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A Preliminary Study for Investigating Idiopatic Normal Pressure Hydrocephalus by means of Statistical Parameters Classification of Intracranial Pressure Recordings

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***Abstract*— The objective of this study is to investigate Idiopatic Normal Pressure Hydrocephalus (INPH) through a multidimensional and multiparameter analysis of statistical data obtained from accurate analysis of Intracranial Pressure (ICP) recordings. Such a study could permit to detect new factors, correlated with therapeutic response, which are able to validate a predicting significance for infusion test. The algorithm developed by the authors computes 13 ICP parameter trends on each of the recording, afterward 9 statistical information from each trend is determined. All data are transferred to the datamining software WEKA. According to the exploited feature-selection techniques, the WEKA has revealed that the most significant statistical parameter is the maximum of Single-Wave-Amplitude: setting a 27 mmHg threshold leads to over 90% of correct classification.**

***Index Terms*— Biomedical signal classification, Pattern recognition methods for data mining, Signals and systems**

I. INTRODUCTION

INTRACRANIAL pressure is a consequence of cerebrospinal fluid (CSF) and the circulation of cerebral blood: $\mathrm{ICP} = f\left(\mathrm{ICP_{CSF}}, \mathrm{ICP_{vascular}}\right)$. It's difficult to evaluate the vascular component, since it is related to the pulsation of the cerebral blood volume detected. In fact, multiple variables such as the arterial pressure, autoregulation, and cerebral venous outflow give a non-linear contribute to the vascular component. If the cerebral vessels are not-reactive, an increase in cerebral perfusion pressure may result in several grave forms of pathology [1]. This study focuses on the diagnosis of INPH. The purpose of evaluation and testing of individuals with suspected INPH is to determine if surgical implantation of a ventriculoperitoneal shunt will be beneficial or not. Many experimental methods are used to assess the presence of INPH, however each of them is based on a thorough ICP interpretation. Current state-of-art technology analyzes ICP signal recordings during short and fixed time windows without taking in consideration the single ICP wave created by the cardiac contractions. This may impose survey's limitations since single ICP wave amplitudes (SWA) could more reliably predict intracranial compliance than mean ICP alone [1], [2]. As a matter of fact, the existing relationship between mean ICP and pulse pressure when mean ICP was below 30-60 mmHg is currently under investigation [3]. More recently information about single ICP waves has been derived from spectral analysis using Fast Fourier Transformation (FFT) [4]-[6]. However, information about single ICP waves derived from FFT depends on the quality of ICP signals, which is related to sudden variations in pressures and heart rate. In this paper the authors present a different approach for processing ICP recording. The objective of this study is to investigate INPH through a multidimensional and multi-parameter analysis of statistical data. These data are obtained from an accurate analysis of ICP recording, during lumbar infusion tests, and extracting as much trends of parameter as possible. Such a study could permit to detect new factors correlated with therapeutic response able to validate a predicting significance for infusion test.

TABLE I
LIST OF SYMBOLS

Symbol	Stands for
CSF	Cerebrospinal fluid
ICP	Intracranial Pressure [mmHg]
(I)NHP	(Idiopatic) Normal Pressure Hydrocephalus
$\mathrm{ICP_B}$	Baseline ICP [mmHg]: mean value of ICP before infusing
$\mathrm{ICP_P}$	Plateau ICP [mmHg]: Steady-state level of pressure (plateau) achieved during infusion
$\mathrm{ICP_M}$	Mean ICP [mmHg]
SWA	Single wave amplitude [mmHg]
RAP	Pressure Volume compensation index: shows the correlation between $\mathrm{ICP_M}$ and SWA
$\Delta t_{\mathrm{MIN\text{-}MAX}}$	Time delay between a min and following max [s]
$\Delta t_{\mathrm{MAX\text{-}MIN}}$	Time delay between a max and following min [s]
FWA	Amplitude between a max and following min [mmHg]
$\Delta t_{\mathrm{MAX\text{-}MAX}}$	Time delay between two following max [s]
$\Delta t_{\mathrm{MIN\text{-}MIN}}$	Time delay between two following min [s]
$\mathrm{SLP_{UP}}$	Leading-edge slope [mmHg/s]
$\mathrm{SLP_{DW}}$	Trailing-edge slope [mmHg/s]
ΔICP	Mean ICP gradient [mmHg/s]
$\mathrm{R_{OUT}}$	The resistance to CSF reabsorbition [mmHg min $\mathrm{ml^{-1}}$]

