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Intracranial Pressure Processing with Artificial Neural Networks: Classification of Signal Properties

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Summary

Intracranial pressure (ICP) is commonly used by neurosurgeons as a source of valuable information about the current condition of the neurosurgical patient. Nevertheless, despite years of effort, extracting clinically valuable information from the ICP signal is still problematical. Approaches, using current values of ICP, may fail to disclose imminent risk, because unpredictable factors can rapidly change the properties of the signal. An alternative approach is to determine some global characteristics of the signal within a longer time interval and such statistical analyses have been proposed by several authors. A further, rarely considered, problem is assessment of the results obtained from the point of view of their practical utility and/or such classification of the obtained properties of the signal that they correspond to certain clinical states of the patient. While this might be a typical task for discriminant analysis, we approached the analysis using an alternative methodology, that of computational intelligence, implemented in artificial neural networks (ANN).

We tested two variants of the ANN algorithms for classification and discrimination of global properties of the ICP signal. In a "dynamic pattern classification" the network was presented with several sections of ICP records together with information from the expert-neurosurgeon, classifying 4 risk groups. In this mode no data pre-processing was carried out, in contrast to our second approach, in which the signal had been pre-processed using published statistical analyses and only these intermediate coefficients were fed into the ANN classifier.

The results obtained with both classification methods at their current stage of training were similar and approximated to a 70% rate of judgements consistent with the expert scoring. Nevertheless, the method based on the assessment of global parameters from the ICP record looks more promising, because it leaves the possibility for modification of the set of parameters analysed. The new parameters may include information extracted not only from the ICP signal, but also from other diagnostic modalities, like colour coded Doppler ultrasonography.

The ultimate goal of this work is to build up a pseudo-intelligent computer expert system, which would be able to reason from a reduced set of input information, available from a standard monitoring modality, because it had been taught salient links between these data and higher-order data, upon which expert scoring was based.

Keywords: Signal processing; neural classifiers; feature extraction.

Introduction

The problem of reliable detection of life-threatening situations in a neurosurgical patient treated in the ICU is still far from reaching a satisfactory solution, though several methods of clinical and instrumental evaluation have been developed to bring to notice signs of oncoming danger [3, 4]. The intracranial pressure (ICP) is commonly used by neurosurgeons as the primary source of valuable information about the current condition of the neurosurgical patient. However it is increasingly felt that traditional statistical methods of extracting information from the ICP signal have reached their natural limits, mostly because of difficulties in fitting the appropriate mathematical model to the non-linear, non-stationary process, which generates this signal.

Artificial neural networks (ANN) are a group of Artificial Intelligence (AI) algorithms, which in many problems of medical data analysis have demonstrated better efficiency than traditional statistical methods [1]. As occurs in many medical applications, the input factors affect the outcome in somewhat inconsistent or imprecise ways. Such problems are especially amenable to neural network analysis, as the ANNs learn directly from the examples presented. Typical applications of ANNs are signal processing and forecasting, pattern recognition and discrimination [2]. The number of applications of ANNs in medicine has been reported to be growing fast over the last few years [7]. Typical examples are detection of the signs of a heart infarct in the ECG signal, diagnosis of the type of neoplasm from microscopic smears, or recognition of the outline of cerebral structures in MRI scans. Successful implementation of ANNs in medicine encouraged us to apply neural networks to the problem of recognition and discrimination of a configuration of unfavourable symptoms in the neurosurgical patient.

Patients and Material

Acquisition of the ICP Signal

In this study we included data obtained from patients with intracerebral haemorrhages, treated in the ICU over the period 1997–1999. Intracranial pressure was recorded before and after surgical removal of intraparenchymal brain haematoma. This selection of subjects offered us the possibility of dealing with distinct situations corresponding to relatively unambiguous clinical ratings, then used for the training of the ANNs.

Intracranial pressure was measured with a miniature silicon strain gauge type sensor (*CODMAN Neuro Monitor Skull Bolt Kit, Codman & Shurtleff, Inc., Randolph*) and transmitted to a computer via a specialised multi-channel data acquisition card. The ICP signal was sampled with a frequency of 51 Hz and visualised on screen, then one-hour sections of ICP were routinely logged on disc for further processing. In this way a library of records obtained from more than 60 patients in various clinical conditions has been collected to date to enable different methods of analysis to be tested.

