Statistical and Neuro-fuzzy approaches for emboli detection

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Abstract— **Relation between cerebral emboli occurrence and stroke has been suggested these last years. Emboli detection has then become a constant concern while monitoring cerebral vascular pathologies. This detection is based on analysis of embolic TransCranial Doppler (TCD) signal. In practical experiments, most of detected emboli are big-size emboli ones, because of their easy-to-recognize signature in the TCD signal. The problem of small size emboli detection is an opened one and remains a challenge. Different approaches have been proposed to solve this problem. They use exclusively human expert knowledge or automatic collection of signal parameters. In this paper we propose to used both expert knowledge and automatic processing through neuro-fuzzy approach. Performances evaluation and comparison with high performance micro-emboli detection technique, namely Autoregressive (AR) modelling are provided, using *in vitro* in this work.**

I. Introduction

An embolus, foreign particle, of different size, freely moving in blood flow is at the origin of abrupt obstruction of an artery. This is referred to as an embolism. The consequence of cerebral embolism may be particularly severe, including stroke. Depending on its origin an embolus can be aggregates such fat, gas bubble, or any other foreign body, carried by blood flow. Micro-emboli (small size emboli) and therefore emboli detection has several interests: preventing cerebral vascular accidents, finding the cause of the emboli and validating the effectiveness of the treatments. The main technique used to detect emboli is the recording of transcranial ultrasound Doppler signal from cerebral artery, *e.g.* [1]. Embolic signature in blood flow is then assumed to be a non predicted high intensity transient signal (HITS) superimposed on the Doppler signal backscattered by the blood. Concerning detection, most of existing systems use an intensity measurement via the classical Fourier spectrogram, or any other time frequency distribution[2]. An embolic signal is detected when this intensity is above a reference one. However, it has been shown that parametric modelling namely, AutoRegressive (AR) modelling associated with abrupt change detection technique [3] is far one of the most reliable approach to automatically detect micro-emboli. At the same time, it has been shown that integrating human expert system in a detection procedure allows good emboli detection [4]. The common drawbacks of these last two techniques are that they are exclusive one another, whereas their advantages could be gathered together in a approach. To achieve this goal, human expert system should be taken into account by using fuzzy logic. In order to fit the variability of emboli signature, adaptive fuzzy approach must be considered. After having briefly revisited the AR technique and introduced adaptive fuzzy modelling, experimental results are used for purpose of comparison between parametric modelling and the fuzzy approach.

II. methods

A. Parametric Autoregressive method

This method consists, unlike commonly used methods, in working not directly on the signal, but on a model of the signal. Consider a discrete time complex signal x. Assuming that it is the output of an AR model, it can be expressed by :

$$x(n) = -a_1(n)x(k-1) - a_2(n)x(k-2) - \\ ... - a_p(n)x(k-p) + \eta(n)$$

where the $a_i(n)$ are complex coefficients defining the AR model, p is order of the model (number of coefficients) and $\eta(n)$ is a complex white noise. This model is referred to as AR(p) model. For convenience the previous expression is commonly expressed in matrix form as :

$$x(n) = \varphi^T(n)\theta(n) + \eta(n) \quad (1)$$

where

$$\varphi^T(n) = [-x(n-1), ..., -x(n-p)], \text{and}$$

$$\theta(n) = [a_1(n), ..., a_p(n)].$$

Modelling the signal x as an AR process then corresponds to obtain from x, the vector $\hat{\theta}(n)$ which is an estimate of the vector $\theta(n)$. This estimation can be performed using for example the Recursive Least Squares (RLS) algorithm. Its principle consists in minimizing a cost function representing the quadratic mean difference between $x(n)$ and $\hat{x}(n) = \varphi^T(n)\hat{\theta}(n)$. Details on RLS algorithm may be found for example in [12], [5].

$$e(n) = x(n) - \hat{x}(n)$$

is referred to as the prediction error. When the model (1) efficiently fits the signal, the prediction error is asymptotically a white noise. Since the autocorrelation function (AF) of a white noise, equals zero at any lag, except initial one (n=0), the AF of prediction error is therefore an interesting Decision Information or DI (information containing emboli signature) for this parametric method. Indeed, when an embolus crosses the sample volume, the predicting error will no more be asymptotically a white noise, and its AF

at lag 1 (for example) will differ from zero. The AF at lag 1 can be expressed by:

$$C_N \stackrel{def}{=} C(1) = \frac{1}{N}\sum_{k=1}^{N} e(k)e(k-1)$$

This can be estimated recursively each time n using a forgetting factor α $(0 < \alpha \leq 1)$ by :

$$C_n = \alpha C_{n-1} + (1-\alpha)e(n)e(n-1)$$

Here $\alpha = 0.9$. Due to the previous remark, C_n will be almost zero for a normal Doppler signal, and the presence of an embolus will be characterized by an abrupt change. Therefore, to detect an embolus, we have to construct (DI). Here, then :

$$DI = \mid C_n \mid$$

The probability density function of this DI is [5]

$$P(x) = \frac{1}{\pi}\int_0^\infty exp[- \mid x \mid \cosh(u)]du \, , x \neq 0$$

