

## Intelligent Monitoring of Subjects with Severe Disorder of Consciousness

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**Abstract** — We describe an integrated system for continuous acquisition, storage, handling and analysis of clinical and functional data from subjects in the vegetative or minimally conscious states. Data from different sources are stored in a centralized database and analyzed off-line by commercial or open source tools. Custom modules have been developed in order to convert proprietary data formats to the standard SQL data format. The centralized database is directly accessible when the patient's clinical record and data are needed to support decision (diagnosis, prognosis, selection of rehabilitation protocols) as well as in the patients' monitoring or for research purposes. The system is supported by web and open source technologies and interfaced with advanced support systems; it allows an integrated view of clinical and functional data flows.

**Keywords**-severe disorder of consciousness; autonomic nervous system; intelligent monitoring; decision support system.

### I. INTRODUCTION

Patients in vegetative or minimally conscious states need constant monitoring and a continuous stream of clinical/neurobiological information is required for appropriate healthcare by the medical and nursing staff and to optimize the rehabilitation therapy [1,2]. In the framework of the rehabilitation protocol, patients are also given sensory stimuli in order to improve their responsiveness to the environment and reduce isolation; responses to stimuli can vary and depend on the ortho/parasympathetic functional balance in the autonomic system [3].

#### A. Structure of the article

The article includes the following sections: Acquisition and integration systems summarizing the system and its use, The decision support system, describing the main tools for analysis, Summary.

### II. ACQUISITION AND INTEGRATION SYSTEM

The data acquisition and integration system (Figure 1) is implemented to record:

- Biometric and biological functional data and environmental information;
- Heart Rate and measures of Heart Rate Variability (HRV) in the time and frequency domains;

- Information about the individual neurorehabilitation program and training protocols.

Data collected by automated sensors are numerical measurements represented in ASCII (American Standard Code for Information Interchange) format that have minimal memory footprint and impact on the network requirements, so to make a standard 100 Mb LAN sufficient to sustain the system efficiency.

The system is deployed on a LAN environment not accessible via web from unauthorized users. The chances of the patient's data leaking are, therefore, limited and the system complies with the modern standards of information security.

The system is neither a remote health monitoring system, nor a telemedicine system; it is intended to support the daily work and research activities of the specialized public/private institutions dedicated to the treatment of subjects with severe Disorder Of Consciousness (DOC). One main goal is to collect over time a very large dataset of biological data from patients with severe DOC and their (statistical) correlations with environmental data and clinical condition. Purpose is to use these data and their relations to obtain objective diagnostic criteria, predict early and accurate prognosis of patients and define therapeutic pathways.

The centralized database is hosted on a PostgreSQL [22] instance, version 9.2, and its main tables, namely:

- *Gateway* – wireless access point that collects and forward to the database the data from sensors;
- *Sensors* – collecting information from environment and patients;
- *BiologicalMeasurements* – storing biological data;
- *EnvMeasurements* – storing environmental data.

For security reasons, the centralized database is installed on a server different than the web-server.

#### A. Biological and environmental data

A hard/software system with Hx24 high-availability acquires biometric and environmental raw data measured by a series of traditional or innovative wireless sensors. The system includes a gateway connected to the LAN (Local Area Network) to detect environmental data (ambient temperature, environmental humidity, light intensity, noise, etc.). Wireless sensors are positioned at proper locations on

the patients and measure biometric parameters such as body temperature, heart rate and systolic/diastolic blood pressure, breathing, pO<sub>2</sub>, pCO<sub>2</sub>, spontaneous movements, voice, eye movements and blinking, to be transferred to the gateway. All data are forwarded to a server that collects the byte stream and stores it, after appropriate transformations, in the centralized data base for further processing or sends data to user interface software (example in Figure 2). The system is operative and already collected about 1GB of data. Measures are from sensors detecting/quantifying: Environmental Temperature, Light, Humidity, Noise, Body Temperature, Heart Rate, Oximetry and Eyes blinking.

### B. Heart Rate Variability

Heart Rate Variability (HRV), i.e., the heart rate fluctuations around the mean value over the time sample, mirrors to a substantial extent the cardiorespiratory control system and is regarded as a reliable index of the sympathetic/parasympathetic functional interplay [4] and intrinsic influence on heart rate. HRV is also thought to provide independent information on the autonomic nervous system and its functional integration with the brain, to reflect the action of physiological factors modulating the heart rhythm and homeostatic adaptation to the changing conditions, and to describe modulation by Central Autonomic Nervous network (CAN) [5]. CAN influences heart rate adaptation through multiple connections (inputs from sensory and baroreceptors within the heart and great vessels, respiratory changes, vasomotor regulation, thermoregulatory system and changes in endocrine function and neuroendocrine interaction) [6]. There is indication that the autonomic system may also mediate patterns of brain activation of varying complexity. HRV is thought to reflect the organization of affective, physiological, cognitive, and behavioral elements and is emerging as a possible descriptor of the brain functional organization contributing to homeostasis and homeostatic responses [6]. The basic objective of the survey is to identify patterns of correlation between the HRV data and functional models available today for the CAN.

