signals before sending them to the computer. Auditory stimuli are presented via earphones and are also controlled by the computer.

60 Hz mains and other sources of noise. The headset, electrodes, and earphones are designed to be both reusable and disposable. The headset plugs into a permanent electrode interface that connects to the data collection hardware. The hardware employs multistage amplification using instrumentation amplifiers. The design of the electrode lead cabling includes shielding and incorporates guarding circuits for noise attenuation. The amplifier uses driven right leg circuitry to minimize common mode voltages, which can result in erroneous conclusions of biological activity [18]. Postamplification, the EEG signals are processed using hardware bandpass filters and then sampled using a 16-bit ADC before being transmitted to the host computer. The amplifiers are designed as a low cost, stable, and differential system, with active noise cancellation electronics. The hardware is preset to a specific impedance and noise verification test, analogue-to-digital sampling rate (256 Hz), and bandpass filter (0.1–100 Hz).

The computer is small, portable, and integrated within the device. It is wireless-enabled and communicates test results to other devices. The computer is comprised of a display screen, keyboard input, and system "test" and "run" buttons. It has headphone, USB, and battery charging interfaces. The computer interfaces with the EEG data collection hardware with the help of bluetooth communication protocol. The amplifier receives and logs external triggers coded using TTL pulses from the computer. The triggers are used as event markers for signal averaging to derive ERPs. Stimulation, acquisition, and analysis are coded as scripted routines.

B. HCS Algorithm Development

An overview of the HCS method is provided in Fig. 2, with preprocessing (digital filtering, signal averaging, artifact correction, etc.), peak identification, and score generation representing the three main stages. The algorithm converts the recorded EEG data into a numerical score of conscious awareness. The results provide quantitative data for the evaluation of five key indicators: 1) sensory processing; 2) perceptual processing; 3) attentional processing; 4) memory processing; and 5) language processing. A quantitative scale is the main test result

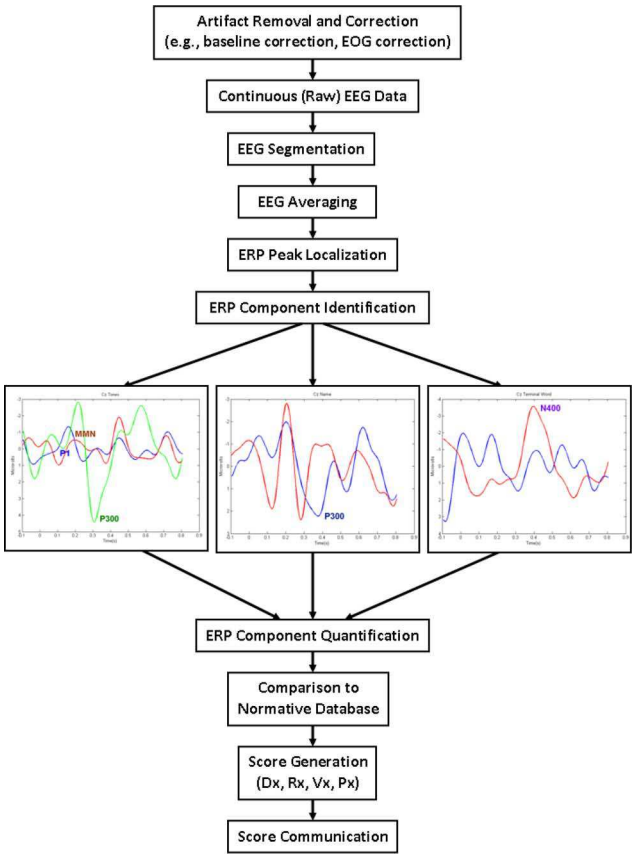

Fig. 2. Overview of HCS method.

and is designed to be fast and easy to interpret. Scale bars depict the results for each of the five indices ranked against their respective normative data. The score is designed such that alterations in consciousness will lead to a drop in ERP peak amplitude, and subsequently the total possible score.

Computer software has been developed to preprocess the EEG data and derive the signal-averaged responses. This software includes (but is not limited to) down sampling, digital filtering (bandpass 1–20 Hz and 60 Hz notch filter), segmentation (−100 to 800 ms), ocular correction [19], baseline correction, and conditional averaging. Stimulus presentation is temporally varied (e.g., jittered) to reduce the influence of ongoing EEG rhythms that obscure the ERP (e.g., alpha waves). Both transient and steady state signal-averaged data are analyzed. S/N optimization is done through ocular correction (rather than rejection), trial averaging, and specific denoising routines (such as pattern recognition for artifacts). Stimulation uses both auditory tones and speech stimuli to elicit the five indicators for conscious awareness. The test duration is approximately 5 min.