ANN in on-Line Classification of ICP Signals

The aim of this study was to construct a neural network, which could automatically assign an observed ICP waveform to one of several classes, corresponding to a certain scale of risk. We plan ultimately to come to a semi-quantitative scale of 10 levels. As this requires a large number of observations, for the purposes of this study we allowed a qualitative scale, which consisted of four classes. The arbitrarily selected classes may be regarded as corresponding to "good", "moderate", "serious" and "severe" clinical states of the patient.

Four groups of ICP recordings, which contained typical representatives from each class, were carefully selected from all the ICP recorded samples by one experienced neurosurgeon (Z. M.) to be used as the training data. Assignment of an ICP recording to a certain class was based on expert scoring, drawn from visual analysis of the recorded ICP signal, clinical examination, measurements of additional vegetative parameters, colour-coded transcranial Doppler study of cerebral circulation, and most importantly, full knowledge of the further evolution of the clinical condition of the patient. The neural network could then learn how to adjust its internal parameters to properly categorise a given segment of the ICP signal, presented to its input.

Having completed the training, the network could proceed with solving the essential discrimination task. The neural classifier was expected to select the class of risk that the observed signal most probably belonged to, and also to give a quantitative measure of the probability of this membership. The classification task was solved by a modular hierarchical structure, based on the Predictive Modular Neural Network (*PREMONN*) architecture [9].

It is assumed that the time series to be classified is generated by a source (in this case – corresponding to a certain class of emergency), which belongs to a finite search set. So, the classification problem may be regarded as selection of the source that best represents the dynamic features of the observed data. The ANN classifier consists of a "bank" of neural models (at the lower level) and an "intelligent" upper-level decision module which evaluates the errors between the

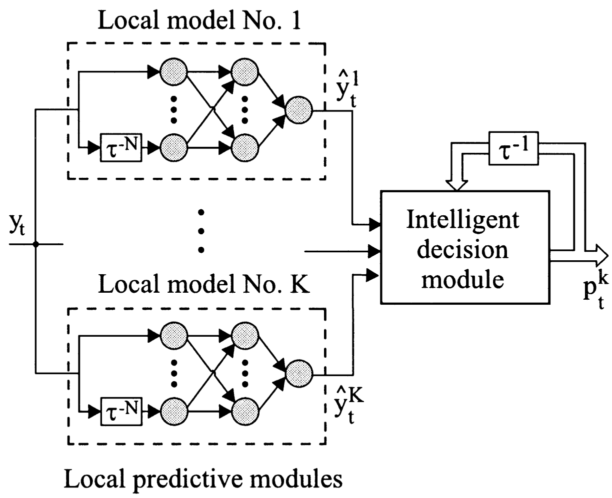

Fig. 1. Architecture of predictive modular neural network for time series classification: y_t current value of classified signal; $\hat{y}_t^1, \ldots, \hat{y}_t^K$ outputs of local predictive models; p_t^k generated probability; τ^{-N} coefficient expressing delay-weighted extent to which past results of classification influence current assessment of ICP

classified signal and the model outputs and performs the final classification (Fig. 1) [9]. Each local neural model represents one risk category and approximates the typical dynamic properties of the signals, which belong to this class.

The lower-level models are used to perform parallel prediction of ICP, based on historical samples of the signal. It is intuitively obvious that the local model best fitting the signal dynamics will produce the smallest error, so it (and consequently, the corresponding class of risk) will be selected by the decision module. The selection is based not only on the prediction errors computed currently, but also on the time-weighted past values of the error, within the user-selected time interval.

