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Classification of Morphological Features Extracted from Intracranial Pressure Recordings in the diagnosis of Normal Pressure Hydrocephalus (NPH)

M. Galeano, *Student Member, IEEE,* A. Calisto, *Student Member, IEEE,* A. Bramanti, *Student Member, IEEE*, F. Angileri, G. Campobello, S. Serrano, B. Azzerboni, *Senior Member, IEEE*

***Abstract*—The intracranial pressure (ICP) monitoring is a common procedure in neuro-intensive care for pathologies such traumatic brain injuries or hemorrhages, but also for chronic ones as the Normal Pressure Hydrocephalus (NPH). The only available treatment for NPH is the surgical implantation of a shunt with the aim of routing cerebrospinal fluid (CSF) away from the brain to another part of the body.**

In this study, using the classification software WEKA, an intensive investigation of ICP signals has been conducted. In particular we studied 14 ICP recordings of different patients who underwent an infusion test, with the aim of investigating the presence of NPH through the ICP recording. More precisely, 20 morphological features are extracted from the ICP pulsed wave, the trend have been computed and, for each one, 9 statistical functions determined. The 180 features have been selected and passed for the classification. The results obtained shows how, among the 14 patients, a number of 12 out of 14 (85.7%) have been correctly classified, looking at just 3 features. In particular 8 out of 9 not-NPH-affected patients were correctly identified (88.89%) while 4 out of 5 NPH-affected patients were correctly identified (80%).

I. Introduction

THE intracranial pressure (ICP) monitoring is a common procedure in neuro-intensive care for pathologies such traumatic brain injuries or hemorrhages, but it is commonly employed also in neurosurgery to diagnose chronic pathologies.

A small pressure transducer is inserted through the skull into the brain parenchyma or CSF filled cavities called ventricles to measure the CSF pressure. In some cases, ICP is obtained through a lumbar access to the intradural CSF inside the vertebral canal. ICP signal is obtained through the use of a catheter with a micro miniature silicon strain gauge type sensor mounted at one end.

It is difficult to establish a universal "normal value" for ICP as it depends on age, body posture, and clinical conditions. In the horizontal position, the normal ICP in healthy adult subjects was reported to be within the range of 7-15 mmHg [1]. The definition of raised ICP depends on the specific pathology: in hydrocephalus, a pressure above 15 mmHg can be regarded as elevated. Following head injury, anything above 20 mmHg is abnormal and aggressive treatment usually starts above 25 mmHg. In most cases, ICP varies also with the spending of time.

Most of common widely used devices for ICP monitoring provide few information to the clinicians, such a simple "mean" ICP value obtained from the variations considered attributable to diastolic/systolic phases of CSF production inside the ventricles. Limiting the study of the ICP to the mean values, especially if during a short time window, heavily affects the diagnostic and therapeutic success.

Normal Pressure Hydrocephalus (NPH) is an accumulation of cerebrospinal fluid that causes the ventricles in the brain to become enlarged, sometimes with little or no increase in intracranial pressure. In normal conditions, the CSF contained into the subarachnoid spaces and cerebral ventricles is produced and reabsorbed at constant rate, while NPH is caused by an altered CSF hydrodynamics. It is a typical elderly disease characterized by some or all of the following triad of symptoms: gait ataxia, urinary incontinence and short term memory disturbances. The majority of cases of NPH are idiopathic (related to unknown causes). NPH can also be caused by head injury, subarachnoid hemorrhage, tumor or cysts, as well as subdural hematomas, meningitis and other brain infections [2].

The most common and usually the only available treatment for NPH is the surgical implantation of a shunt, a device that routes CSF away from the brain to another part of the body where it can be absorbed. The rate of success for shunting normal pressure hydrocephalus is quite variable; although the success rate for shunting is higher when proper diagnostic and treatment procedures are followed.