Heart signals (EKG) can be recorded continuously by non-invasive techniques and analyses in the time or frequency domains can extract HRV information; the method is now established in the functional investigation of the CAN and has proved reliable in the study of subjects with severe DOC. Records of responses are obtained either from a Nexus 10 or from a Nexus 32 (Mind Media, NL). Nexus systems provide outputs in .edf file format that are transferred through web application to the server for storage in the central database and retrieval off-line for further processing.

### C. Rehabilitation data

These data are obtained by clinical observation according to established rating scales filled by the medical and nursing staff. The scales now in use are:

- The Coma Recovery Scale Revisited – CRS [7];

- The Wessex Head Injury Matrix – WHIM [8];
- The Levels of Cognitive Functions – LCF [9];
- The Nociception Coma Scale – NCF [10].

Dedicated web applications have been developed to enable medical and nursing staff to fill in each scale item with the appropriate values. Data are stored in the central database and integrated with the information for further processing and correlative studies.

## III. THE DECISION SUPPORT SYSTEM

The Decision Support System is composed mainly of **R**, an Open Source statistical package, extended with custom modules [12]. Classical techniques of statistical analysis are used, such as the *Bayesian Statistics*, *Data Mining*, *Neural Network*, *Linear Regression*, etc [12].

In the following sections, we briefly describe the main objectives of our statistical analysis.

### A. Ambient Intelligence

Analyses of information from environmental and biometric sensors follow a straightforward strategy, with major focus on spontaneous variability or in response to changes in the environment [13-15]. Sources of variation are manifold and can reflect changes in the functional status or in responsiveness as well as the existence of residual endogenous mechanisms of self-regulation or circadian/ultradian cycles. For patients in vegetative or minimally conscious state, changes can also depend on interaction with the staff or relatives and effects of the procedures of nursing and rehabilitation services, or reflect endogenous mechanisms [16]. The rationale for the analysis of each vital parameter aims at assessing the existence of cyclic or non-cyclic changes and at correlating each parameter or pattern of variation with environmental changes [17].

Investigation in this field has several goals:

- To verify whether circadian/ultradian pattern of change are partially preserved or have recovered to a significant extent in individual subjects;
- To recognize processes to be relied on as prognostic indicators;
- To identify changes in the vital parameters related to contingent events and indicative of residual/recovered responsiveness or of use when customizing the rehabilitation treatments according to tolerability;
- To to achieve an integrated model of analysis and prediction.

The regression analysis (to identify relationships among variables), the Neural Network (a sophisticated pattern detection algorithm using machine learning techniques to generate predictions), the Clustering/Segmentation processes (to create groups for applications), the Association Rules techniques (to detect related items in a dataset) are widely used for performing above investigations [18].

*B. Parameters and Analysis*

Two main lines of analysis were identified:

*1) Stimuli Response Distribution Analysis*

The stimulus conditions to be administered to patients with severe DOC (Disorder Of Consciousness) can be characterized in order to activate simple or complex functions of the auditory or visual sensory channels (including highly integrated extrinsic eye mobility, e.g., the visual pursuit response) or the somatosensory system.

Analyses are purported to distribute the recorded HRV descriptor values vs. the response, by selecting at pre-determined conditions and time points the parameters qualifying as possible biomarkers. The obtained distribution is classified by Data Mining techniques and/or Linear Regression and/or Sequence Association tools (to detect causality and association between time-ordered events) in order to assess the subject’s state of consciousness (e.g., vegetative vs. minimally conscious states) or identify and monitor stimulus- or environment-related changes or spontaneous fluctuations over time.

Statistical techniques used include: the regression analysis, the Neural Network, the Clustering/Segmentation processes, the Association Rules techniques.

*2) Central Autonomic Nervous System (CAN)*

HRV provides independent information on the CAN and its functional integration with the brain [19-21]. The basic objective of the survey is to identify patterns of correlation between the HRV data and functional models available today for the CAN. Parameters “representing” CAN are reported in table 1.

Statistical techniques used include: the regression analysis, the Neural Network, the Clustering/Segmentation processes, the Association Rules techniques.

IV. SUMMARY

The functional state/recovery of CAN recovery, the impact of ambient condition and/or changes, sleep quality, circadian symphato/vagal alternance, organization of the brain electrophysiological activities, infra-ultra/circadian rhythms, and responsiveness to stimuli are fundamentals in the rehabilitation project of patients with severe DOC.