II. PATHOLOGY, PATIENTS AND METHODS

A. Normal Pressure Hydrocephalus Investigation

Normal Pressure Hydrocephalus is a typical old patients' pathology characterized by the clinical triad: gait ataxia,

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urinary incontinence and short term memory disturbances associated with abnormal increase in cerebral ventricular size. The cerebrospinal fluid, normally contained into the subarachnoid spaces and cerebral ventricles, is produced and reabsorbed at constant rate. Assuming that NPH is caused by an altered CSF hydrodynamics, many tests have been proposed to study this aspect. If correctly identified, NPH patients show a significant clinical improvement after the surgical positioning of a CSF ventriculoperitoneal shunt. Basically the shunt allows CSF to be drained out from the ventricles to the peritoneal cavity; the CSF flowing into the shunt is controlled by a pressure-dependent valve. Shunting is now a common neurosurgical procedure, but it is one associated with risks and complications, which makes evaluation of "shunt-responsiveness" essential [7]. Although numerous techniques are used to identify patients who are likely to have NPH, no definitive method exists to prove diagnosis. Furthermore, many models of CSF circulation have been determined since the early 1970s, the first was presented by Marmarou (1973) [8], nowadays the studies are focused on the research of parameters describing the state of the pressure-volume compensation. The parameters of Marmarou's model, in particular the R_{OUT} and the cerebral elasticity are still considered as evaluation markers of hydrocephalus [9].

B. Patient Database

All data analyzed come from continuous CSF pressure recordings of 12 patients (8 males and 4 females, age range 24-78) affected-or-not by idiopathic NPH. Selection criteria included at least 2 clinical signs and symptoms of the triad associated with a neuroradiologically demonstrated hydrocephalus. Patients underwent an infusion test to investigate the dynamics of cerebrospinal fluid so that this study is particularly focused on the analysis of the infusion time-window, i.e. just the part of the signal recorded during the infusion time. The surveys have been conducted at Neurosurgical Department of University Hospital of Messina (Italy) between 2006 and 2008.

C. ICP Recording during Infusion Test

The infusion test is used to investigate the dynamic ICP trend. It is generally performed through a lumbar puncture by 1 or 2 needles inserted into the lumbar subarachnoid space. One needle is connected via a stiff saline-filled tube to a pressure transducer Codman®, and the other one to an infusion pump that instills a 0.9% NaCl solution at constant rate of 1.5 ml/min. The analogical signal from the transducer, i.e. the imbalanced output voltage of a resistive bridge sensor, is displayed on a Codman® ICPexpress monitor and, at the meantime, transferred to a laptop data through an acquisition board (NI® DAQCard-6024E). The signal is sampled at 128 Hz and stored as a binary file. The measuring scheme is shown in fig. 1. After a sensor calibration phase, required to offset the atmospheric pressure, the test is started. About 2 or 3 minutes are requested to compute the baseline ICP

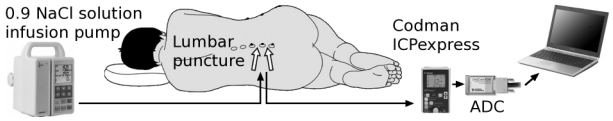

Fig. 1. ICP monitoring diagram using to perform infusion test

(ICP_B), afterwards the pump is switched on. The constant-rate infusion is continued until the ICP reaches a steady state (ICP_P), then the infusion is stopped.