In order to evaluate the reliability of emboli detection, this detection is performed in the framework of binary hypothesis testing. Two hypothesis say H_0 representing the fact that there is no embolus and H_1 that an embolus is present have to be tested. A decision concerning the presence emboli (D_1) or the absence of emboli(D_0) may be summarized as follows. Assume that the made decision is based on a single observation of the process or the received signal, represented by random variable X and that the possible values of X constitute the observation set denoted O. The set O is then divided into two subsets O_0 and O_1 such that if values of X belong to O_i the decision is D_i, with $i = 0, 1$. The probability density functions of X corresponding to each hypothesis are denoted $f_{X|H_\bullet}(x|H_0)$ and $f_{X|H_1}(x|H_1)$, where x is a particular value of the random variable X. Denoting $P(D_i|H_j)$ the probability of deciding D_i when H_j is true, it follows that,

$$P_{ij} \stackrel{def}{=} P(D_i|H_j) = \int_{O_i} f_{X|H_j}(x|H_j)dx.$$

With these definitions we have

$$\begin{aligned} PFA &= P_{01} = 1 - P_{00} \\ PND &= P_{01} = 1 - P_{11} \end{aligned} \tag{2}$$

where PFA is the probability of false alarm and PND is the probability of non detection. In practice each hypothesis is characterized by a decision information (DI) and belonging to the O_0 or O_1 is represented by a threshold, say λ. So PND or PFA can be obtained by inverting eqs.(2). For example if DI had been unit variance centered gaussian variable, and H_0 being "$DI \leq \lambda$", $PFA = 1 - P(DI \leq \lambda)$, the probability of false alarm would be related to the threshold via explicit expression. In this particular case, $\lambda = erf^{-1}(PFA)$ where erf^{-1} is Inverse function of the integral of the unit variance centered Gaussian distribution. PFA and or PND are reliability measure.

Finally note that, from eq.(1), the power spectrum density $P(f)$ can be obtained each time n as $P(f) = \frac{K}{1+\mid\sum_{i=1}^{\bullet} a_k(n)\exp(-2\pi fk)\mid^2}$; where K is the power of the noise η and f is normalized frequency $-0.5 \leq f \leq 0.5$.

B. Neuro-Fuzzy approach

We will give in this section a brief introduction of the concepts useful to study a problem with neuro-fuzzy approach. Introduced in 1965 by Zadeh [6], fuzzy approach lies on fuzzy reasoning or approximate reasoning which is an inference procedure used to derive conclusion from a set of fuzzy if-then rules, in the following way : "IF conditions THEN conclusion". Conditions and conclusion are respectively of type :" x is A", "y is B"; x and y are variables representing respectively for example input and output of the system under consideration. A and B are referred to as linguistic terms such as for instance "BIG", "LOW",... and are characterized by membership functions μ_A and μ_B. For a particular value x_0 of x, it can be said that "x is A" with a truth degree of $\mu_A(x_0)$. An important characteristic of such a system is that, due to its structure it is immediate to insert human expertise through the rules. Direct use of this fuzzy reasoning may need in complex problems a high number of manual and cumbersome settings. To account for this and fit the possibly change of the system, neuro-fuzzy modeling was introduced *e.g.* [7],[8]. Here, due to our application, we consider the case of Sugeno model. That means the conclusion of rules are crisp linear combination of variables, as in the example of two rules (R1 and R2), two inputs (x_1 and x_2) and one output (z) below :
R1 IF x_1 is A_{11} and x_2 is A_{12} THEN $f_1 = p_1x_1 + q_1x_2 + r_1$
R2 IF x_1 is A_{21} and x_2 is A_{22} THEN $f_2 = p_2x_1 + q_2x_2 + r_2$
The resulting output is $z = \frac{\mu_1 f_1 + \mu_2 f_2}{\mu_1 + \mu_2}$; where $\mu_i = \mu_{A_{1i}}(x) \times \mu_{A_{2i}}(y)$ with i=1,2, as shown in fig.(1-a). The symbol $\times$ may be either product symbol or any other T-norm symbol [6],[7],[8]. This system can be modelled as a four layers neural network fig.(1-b).

This can be generalized for a system with N rules as in fig.(2).