ANN in Classification of Global Properties of ICP Signals

This approach attempts to imitate the way in which the ICP recording would be judged by a human expert. The expert takes into consideration not only the current values of intracranial pressure, but also some general properties of a sufficiently long ICP segment, e.g. the amplitudes of fast fluctuations, the appearance of very slow ICP waves, average ICP values and other features of the signal. In keeping with this way of making decisions, the ICP segment was preprocessed using statistical and spectral methods and the intermediate results were passed as the inputs to the ANN. The neural network processed these inputs, which represented "global" information extracted from an ICP segment, and tried to establish associations between the complex parameters of the ICP recording and the resultant level of risk to give a judgement of the patient's clinical condition on an arbitrarily selected risk scale. The same, as defined above, four-level scale of risk was used for this mode of ICP classification.

We employed a combination of various statistical and non-statistical approaches to extract clinically valuable information from the original ICP signal to be passed on to the ANN (Fig. 2)

- Spectral analysis (FFT) and digital filtering: this enables detection of the main signal harmonic components originating from the heart rate (cardiac component) and breathing (respiratory component) and, finally, to obtain average heart and breathing rates just from the ICP signal.

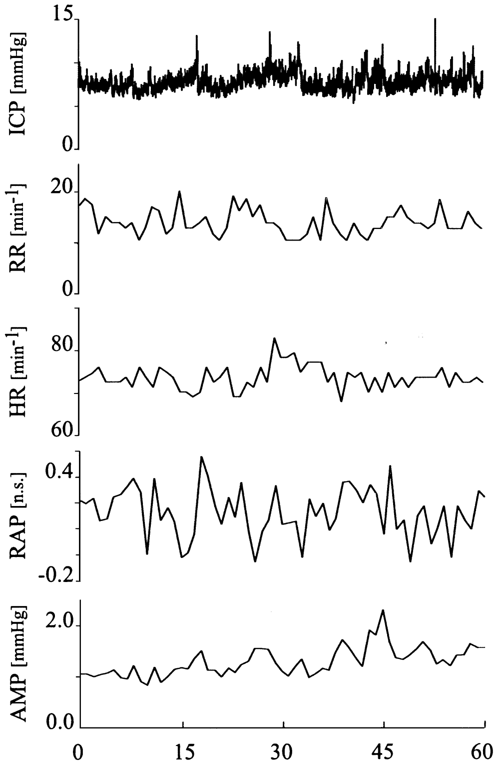

Fig. 2. Preprocessing of ICP for extraction of versatile information to be presented to the input of ANN. *RR* Respiratory rate; *HR* heart rate; *RAP* correlation coefficient between amplitude of fundamental harmonic component and mean ICP; *AMP* amplitude of fundamental harmonic component

- Second-order statistics of ICP: calculation of mean value, median, variance and histogram of a given section of the ICP record.
- Computation of RAP (correlation coefficient between the amplitude of the fundamental harmonic component and the mean ICP); this was done according to the algorithm developed by Czosnyka *et al.* [3]. The amplitude of the main harmonics is usually plotted against the range of pressure occurring in the analysed segment of ICP. The piece-wise linear approximation of the resultant scatter of points gives a rough measure of the compensation reserve of the intracranial space. The slopes of the two lines fitted to the scatter of points were used to construct the ANN input vectors.
- The non-stationary indices of the ICP signal, obtained from a procedure in which the variance of ICP was calculated over one-hour segments of the recorded signal in time periods increasing by a factor of two from 10 seconds to 43 minutes. The distribution of the averaged variance values was estimated according to a logistic model. The coefficients of the resultant logistic curve were regarded as a measure of the non-stationarity of the process and entered as the inputs to the ANN. Numerous analyses of the ICP signals have proved that the above algorithm describes the content of very low frequencies in the signal better than frequency analysis. In particular, it was able to model the circumstances related to the long periods (range of 20 minutes) of high-level, high-amplitude waveforms of the ICP, following rapid increases of the signal (*plateau waves*).

The input information passed on to the ANN consisted of various combinations of the parameters, selected from the above set of global characteristics of a standard one-hour ICP segment [11]. The result the ANN was expected to produce was a number, corresponding to exclusively one of the four previously defined classes of danger.