II. NPH diagnosis

Once NPH is suspected by a primary physician, specific tests are usually performed to confirm the diagnosis and assess the person's candidacy for shunt treatment. The decision to perform a test may depend on the specific clinical situation and on the medical team. Different tests or examinations are available to investigate NPH presence:(1) Clinical exams to evaluate symptoms, (2) Brain images to detect enlarged ventricles (i.e. resonance imaging, MRI, and computerized tomography, CT), (3) CSF tests to predict shunt responsiveness and/or determine shunt pressure (i.e. Lumbar puncture, or spinal tap, Spinal fluid drainage), (4) the measurement of CSF outflow resistance, (5) Isotopic cisternography [3]. Anyway, even if numerous techniques are used to identify patients who are likely to have NPH, no definitive method exists to prove diagnosis.

M. Galeano, A. Calisto, A. Bramanti, S. Serrano, G. Campobello and B. Azzerboni are with Department of Matter Physics and Electronic Engineering, University of Messina, Italy (corresponding author to provide phone:+390903977375; email: massimiliano.galeano@unime.it).
F. Angileri is with Neurosurgical Department of University Hospital of Messina, Italy

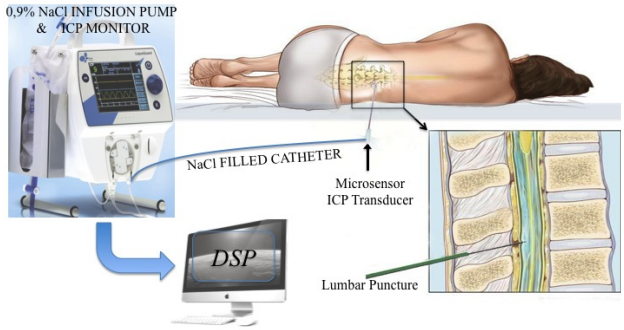

Fig.1 – The ICP monitoring diagram adopted to perform the infusion test.

In this contest, a deep study for investigating ICP signals recordings has been addressed. Nowadays, with the advent of computer and with the development of proper computing tools in the field of digital signal processing, it seems clearly evident the need for reliable automatic recognition techniques for NPH pathology identification.

The authors have developed a system that allows to extract all those morphological features from the ICP pulsed wave that have been left out till today. These extracted features are properly selected and passed to the classification software in order to investigate NPH presence. This work particularly focuses on the automatic classification of the pathology by means of data mining techniques. For this study the classification software WEKA [4] has been utilized.

III. Clinical Materials

We collected the intracranial pressure signal of 14 patients, of whom 5 were being investigated for NPH. The used selection criteria included at least 2 out of the 3 clinical signs and symptoms of the characteristic triad associated with a neuro-radiologically demonstrated NPH. The database is composed by CSF pressure recordings of different patients who underwent an infusion test to investigate the altered dynamics of cerebrospinal fluid. The test is performed through the scheme shown in Fig.1: the infusion pump instills a 0.9% NaCl solution at settable constant rate by means of a stiff saline-filled specific catheter which has a pressure transducer mounted on it.

The used device during our performed investigation is the *Codman MicroSensor ICP Transducer*®. The test follows these steps: (1) a calibration phase to offset the atmospheric pressure; (2) the determination of *Baseline ICP* (ICP_B), i.e. the ICP mean value in a static condition; (3) the pump is switched on until the ICP reaches a steady state mean value called *Plateau ICP* (ICP_P) related to a safety condition for the patient; (4) the infusion is stopped but the recording still goes on to capture the reabsorbition phase (see Fig.2).