The development of *acquisition and integration systems* will provide the information needed to design efficient five plain of protocol for the observation, rehabilitation and monitoring of patients with severe DOC. The approach will contribute in the process of acquiring new knowledge on the neural mechanism underlining recovery in these patients and help planning better rehabilitative routines.

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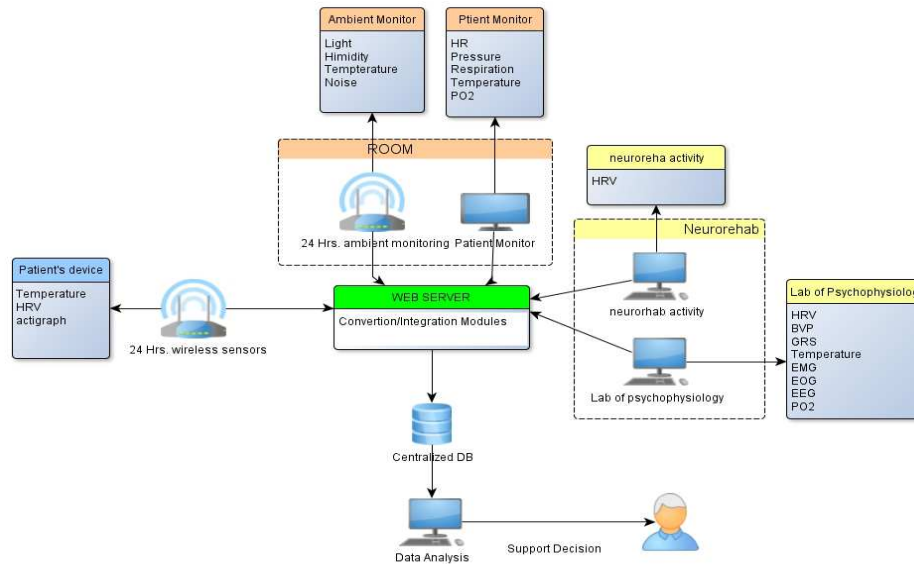


Figure 1. The architecture of the acquisition and integration system.

RDA		Ricerca base				
Ricerca base		Biometrico	Status	00 (Misura affidabile)	Byte	2012-09-04 05:24:29.972
Ricerca avanzata		Biometrico	pO2	95	%	2012-09-04 05:24:29.972
Visualizzazione grafici		Biometrico	HR	105	Puls	2012-09-04 05:24:29.972
Configurazione		Biometrico	Temperature	32.398081	C	2012-09-04 05:24:29.972
		Biometrico	Movement	32	au	2012-09-04 05:24:29.972
		Biometrico	EyeBlink	0	Blinks	2012-09-04 05:24:29.972
		Biometrico	Battery	14	au	2012-09-04 05:24:29.972

Figure 2. Some biological data acquired by the system.

Statistical Parameters	Mean RR interval (Mean RR [ms]); Standard deviation of RR values (STD RR [1/min]); Mean Heart Rate (Mean HR [1/min]); Standard deviation of heart rate values (STD HR [1/min]); Square root of the mean squared differences between successive RR intervals (RMSSD [ms]); Number of successive RR interval pairs that differ more than 50 ms (NN50); NN50 divided by the total number of RR intervals (pNN50 [%]); The integral of the RR interval histogram divided by the height of the histogram (HRV triangular index); Baseline width of the RR interval histogram Frequency-Domain (TINN [ms]);
Spectral Parameters	Peak frequency in FFT and autoregressive spectra of Very Low Frequency (VLF), Low Frequency (LF) and High Frequency (HF) band [Hz]; Power Spectrum of VLF, LF, HF and Total in FFT and autoregressive spectra [ms <sup>2</sup> ]; % of VLF, LF, HF in FFT and autoregressive spectra [Spectral band [ms <sup>2</sup> ]/total power [ms <sup>2</sup> ] × 100%]; Ratio between LF and HF band powers (Ratio LF/HF); normalized unit of LF (nu LF) and normalized unit of HF (nu HF), in FFT and autoregressive Spectra, [Spectral band [ms <sup>2</sup> ]/(total power [ms <sup>2</sup> ] - VLF [ms <sup>2</sup> ])];
Nonlinear	The standard deviation of the Poincaré plot perpendicular to (SD1) and along (SD2) the line-of-identity, [ms]; Approximate entropy ApEn; Sample entropy SampEn; Correlation dimension; Detrended fluctuation analysis DFA (α1 Short term fluctuation slope and α2 Long term fluctuation slope);
Galvanik Skin Response	Measure of the electrical conductance of the skin. It's used as an indication of psychological or physiological arousal.
Actigraphy	Monitoring of rest/activity cycles.
Blood Volume Pulse	Measured by a process called photoplethysmography, which produces a graph indicating blood flow through the extremities.

Table1: Principal parameters extracted for the ANS analysis