Experimental Results

ANN in On-Line Classification of ICP Signals

According to the classification concept described above, four one-step neural predictors were trained in the *off-line* mode on selected signals, which were unambiguous representatives of the specified risk categories. Small ANN structures were used at the bottom level; they contained from 3 to 5 neurons with logistic activation functions in the hidden layer and one linear neuron in the output layer [6]. The averaged signal (now with a sampling period of 10 s) was further preprocessed using a logarithmic transformation, to decrease the variations of ICP values for patients in different clinical conditions. The samples from the last minute of observation were used to train local predictors; so each local neural network forecast the future sample using six historical samples. The local predictors behaved reasonably; the absolute errors did not exceed 5–7% of the signal value.

Figure 3a shows an example of the classified ICP signal; it takes 6 hours and has been created as a concatenation of a few real signals recorded from four patients in various clinical states. At each time step the decision module of the neural network generated four numbers, which represented relative measure of prediction errors, computed by each local model (i.e. the "fitness" of a local model to the real signal). As the numbers are positive and always add up to one, they may be regarded as the probabilities: $p_t^1, p_t^2, p_t^3, p_t^4$ of assigning the signal to a certain class of risk [9]. The decision module simply indicates the model with the biggest value of current probability, which corresponds to a certain class of risk. The plot of the probabilities p_t^k for this signal is shown in Fig. 3b.

It can be seen that the decision module modifies the judgement as the average value of ICP and dynamic properties of the signal change. For some parts of the ICP signal the classification is unambiguous, i.e. one probability is much bigger, than are the others. However at some moments, no one of the classes of risk is dominant; at these time intervals the neural network detects the changes of signal properties, which may correspond to changes of the clinical state of the patient.

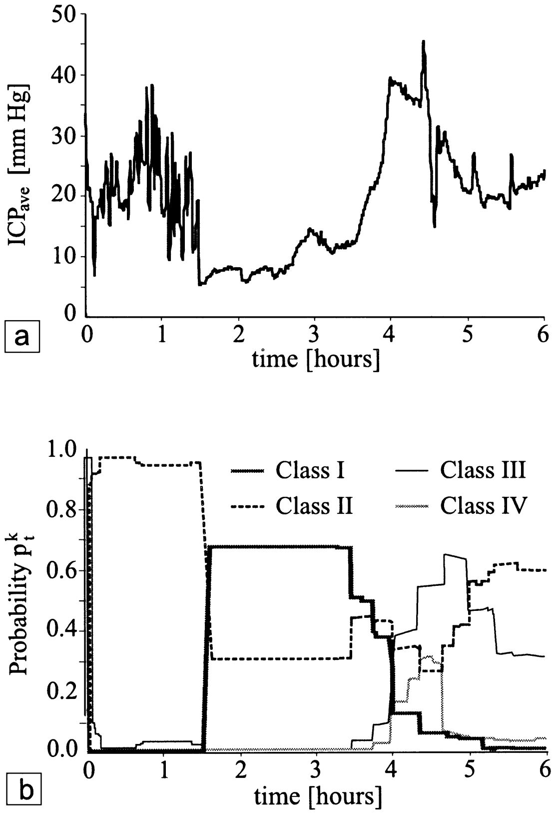

Fig. 3. Sample of ICP records (a) and result of signal classification (b). The ordinate shows probability p_t^k, with which at given time moment (t) neural classifier assigns signal to one of four classes of risk

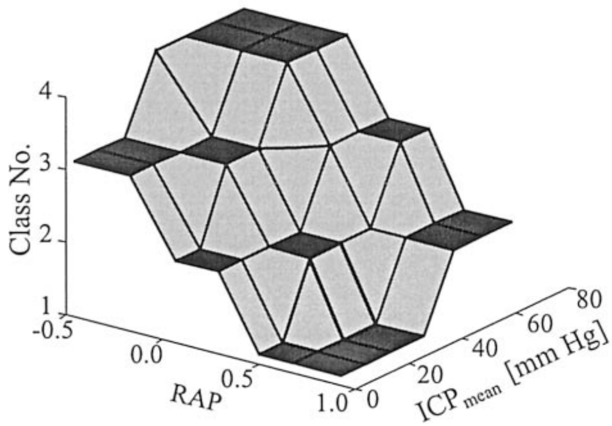

Fig. 4. Results of ICP patterns classification with ANN classifier. The surface obtained represents resultant class of risk as function of mean ICP and correlation coefficient (*RAP*). In reality ANN considered five such parameters and the real output is a surface located in 5-dimensional hyperspace. Obviously this can not be displayed on a 3D graph