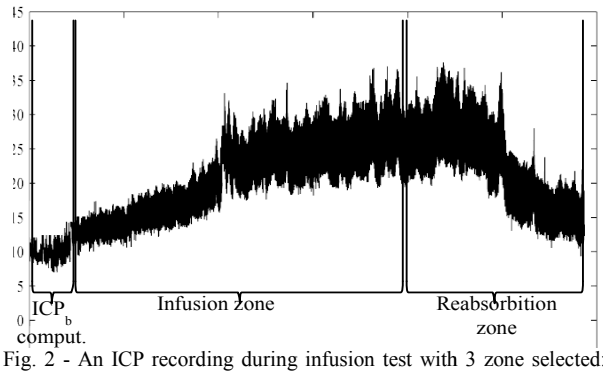

Fig. 2 - An ICP recording during infusion test with 3 zone selected: ICP_B comput is the time required for computing ICP_B, the Infusion and the Reabsorption zone intervals for the investigation of CFS.

IV. Methods

A. Features extraction algorithm

This works has to be intended as the sequel of a previous author's project , i.e. an automatic system for morphological features extraction from ICP recording, that has been presented in [5]. It allows a deep and an easy-computing analysis of intracranial pressure. It starts from the rough data that are filtered and preprocessed to extract the morphological features and parameters which compose the ICP signal itself, and finally provides the parameters trends. In Fig. 3 is shown the flow chart of the features extraction algorithm. There are 8 blocks in the flow chart representing related processing steps detailed in the next subsections.

B. Features selection

For all the ICP recordings the software creates 20 output vectors, one for each calculated trend (see Fig. 4). So, a number of 20 trends are determined by each recording. For each one, 9 statistical functions have been computed. They are: mean value; variance; maximum; minimum; difference between maximum and minimum (kurtosis); 1st quartile; 2nd quartile (median); 3rd quartile; interquartile range or skewness (3rd quartile - 1st quartile). So, it is determined a number of: 20x9 = 180 features for each segment to be classified.

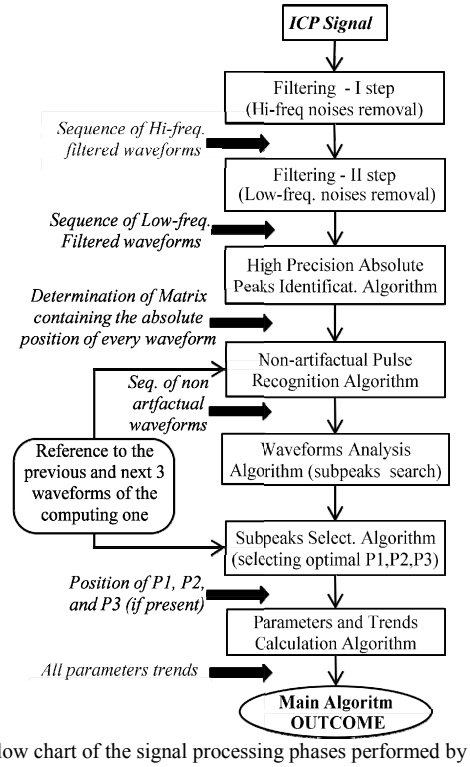

Fig.3 – Flow chart of the signal processing phases performed by the proposed algorithm.

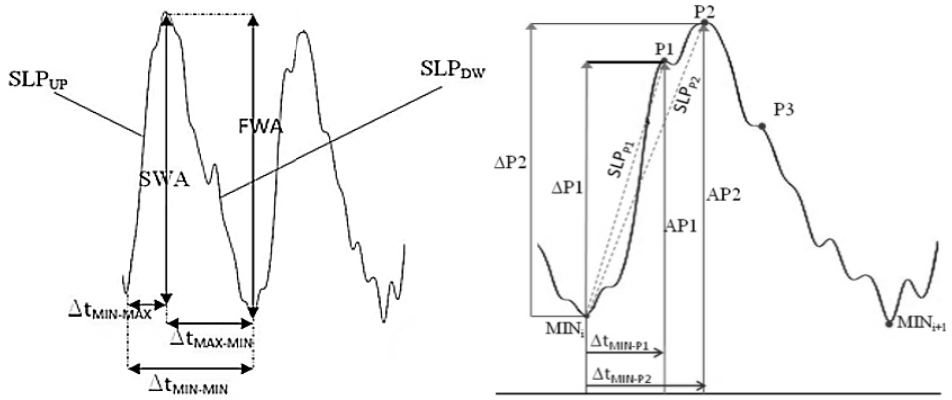

Fig. 4 – Single wave's parameters. In table are shown parameters' meaning.