D. Signal Conditioning and Data Analysis

Digital signal processing of ICP recordings consists of 7 main steps: text conversion, signal filtering, location of single pressure waves, peaks identification, extraction of features from each single wave, trend analysis and gathering of all data computed (trends and single value parameters). For each recording an output text file is created. All these steps have been performed by means of MATLAB® codes. As first step, the signal is filtered through a Butterworth low pass FIR filter with a 20 Hz cut-off frequency. This procedure let the pruning of no-relevance information contained in the signal, such as noise and irregular waves due to unwanted patient's movement or speech during the recording. In fig. 2 it is shown an example of filtering and peaks identification spikes of a ten seconds window recording. In this work we propose a new time-domain algorithm for high precision signal period identification and single waveform location. It is based on the key idea discussed in a previous work [10], where a similar algorithm is applied for biometric identification through cardiac sounds.
The algorithm computes the autocorrelation function of the entire filtered signal, obtaining the fundamental period of the signal: this value is considered the mean period of the whole signal. After that the absolute maximum is found, by moving from that point to left another maximum is searched within the mean period just computed. The value and the index number of the corresponding sample is stored into a vector (the Maxima vector), then the algorithm estimates the distance in samples between the two maxima updating the new mean period of the signal. This procedure is repeated till the first sample of the waveform is reached, and then it

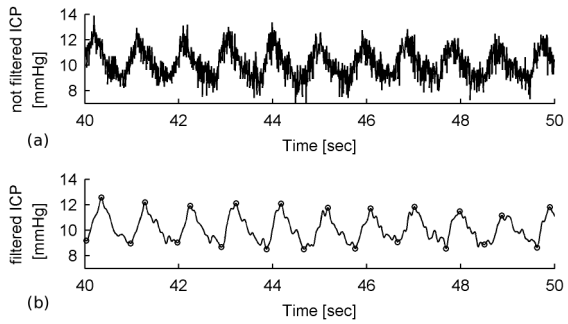

Fig. 2. (a) A ten seconds window of not filtered signal as it is recorded in database file and (b) the same window after filtering and peaks identification spikes by means of author's algorithm.

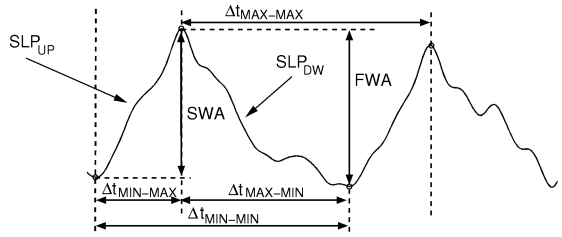

Fig. 3. It is shown two consecutive single waves (SW) and most of features computed on each of it.

restarts again from the position of absolute maximum to the end of the sequence to search the maxima on the right part of the waveform. The same algorithm is applied for minima searching. An additional error correction control cuts off those maximum or minimum values out of expected range, according to the criteria suggested by the medical staff. The main algorithm proceeds determining the following trends (see fig. 3):

- The ICP_M trend is determined by implementing a one-dimensional sliding window filter to the signal sequence. Such filtering computes the mean value of the points within the current window and then shifts the window, by overlapping part of samples. When the sliding window is exceeding the lower or upper boundaries of the input vector, the average is computed only among the available points. When compared to a standard first-order low-pass filter, it is important to note that the average performed here does not only involve the past history of the signal but the future samples as well.
- The ΔICP is the gradient of mean ICP.
- The $\Delta t_{MIN\text{-}MAX}$ ($\Delta t_{MAX\text{-}MIN}$) is the distance in number of samples between each minimum (maximum) and the following maximum (minimum) occurring within the mean period. Exceeding-in-time distances will be discarded as a consequence of peak' skip. This procedure is repeated for the entire minima and maximum vectors, so it will return the $\Delta t_{MIN\text{-}MAX}$ ($\Delta t_{MAX\text{-}MIN}$) vector. These considerations are valid for the following trends too.
- The $\Delta t_{MAX\text{-}MAX}$ and $\Delta t_{MIN\text{-}MIN}$ represent the period of each single wave composing the signal, computed as the numbers of samples between two consecutive maxima or two consecutive minima.
- The SWA (FWA) is computed as the absolute value of difference between minimum (maximum) and the following maximum (minimum) occurring within the mean period.
- The SLP_{UP} computed as SWA/$\Delta t_{MIN\text{-}MAX}$, is the value of leading edge slope of each single wave.
- The SLP_{DW} computed as FWA/$\Delta t_{MAX\text{-}MIN}$, is the value of trailing edge slope of each single wave.
- The R_{OUT} trend is evaluated, according to the Marmarou's model, by:

$$R_{OUT} = \frac{ICP_P - ICP_B}{\text{InfusionRate}} \qquad (1)$$

where the ICP_P is the steady-state pressure level achieved during infusion. During the infusion test, the algorithm returns acceptable values for ICP_P only when ICP_M starts to slow down its increasing rate (the ΔICP gets to a minimum threshold).

- The RAP (R - correlation coefficient, A - pulse amplitude, P - mean ICP) is a Pressure-volume compensation index and could be considered as an adequate indication of hydrocephalus [6], [11]. In this study, it is numerically computed through the Pearson's correlation coefficient between the two variables SWA an ICP_M, and represents a measure of the strength of linear dependence between SWA and ICP_M.

$$RAP = \rho_{SWA,ICP_M} = \frac{\sigma_{SWA,ICP_M}}{\sigma_{SWA} \cdot \sigma_{ICP_M}} \qquad (2)$$

An example of all the trends computed by the algorithms on the recording of a NPH supposed patient is displayed in figure 4. For all the ICP recordings the software creates 13 output vectors, one for each calculated trend. A number of 13 trends are determined by each recording; for each one has been computed 9 statistical functions: mean value; variance; maximum; minimum; difference between maximum and minimum; 1st quartile; 2nd quartile (median); 3rd quartile; interquartile range (3rd quartile - 1st quartile). As a consequence, for each patient's ICP recording, a total of 117 statistical parameters are made available to classification.

III. FEATURES SELECTION AND RESULTS

It is a false assumption that a large number of features would improve the discrimination capabilities of a classification system. In fact, by reducing the size of the classification vector, the system provides a more compact and more easily interpretable set of data. Thereby, the performance of the learning algorithm is improved and the speed of the system increased [12]. Two are the most common feature selection methods:

- Wrapper methods, where the set of components is established by interacting with the classification algorithm.
- Filter methods that do not interact with the classification algorithm.

When there is a large amount of training data, filter methods are preferred for computational efficiency due to the fact that they are independent of the learning algorithm. As classification software, the authors have used the Waikato Environment for Knowledge Analysis (WEKA) [13] to eliminate redundant and unimportant components, and to identify components that are closely correlated with one class but not with each other too. Analysis can be in the form of forward selection, starting with an empty list and at each step inserting a new attribute until the increase in performance drops below a pre established threshold, or by backward elimination, starting from a vector containing all the components and eliminating the worst step by step. In this study, the authors have exploited the CFSSubsetEval-BestFirst WEKA feature-selection technique.
CFSSubsetEval uses the Correlation based Feature Selection