ANN in Classification of Global Properties of ICP Signals

In a general sense, what the network was expected to do in this part of the study was to solve a pattern recognition task. This resembles a more conventional discriminant analysis, which may be understood as partitioning a multi-dimensional space into subspaces corresponding to the required classes of discrimination and the number of dimensions of this hyper-space equal to the number of analysed parameters [8]. In our task, which required discrimination of the four patterns of intracranial pressure, 5 parameters (such as mean value of ICP, its variance, heart rate, respiratory rate and RAP coefficient) were presented to the input of the ANNs and the boundaries of four sub-spaces, corresponding to four classes of risk were delineated.

The results of the classification (according to the four-level scale of risk, described above) obtained using the methodology of global feature extraction from the ICP segment are presented in Fig. 4. The figure shows the class assignment projected onto a subspace reduced to only two input parameters, because only this number may be displayed as a 3-D graph. The parameters chosen for this presentation are mean ICP value and RAP.

At present, we have completed the construction of the neural models for on-line and global classification of ICP signals and a library of about 50 1-hour segments of ICP records have been collected. From among them only about 30 were selected as unambiguously representative of one of the four arbitrarily selected classes of risk. Nevertheless, not all classes were evenly represented in this material. From the number of input parameters of interest, one can assess the number of ICP samples necessary for effective training of the ANNs as being at least 50, assuming that all classes would be evenly represented. So, we consider our network model not fully developed in this aspect and that it still needs further training with a sufficient number of ICP samples. Nevertheless, we attempted to evaluate the practical performance of our model by presenting to its input a set of 10 new samples of ICP. The network assessment agreed in 7 instances with the expert classification using both the on-line and global classifier schemes.

Discussion

The method of "dynamic pattern" classification has been proved to be especially efficient for nonstationary signals with the parameters of their dynamic models occupying overlapping regions in the parameter space [9]. More importantly, the local dynamics can be modelled by any type of predictors (including linear, neural or fuzzy ones), which may also utilise prior knowledge about signal properties.

The results obtained with both classification methods at their current stage of training were similar. Nevertheless it is our impression, based on hitherto performed numerical analyses, that the classification method, based on extraction of global parameters from the ICP record, looks more promising. It can reveal some relationships between salient parameters of the ICP signal, which relate to the clinical condition of a patient, and gives the researcher the possibility to customise parameters and select those, which have proved to be most informative. Even more importantly, these new parameters, which can be introduced to the neural model, need not necessarily be immanently taken from the ICP signal. At the next stage of our experimental work we plan to incorporate some synthetic parameters of colour coded Doppler examination of cerebral haemodynamics and perfusion pressure into the set of training data. On the other hand, our experiments clearly indicate that some of the parameters used hitherto may be discarded, for their information load is insufficient. Thus, more numerical experiments should be performed to establish the set of parameters, which optimally describe the current state of risk.

The accuracy of classification obtained by using both methods cannot be reliably estimated at the present stage of the ANN development. It may be expected that after the training procedure is completed, the agreement with expert scoring will improve above the present 70%. However, we are cautious in our expectations, because the ANN algorithm is not the only source of error. Expert judgements, even when supported by such data as Doppler studies of cerebral circulation [5, 10], are by no means an objective measure of the clinical condition of the patient. In fact, construction of the scale of risk (which is no more, no less, than a database of several dozen ICP records, ascribed to a class representing the patient's clinical state) is one of the biggest problems in this research set-up. For example, using the TCD findings for construction of the expert scale of risk strictly prevents incorporating them into the set of training data. So, extending the input data of the ANN by TCD parameters, is possible only when this information is replaced in the construction of the risk scale by other sources of information about the clinical state of the patient, for example by measurement of pO_2 and CO_2 within the brain parenchyma.