Num.	*Symbol*	*Parameter*	*Num.*	*Symbol*	*Parameter*
1	ICP_M	Mean ICP	***11***	SLP_{DW}	Traling Edge Slope trend of each pulse wave
2	ICP^I	ICP time derivative	***12***	R_{OUT}	Outflow resistance of CFS
3	MIN	Absolute minima	***13***	AP1	P1 subpeak absolute amplitude
4	MAX	Absolute maxima	***14***	AP2	P2 subpeak absolute amplitude
5	SWA	Single-wave amplitude	***15***	ΔP1	P1 subpeak absolute amplitude referred to MIN
6	FWA	Following-wave amplitude	***16***	ΔP2	P1 subpeak absolute amplitude referred to MIN
7	$\Delta t_{MIN-MAX}$	Time latency of each SWA	***17***	Δt_{MIN-P1}	P1 time latency referred to MIN
8	$\Delta t_{MAX-MIN}$	Time latency of each FWA	***18***	Δt_{MIN-P2}	P2 time latency referred to MIN
9	$\Delta t_{MIN-MIN}$	It is the period of the pulse wave	***19***	SLP_{P1}	Leading edge slope referred to P1
10	SLP_{UP}	Leading Edge Slope trend of each pulse wave	***20***	SLP_{P2}	Leading edge slope referred to P2

Whereas it would appear, intuitively, that a large number of features would improve the discrimination capabilities of a classification system, in reality various studies have shown that this is not always true. In fact, by reducing the size of the classification vector, the system is provided with a more compact and more easily interpretable set of data, the performance of the learning algorithm is improved and the speed of the system increased [6-8].

The classification software used, WEKA, has proved itself to be a useful and even essential tool in the analysis of real world data sets. Analysis can be in the form of forward selection (it starts with an empty list and at each step inserts a new attribute until a pre-set threshold is reached), or by backward elimination (it starts from a vector containing all the components and prunes the worst step by step). There are also more complicated search methods, including the *Best-First* method, which keeps a list of all the subsets of components evaluated, ordered according to performance [9].

V. RESULTS

For this work, it has been exploited the *CFSSubsetEval* method. This algorithm uses as a feature evaluator Correlation-based Feature Selection, which tries to identify and discard components that are closely correlated with one another. To determine the best subset we used a *Best-First* search strategy and a stratified cross validation procedure. *Best-First* takes the best component among all the factors, after that it tries to add another one repeating the procedure until no more improvements are obtained.

Among the 180 determined features, and according to the Attribute Evaluator exploited, i.e. the *CFSSubsetEva*l, WEKA has revealed that 3 are the most meaningful features to identify the presence of the pathology:

1. The Skewness of the single wave amplitude (SWA).
2. The Skewness of the absolute amplitude value of P2 subpeak (AP2).
3. The Skewness of the leading edge slope (SLP_{P2}) referred to P2.

WEKA currently incorporates a variety from the areas of supervised and unsupervised learning.

Among all the machine learning schemes incorporated by WEKA, for this work we have tried 4 schemes:

- J48: trees.J48 a clone of the C4.5 decision tree learner;
- NaiveBayes: bayes.NaiveBayes: A Naive Bayesian learner;
- SMO: functions.SMO Support Vector Machine (linear, polynomial and RBF kernel) with Sequential Minimal Optimization Algorithm;
- KStar: lazy.KStar Instance-Based learner.

Each of the 4 schemes has been tested with two sets of features. The first is composed by all the 180 features extracted for every recording of the database. The second set is formed by the 3 most significant provided by the selection technique CFSSubsetEval which are the skewness of SWA, the skewness of AP2, the skewness of SLP_{P2} (the *selected* ones).