The HCS scores are derived from the signal-averaged waveform data by quantifying ERP component amplitudes. This requires, first, identification of the relevant peak, and second, measurement of its amplitude. Peaks are identified based on the time latency and polarity that are known for the ERP component in question (e.g., P1 is a positive deflection that peaks between 50 and 150 ms poststimulus). Traditionally, ERP amplitudes are measured against a prestimulus baseline voltage. At rapid rates of stimulation, however, there is no true prestimulus baseline. The HCS, therefore, measures amplitudes against a component-specific baseline, calculated as the average voltage of ERP onset and offset points. In general, these points are defined as the peaks of opposite polarity that surround the identified ERP component.

The HCS score reflects a comparison of the obtained ERP amplitude to normative data. The normative data include the average amplitude values (as measured against either baseline or a comparison condition) as well as a measure of the variance. The normative data can be tailored to the specific patient (e.g., taking factors like age into account). Scores are quantified based on the individual patient's component amplitude relative to the lower bound of the normative data variance measure. In addition, the normative comparison is converted to a standard reference framework, which allows for the patient specific amplitude data to be plotted against the norm using a numeric index (e.g., $0.5 \pm$ SD). Scores are based on established ERP peaks that have been used to test for sensory and cognitive functions in behaviorally unresponsive patients [e.g., P1, N1, P2, mismatch negativity (MMN), P300, N400, and P600]. These are elicited by a number of different means, including the patient's own name [20], nonverbal emotional exclamations [21], number sequences [22], and standardized neuropsychological tests [11].

III. Results and Discussion

Typical waveforms forall five indicators are presented in Fig. 3. Peaks (open green boxes), inflections (open red boxes), peaks before and after (red boxes with yellow fill) have been identified by the algorithm. Sensation, perception, attention, memory, and language are properly indexed by the P1, MMN, P300 (tones), P300 (speech), and N400. Following peak detection, amplitude is measured and compared to the normative values. Fig. 4 shows score derivation for the P300 (positive-going peak at 300 ms), as an attentional index of increased stimulus intensity.

An overview of the results display is provided in Fig. 5. The results are divided into four different categories: diagnostic score (*Dx*), reliability score (*Rx*), validity score (*Vx*), and prognostic score (*Px*). The total *Dx* is out of ten, with two possible points for each of the five indicators (0 = abnormal, 1 = borderline, and 2 = normal). The *Rx* and *Vx* are allotted based on the repeatability and features of the waveform characteristics, respectively. The *Px* is calculated using a classification approach to assess fit to prior patient data divided on the basis of recovery versus no recovery for a specific indicator. The scores (*Dx*, *Rx*, *Vx*, *Px*) are communicated via graphical output to the screen of the portable device, as well as outputs that are integrated with current communications technologies. The device generates reports that include "On Device Display" (Fig. 5), "Short Reports" in e-mail format (Fig. 6) and "Long Reports" via internet access to a secure domain. The test results can be sent via telecommunication networks for rapid dissemination and easy integration into the critical care cascade.

In summary, a prototype device and algorithm were developed for EEG-based testing of conscious awareness (the HCS). The HCS is portable, stable, and noise-resistant (Challenge 1).

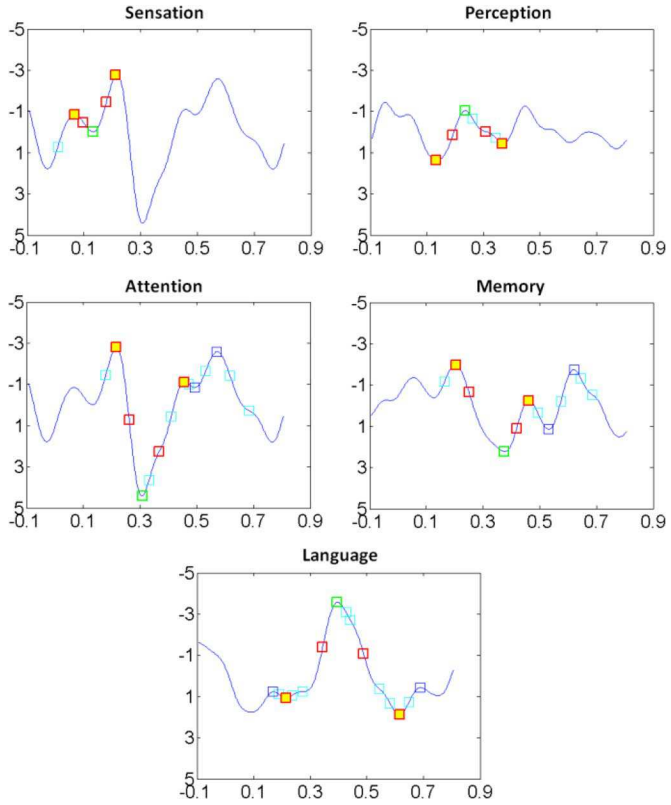

Fig. 3. Typical waveforms for all five indicators plotted in voltage (microvolts) versus time (seconds). Open green boxes delineate ERP component peaks, open red boxes show the inflection points, and red boxes with yellow fill show the peaks before and after.