The idea and the ultimate goal of this investigation (which is far from being complete at the present stage of the study) is to build up a pseudo-intelligent computer bed-side expert system for on-line estimation of risk endangering the neurosurgical patient. What this system ought to be able to do, in essence, would be to reason on the basis of a reduced set of input information, available from a standard monitoring modality. This would be possible because the system had been taught to be sensitive to salient links between this reduced set of data and higher-order data, on which the expert scoring system had been based. A system of this kind might be useful not only in smaller treatment units, but also in fully equipped centres, as very expensive monitoring devices are usually in short supply and not available to all patients who may actually be in need of them.

References

1. Baxt WG (1995) Application of artificial neural networks to clinical medicine. Lancet 346: 1135–1138
2. Bishop CM (1997) Neural networks for pattern recognition. Oxford University Press, Oxford
3. Czosnyka M, Guazzo E, Whitehouse M *et al* (1996) Significance of intracranial pressure waveform analysis after head injury. Acta Neurochir (Wien) 138: 531–542
4. Czosnyka M, Smielewski P, Kirkpatrick P *et al* (1996) Monitoring of cerebral autoregulation in head-injured patients. Stroke 27: 1229–1834
5. Czosnyka M, Richards HK, Whitehouse HE *et al* (1996) Relationship between transcranial Doppler-determined pulsatility index and cerebrovascular resistance; an experimental study. J Neurosurg 84: 79–84
6. Haykin S (1994) Neural networks. A comprehensive foundation. Macmillan College Publishing Co, New York
7. Ifeachor E (1998) (ed) Neural networks & expert systems in medicine & healthcare. Oxford University Press, Oxford
8. Johnson RA, Wichern DW (1992) Applied multivariate statistical analysis. Prentice Hall, Englewood Cliffs
9. Kehagias A, Petridis V (1997) Predictive modular neural networks for time series classification. Neural Networks 10: 31–49
10. Newell DW, Aaslid R, Stooss R *et al* (1997) Evaluation of hemodynamic responses in head injury patients with transcranial Doppler monitoring. Acta Neurochir (Wien) 139: 804–817
11. Swiercz M, Mariak Z, Lewko J *et al* (1998) Neural networks and wavelet technique for detecting emergency states in neurosurgical patients. Med Biol Eng Comput 36: 717–722

Comment

This is a very interesting work attempting to apply principles of computerized neural networks to clinical practise. The authors ought to be congratulated with this careful and intelligent study.

At first sight, one wonders whether it is very worthwhile to teach a machine what the human mind can do better. However, in other fields of medicine expert systems and decision analysis have been demonstrated to greatly contribute to clinical decision taking.

This is just the beginning as the authors themselves point out. A prediction horizon of only three minutes, as in the first manuscript, is very short indeed and much too short to be able to influence clinical action. The best example in this respect is probably the prediction of a plateau wave. Although, sudden steep increments of ICP may also be due to various kinds of Valsalva manoeuvres, such as coughing and straining. With such short prediction horizons, consisting of a number of steps of a few seconds only, the good fit between actual and predicted ICP in figure 2a does not come as a surprise. The model only predicts the continuation of increasing or declining ICP. It does no really predict instantaneous changes, it just follows them. Therefore, I agree with the authors that the evaluation of the ICP signal on the basis of trends or classifications of clinical severity are of much more importance.

Figure 3 in the second manuscript illustrates the early phase of this work. Critically judged, it just shows that high pressure is bad, low pressure is good and moderately elevated pressure is intermediate. However, most interestingly, the high pressure during the first 1.5 hours is judged as class II, whereas class IV has, surprisingly enough, a very low probability. The same is true during the steep increase of ICP towards the fourth hour, where the probability of class I is sharply declining and the probability of class IV is increasing, but not to the same extent. These discrepancies are probably due to the clinical input from the expert neurosurgeon. This result is most promising. However, the classification system may by different according to the pathologies. This manuscript is dealing with patients with spontaneous intracerebral haematoma. In head injury, for example, a low pressure may sometimes indicate a poor outcome. Therefore, each pathology should have its own classification system of severity according to the ICP.

I wonder what the results would have looked like when instead of ICP the cerebral perfusion pressure had been used.

C. Avezaat

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