Thus a general neuro-fuzzy system is an equivalent four layers network fig.(2) for a fuzzy system of which the ith rule is :
Ri IF x_1 is A_{1i} and ... x_n is A_{ni} THEN $f_i = p_{ni}x_n + ... + p_{1i}x_1 + p_{0i}$
where "x_i is A_{ij}' is evaluated by $\mu_{ij}(x_i)$. μ_{ij} is a the membership function which is typically gaussian (of course other type can be used) with mean a_{ij} and variance b_{ij}.

Given a set of rules, neuro-fuzzy technique adjusts the parameters of the system under consideration through the four layers defined as :
Layer1. This is input layer. Inputs are x_i, $i = 1...n$

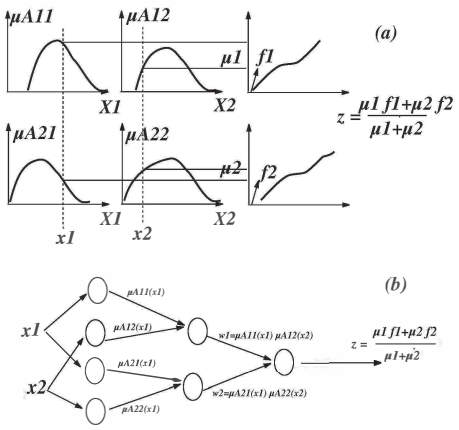

Fig. 1.
Sugeno Fuzzy inference system with two rules (a) and its equivalent neural net model (b).

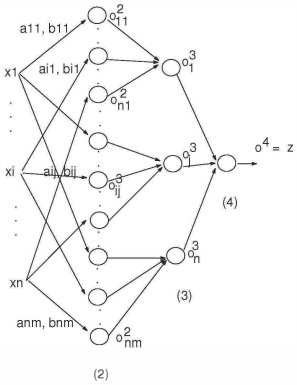

Fig. 2.
N inputs four layers neural net system

Layer2. Each node corresponds to evaluation of the degrees of truth. $o_{ij}^{(2)} = \mu_{ij}(x_i) = \exp(-(\frac{x_i - a_i j}{b_i j})^2); i = 1, ...n,\ j = 1, ..., m$

Layer3. Each node performs implication through T-norm operation : $o_j^{(3)} = \prod_{n=1}^{n} o_{ij}^{(2)};\ i = 1, ...n,\ j = 1, ..., m$

Layer4. This output node performs defuzzification : $z = \frac{\sum_{j=1}^{m} o_j^{(3)} f_j}{\sum_{j=1}^{m} o_j^{(3)}}$, where f_j is the consequent part of the j^{th} rule : $f_j = p_{nj}x_n + ... + p_{1j}x_1 + p_{0j}$

a_{ij} and b_{ij} are referred to as premise parameters and p_{ij} consequent parameter. Estimating and adjusting parameters lies on hybrid algorithm in which, in the forwards pass the consequent parameters are identified by least square method. In order to speed up the convergence rate we use δ-operator Recursive Least Squares method [9],[10]. In the backwards pass, the premise parameters are updated by the gradient descent method. In order to overcome the problem of rules number selection we use matrix decomposition UDV^H technique [11].

Here due to the complexity of our application, even if one can be sure that the detected high intensity transient signal (HITS) is an embolus signature, there is no absolute warranty that it is indeed. To take into account this fact we decided to provide for each detected HITS a PFA for the parametric method. For the neuro-fuzzy method, instead of giving a binary decision (absence/presence of embolus) we gave a measure of detection or a score which is between 0 and 1. This thus imply that a score above 0.7 reveals presence of embolus and a score below 0.3 reveals absence of embolus.

III. Application

In order to validate the above techniques, we here used experimental *in vitro* data obtained by blood mimicking fluid circulating thanks to a pump. Emboli were simulated by acrylic particles of different sizes. Blood were simulated by a fluid referred to as blood mimicking fluid, which had acoustical properties similar to the ones of blood. Signals are recorded using a 2 MHz-emitting-frequency and 6 KHz-PRF-Transcranial Doppler system, *WAKI 2* from *ATYS MEDICAl.*

The input of the parametric method is simply the Doppler signal and the output is the decision. For the neuro-fuzzy approach the inputs were defined using the characteristics of the signal. For example, for a single gate system they were:
- DI (Decision information, see section II-A). Range went from 0 to 50 dB above the detection threshold.
- (HITS) duration. Range went from 0 to 300ms.
- $Amaxn/Amaxp$ which is the ratio between maximum of power spectrum density in the domain of negative and positive frequencies respectively. Range went from 0 to 50dB.
- $fmaxn$ which is the the normalized frequency of the maximum of power spectrum density in the domain of negative frequencies. Range went from : -0.5 to 0
- $fmaxp$ which is the the normalized frequency of the maximum of power spectrum density in the domain of positive frequencies. Range went from : 0 to 0.5

All these parameters are computed from the parametric model section II-A

IV. Results

Sets of 130 signals, consisting of different types of artifact together with acrylic particles were recorded. In fig.(3) is shown a typical *in vitro* circulating acrylic Doppler signal, with its relevant DI.