The WEKA returns 2 confusion matrix (i.e. a matrix that contains information about actual and predicted classifications) for each (of the 8) scheme. The first is obtained considering all the 14 recording both to train and to test the system, while the second is computed through the

Stratified Cross Validation: it trains the system with the 90% of the database, while the remaining 10% is used to test the classifier. The procedure is repeated 10 times using a different training and testing set. This ensures that the training files never take part to the testing set; so the second confusion matrix is more significant. The results, evaluated by the *Stratified Cross Validation* confusion matrix, are showed in Tab.1.

It must be underlined that the best results are obtained through the SMO scheme for the complete features set and through the KStar scheme for the reduced (or selected) set of the 3 above mentioned selected features.

Whereas it would appear that the complete set of features would improve the discrimination capabilities of a classification system, actually, by reducing the size of the classification vector, the system is provided with a more compact and more easily interpretable set of data. So the performance of the learning algorithm can be improved and above all the speed of the system increases because the system classifies a number of 3 features instead of 180.

In fact, as it can be seen in Tab.2, looking at the SELECTED - KStar (Stratified Cross Validation) confusion matrix, among the 14 patients who underwent the infusion test, a number of 12 have been correctly classified. In particular 8 out of 9 not-NPH-affected patients were correctly identified while 4 out of 5 NPH-affected patients were correctly identified. In Tab.2 are reported a summary of the achieved results expressed in percentage of correct classification, for each of the 8 exploited machine learning schemes.

VI. Conclusion

The automatic system for NPH identification developed must be intended as a valid, consistent, reliable and easy-computing tool that might be used by the medical team in all those cases that involve brain damages or diseases. In fact, a deep analysis of intracranial pressure data, in terms of morphological features extracted by the method, radically helps the clinicians to make a diagnosis easier and more precise. It is plausible to suppose that enhancement to the automatic classification system can be made by improving the filtering steps and refining the optimal subpeaks selection algorithm. Thereby, most reliable results are expected by using a plentiful database, in order to apply more sophisticated learning classifiers.

Further improvements on the reliability of the developed automatic system can be reached using multi-channel signals of intracranial pressure (ICP), arterial blood pressure (ABP) and electrocardiogram (ECG).

		A	B	
J48		5	4	a=0
		4	1	b=1

		A	B	
Kstar		9	0	a=0
		5	0	b=1

		A	B	
NaiveBayes		6	3	a=0
		4	1	b=1

		A	B	
SMO		8	1	a=0
		2	3	b=1

		A	B	
SELECTED - J48		6	3	a=0
		1	4	b=1

		A	B	
SELECTED - Kstar		8	1	a=0
		1	4	b=1

		A	B	
SELECTED - NaiveBayes		7	2	a=0
		1	4	b=1

		A	B	
SELECTED - SMO		8	1	a=0
		4	1	b=1

Tab. 1 - The results, evaluated by the Stratified Cross Validation confusion matrix, 4 different learning machine schemes exploited.
a stands for "not NPH affected patients"
b stands for "NPH affected patients"
A stands for "supposed (by the system) not NPH affected patients"
B stands for "supposed (by the system) NPH affected patients"
A great number of elements on the principal diagonal means a trust scheme.

METHOD		NPH Affected Accuracy	Not NPH Affected Accuracy	TOTAL Accuracy
ALL FEATURES (180)	J48	55.56%	20.00%	37.78%
	Kstar	100.00%	0.00%	50.00%
	NaiveBayes	66.67%	60.00%	43.33%
	SMO	88.89%	60.00%	74.44%
SELECTED FEATURES (3)	J48	66.67%	80.00%	73.33%
	Kstar	88.89%	80.00%	84.44%
	NaiveBayes	77.78%	80.00%	78.89%
	SMO	88.89%	20.00%	54.44%

Tab. 2 - Summary of the achieved results expressed in percentage of correct classification, for each of the 8 exploited machine learning schemes

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