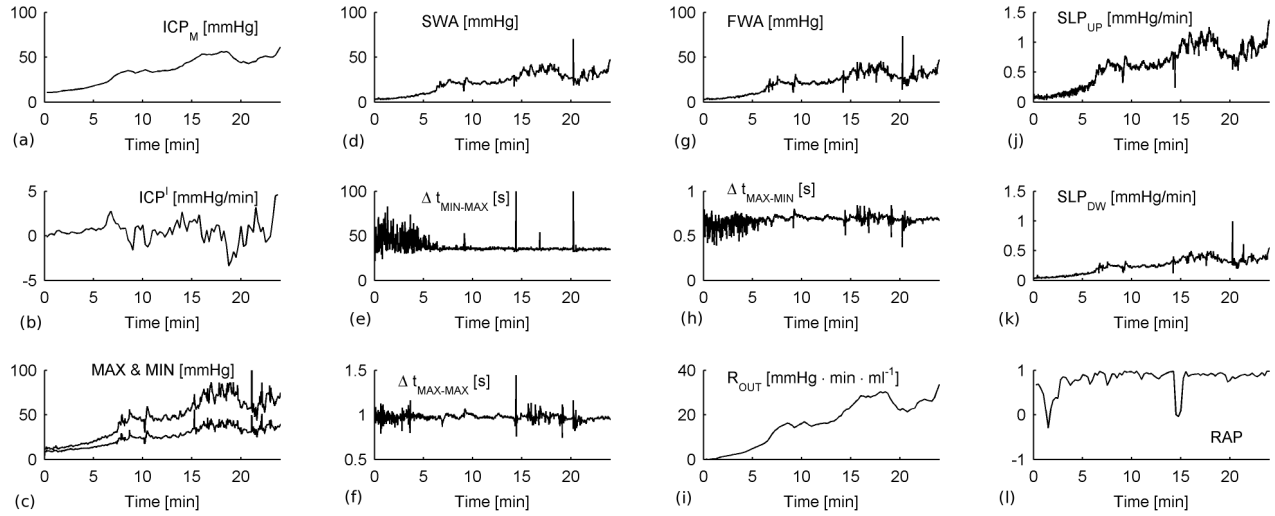

Fig. 4. It is shown an example of 12 out of 13 trends computed by the algorithm on one recording of a NPH-supposed patient: (a) the mean ICP, (b) the ICP time derivative, (c) the maxima and minima trend, (d) the single-wave amplitude trend, (e) the time latency of each SWA, (f) the period of each single wave computed between two following maxima, (g) the following-wave amplitude (i.e. the difference between a maximum and its following minimum), (h) the period computed between a maximum and its consecutive minimum, (i) the Outflow Resistance of CFS, (j) (k) the two slope trend (leading and trailing edge) of each single wave and (l) the RAP (index of correlation between amplitude and mean ICP) of each single wave.

trying to identify and discarding components closely correlated with one another. The best-first search strategy is used to determine the best subset. It takes the best component among all the factors, after that it tries to add an other one repeating the procedure until no more improvements are obtained.

According to the feature-selection techniques exploited, the WEKA has revealed the most significant statistical parameter: the maximum of SWA. The results achieved in this investigation seem to be interesting: setting at 27 mmHg the hard limiter (threshold determiner) leads to over 90% of correct classification, as it is shown in fig. 5

IV. CONCLUSION

In this paper we have addressed an investigation for automatic recognition of INPH, by means of statistical parameters classification obtained through features extraction from an ICP signal registered using a Codman transducer. It's worth mentioning that, by means of the classification method deduced, we could prevent 6 operations out of 12.

Anyway, it is the authors' opinion that the outcome seems to be strictly affected by database shortage. Thereby, a most reliable result is expected by using a plentiful database, in order to apply more sophisticated learning classifiers.

Notwithstanding the fulfilling result obtained, a further investigation is requested.

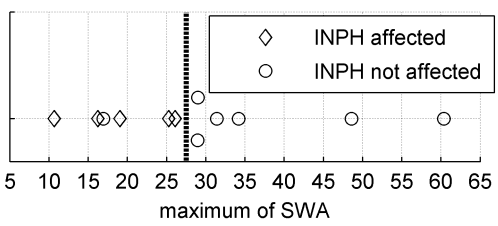

Fig. 5. It is shown the distribution of the 12 suspected INPH using the decisional rule. 11 out of 12 are correctly predicted with this method.

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