Two sizes acrylic particles (240μm and 300μm) are used. In figure(4) are shown for the purpose of illustration, an example data consisting of artefacts (slight tapes on the transducers) and acrylic particles. 40 signals were used to train the neuro-fuzzy system. The result in figure was representative of the different tests made on acrylic particles of different sizes. Artefact were detected with a score close to zero. Concerning acrylic particles the scores were always greater than 0.7, excepted less than 5% of the cases. Due to pages limitation all these results cannot be shown here.

Although we cannot in the strict sense, talk about PFA and PND, these results are equivalent of $PND \simeq 0$ and $PFA \leq 5\%$

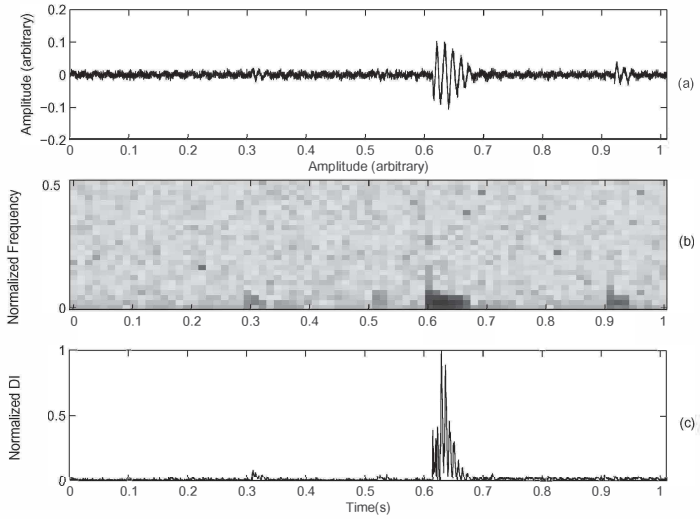

Fig. 3.
Typical in vitro circulating acrylic (of 240μm) signature. (a) real part Doppler signal, (b) spectrogram, (c) DI

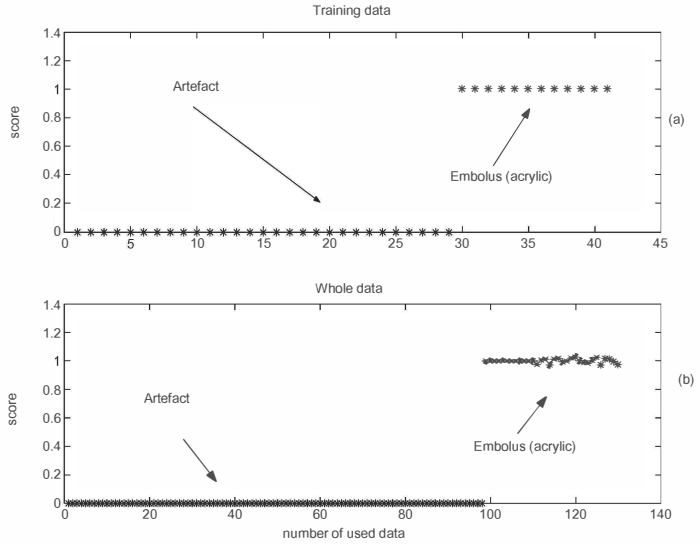

Fig. 4.
Score evaluated using neuro-fuzzy methods. (a) training data (40 signals). (b) Whole data (130 signals)

Concerning, parametric method the results summarized in Table.I. PFA is less than 5% and PND is less than 7% for a threshold of 3dB. It is important to notice that, as most of conventional systems, artefact rejection is performed by another procedure (use of additional gates, HITS direction evaluation,...).

The performances of these two techniques are very close to each other. The advantage of our neuro-fuzzy technique is that the processing of artefact is immediate. Only one gate is sufficient to perform emboli detection and artefact rejection. Thus this detection system does not necessitate additional gates such in conventional detection system. In vivo validation of this system is, now being investigated.

TABLE I

	PFA	PND
300 μm	4%	0%
240 μm	3.5%	6.25%

Probability of False Alarm(PFA) and Probability of Non Detection (PND) for parametric method for a threshold of 3dB.

V. Conclusion

In this paper a specific neuro-fuzzy approach has been proposed in the framework of emboli detection. This technique has been compared with automatic emboli detection based on parametric AR method using in vitro data. Although the performances of the two techniques are close to each other, the neuro-fuzzy technique presents the advantage of being able to performed detection using only one gate. This technique is thus a promising way to efficiently detect emboli with low cost system. In vivo validation of this system is being investigated now.

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