33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Artificial Neural Network based Intracranial Pressure Mean Forecast Algorithm for Medical Decision Support

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***Abstract*— Although the future mean of intracranial pressure (ICP) is of critical concern of many clinicians for timely medical treatment, the problem of forecasting the future ICP mean has not been addressed yet. In this paper, we present a nonlinear autoregressive with exogenous input artificial neural network based mean forecast algorithm (ANN_{NARX}-MFA) to predict the ICP mean of the future windows based on features extracted from past windows and segmented sub-windows. We compare its performance with nonlinear autoregressive artificial neural network algorithm (ANN_{NAR}) without features extracted from window segmentation. Experimental results showed that, ANN_{NARX}-MFA algorithm outperforms ANN_{NAR} algorithm in prediction accuracy, because additional features extracted from finer segmented sub-windows help to catch the subtle changes of ICP trends. This verifies the effectiveness of decomposing the whole window into sub-windows to obtain features in making predictions on future windows. Based on the forecast of ICP mean, medical treatments can be planned in advance to control ICP elevation, in order to maximize recovery and optimize outcome.**

I. INTRODUCTION

Intracranial pressure (ICP) monitoring has become the "gold standard" in most Neuro-Intensive Care Units (NICUs) nowadays, since direct correlations have been reported between elevated ICP and adverse outcome in the treatment of severe head injury [1]. Currently, medical interventions are delivered to patients only after clinicians notice sustained and significant ICP elevation [2]. Due to the urgency, clinicians usually have to simultaneously diagnose, make decisions, and conduct interventions. Thus, it is difficult and troublesome for clinicians to take timely interventions, especially in human resources and facilities limited hospitals. Besides, patients cannot wait for too long to receive medical diagnosis and following treatments. Therefore, it is critical to predict the future ICP mean to facilitate and enhance the ability of clinicians to take timely actions in the treatment of critically ill patients with severe head injury.

Up to now, most efforts of prior research of ICP prediction were mainly directed in two directions: (1) identification of the precursors of ICP elevation [2-5]; (2) prediction of the exact ICP waveform [6-7]. The most straightforward way is to recognize precursors to ICP elevation that can be extracted from continuous ICP signals [2]. In [2], twenty-four metrics in five categories (amplitude, time interval, pulse curvature, pulse slope, decay time constant) characterizing the ICP pulse morphology were shown to be critical in predicting ICP elevation. In [3], the frequency amplitudes of the fundamental wave and harmonics obtained by Fourier transform analysis of the pulses were also shown to be significant precursors of ICP elevation. In recent years, discrete wavelet transform (DWT) based artificial neural network (ANN) algorithms were also applied to predict the exact ICP waveform, so as to identify the ICP trend [6-7]. However, satisfactory prediction results were reported for only up to 3 minutes. Although the future ICP mean is of critical concern to many clinicians, the problem of forecasting the ICP mean has not been addressed yet, to our best of knowledge.

In this paper, we present a nonlinear autoregressive with exogenous (external) input (NARX) artificial neural network based mean forecast algorithm (ANN_{NARX}-MFA) to predict future ICP mean. The ANN_{NARX}-MFA algorithm predicts the future ICP mean instead of the exact ICP values in [6-7], according to the features (past mean calculated from ICP windows and segmented sub-windows) extracted by window segmentation. Because of the non-linear feature of the neurophysiological signals, we construct the mean forecast algorithm (MFA) based on ANN_{NARX} model, which has been proven to be accurate for modeling nonlinear systems and problems involving long term dependencies [8-9].

To verify the effectiveness of the features extracted from window segmentation in prediction, we chose the nonlinear autoregressive artificial neural network algorithm (ANN_{NAR}) as baseline, which forecasts without the features extracted by window segmentation. Experimental results showed that ANN_{NARX}-MFA algorithm consistently outperforms ANN_{NAR} algorithm in prediction accuracy, for ICP mean prediction.

We also chose autoregressive moving average (ARMA) algorithm, which is a traditional model for forecasting time series, for performance comparison. Results showed that ANN algorithms are superior to ARMA algorithm in prediction accuracy for long-range ICP mean prediction.

Based on the forecast of ICP mean, clinicians can identify the life-threatening trends early (e.g., ICP elevation), so that diagnosis and following treatments can be planned in advance, to prevent or attenuate secondary brain injury, so as to maximize recovery and optimize outcome. In this way, limited and expensive resources can also be utilized efficiently.

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This work was supported in part by the Agency for Science, Technology and Research, Singapore, under SERC grant 092-148-0067.

II. METHODOLOGY

This study was an analysis of neurophysiological data collected in NICUs of National Neuroscience Institute - Tan Tock Seng Hospital, Singapore. Fifty-seven patients with severe traumatic brain injury (TBI) were admitted between 2009 ~ 2010. All patients underwent continuous invasive monitoring of ICP, MAP, PbtO2 and brain temperature. However, four patients' ICP records have substantial amount of missing data chunks, and therefore were not included in this study. The remaining 53 patients (42 male and 11 female), who have been monitored for at least 24 consecutive hours, were included in our study. All medical records were anonymized and the study received ethics approval from the Institutional Review Board.

ICP was continuously monitored using a fibre-optic intraparenchymal gauge (Codman and Shurtleff, Taynham, MA). All patients underwent multi-modality monitoring with continuous recording of clinical data on a Philips clinical information system. The continuously monitored neurophysiological readings were sampled and recorded at 100 Hz. For all ICP records of patients studied, the ICP sample length has a mean of 92.9 hrs and standard deviation of 65.9 hrs. The mean of patients' ICP varies from 4.3 ~ 73.7 mmHg, while the standard deviation varies from 3.5 ~ 45.1 mmHg.