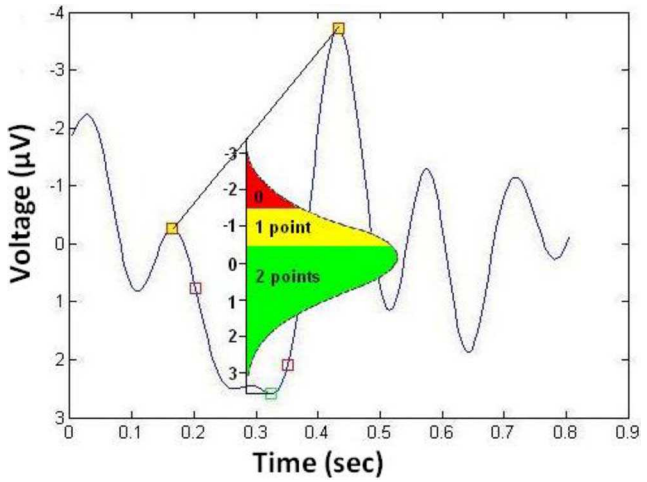

Fig. 4. Sample score derivation methodology.

The hard coded settings and programmed algorithm eliminate the requirement for advanced expertise/training and prior knowledge/training (Challenge 2). A spectrum of EEG-based responses were successfully elicited, identified, and integrated into a rapid clinical test (Challenge 3). The analysis software uses a normative database for comparison purposes, thereby providing standardized results (Challenge 4). The test results are

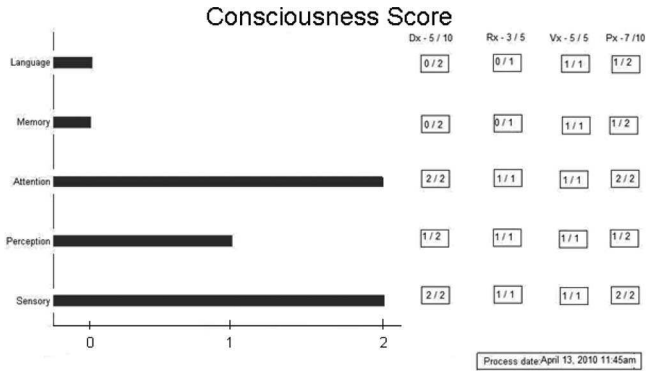

Fig. 5. HCS score as displayed on the device. Note: this is a theoretical result as testing on controls yields perfect scores.

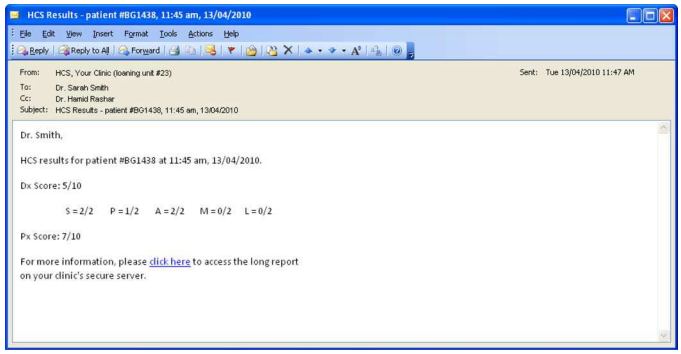

Fig. 6. E-mail sample for the "Short Report". Note: this is a theoretical result as testing on controls yields perfect scores.

presented in a clinically friendly format, which can be readily communicated (Challenge 5).

IV. Future Directions

A clinical study of the device is underway. Continued hardware development will incorporate improved noise cancellation methods, other stimulation modalities (e.g., visual), and expanded clinical applications (e.g., anesthetic monitoring). Wireless capabilities will also be utilized to allow for multi-device data collection and monitoring (i.e., scalability). Additional development will focus on more advanced neurocognitive testing using other brain imaging technologies (e.g., magnetoencephalography).

V. Conclusion

Approximately one in three people are affected by brain disorders and diseases at some point in their lives. Front-end diagnostics have the greatest potential to impact treatment. The market for such devices is estimated to be as high as US$8 billion by 2015. Given the intricate relationship between brain and behavior, diagnostics for one cannot be dependent on the other. Instead, novel solutions must be found at the interface between biomedical engineering and neuroscience. The HCS device attempts to address this challenge.

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