The nonlinear autoregressive with exogenous (external) input (NARX) artificial neural network based mean forecast algorithm (ANN_{NARX}-MFA) predicts ICP mean of a future window, based on a features (e.g., mean of the past windows, and segmented sub-windows) extracted by window segmentation.

The flow chart of the ANN_{NARX}-MFA algorithm is shown in Fig. 1. The whole process of the ANN_{NARX}-MFA algorithm starts, when enough raw neurophysiological data of a patient has been accumulated. Because the raw data usually contains artifacts ("spikes"), our system detects and replaces the artifacts with imputed data [10], to mitigate the influence of the artifacts on the forecast accuracy. Due to patient movement, probe displacement, neurosurgical intervention or human errors, the raw data may also contain missing data. To remove the effects of missing data on the forecast accuracy, our analysis only includes continuous data, because simply removing missing values lead to discontinuities in the data.

After artifact removal and missing data cleaning, ICP data is divided into many time windows, which is illustrated in Fig. 2. All windows have the equal size T (… $|T_{p(j)}|$ = … $|T_{p(2)}|$ = $|T_{p(1)}|$ = $|T_{f(1)}|$ = $|T_{f(2)}|$ = … = T). $T_{p(j)}$ refers to the j^{th} past window, while $T_{f(i)}$ refers to the i^{th} future window, with reference to current zero time point ($t = 0$). Each past window is further segmented into k finer sub-windows ($S_1, S_2, \ldots, S_k$) from right to left ($|T_{p(j)}| = |S_1| + |S_2| \ldots + |S_k| = T$). However, different sub-window has different resolution (size/length). The number of sub-windows to be segmented (k) is decided first. The size of the first sub-window l_1 is can be calculated by Eq. (1). The sizes of the rest of the sub-windows ($l_2, \ldots, l_k$) can be calculated by Eq. (2).

$$l_1 = \frac{T}{2^k - 1} \tag{1}$$

$$l_i = 2l_{i-1} (2 \le i \le k) \tag{2}$$

This way of window segmentation gives lower resolution to the remote data and higher resolution to the close data inside a window. The artificial neural network adjusts the weights given to the features extracted from different sub-windows by training.

Features of each past window and segmented sub-windows are then calculated. For instance, for the j^{th} past window $T_{p(j)}$, the mean ($\mu_{S1(j)}, \mu_{S2(j)} \ldots \mu_{Sk(j)}$), standard deviation ($\sigma_{S1(j)}, \sigma_{S2(j)} \ldots \sigma_{Sk(j)}$) and the slope ($m_{S1(j)}, m_{S2(j)} \ldots m_{Sk(j)}$) of the past sub-windows and the mean ($\mu_{Tp(j)}$), standard deviation ($\sigma_{Tp(j)}$) and the slope ($m_{Tp(j)}$) of the whole window $T_{p(j)}$ are obtained. Since there are $3k$+3 features of a past window, theoretically, there are a total of 2^{3k+3}-1($\sum_{i=1}^{3k+3} C_{3k+3}^{i} = 2^{3k+3} - 1$) possible combinations of the features, which can be the input to ANN for predicting ICP mean.

Nevertheless, both forecast results and correlation analysis showed that the slopes and variances extracted from the ICP windows and segmented sub-windows decrease the accuracy of ICP mean prediction. ICP mean prediction based on mean of the ICP windows and mean of the segmented sub-windows is more reliable.

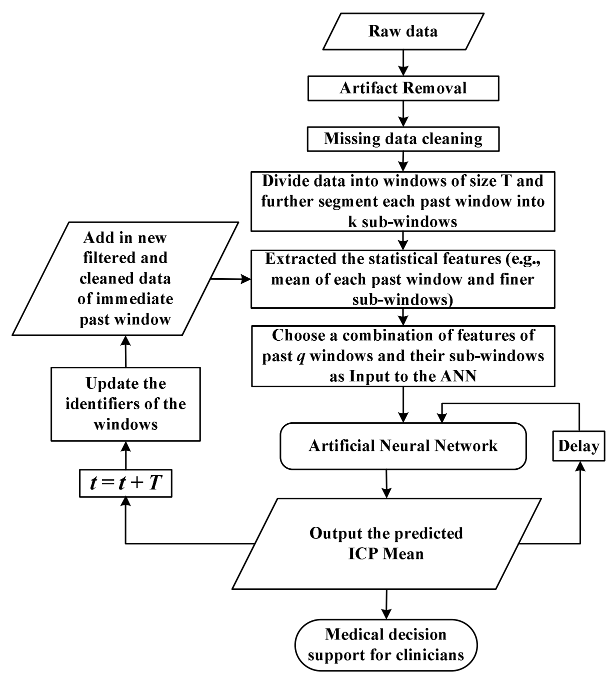

Figure 1: Flow chart of mean forecast algorithm

We choose the nonlinear autoregressive with exogenous (external) input (NARX) ANN model to construct our mean forecast algorithm (MFA), because MFA requires the features of segmented sub-windows as external inputs. A combination of the past features obtained above is chosen to be the input to train the ANN. During the training phase (open-loop process, i.e., the predicted output is not the feedback to the ANN), ANN adjusts its internal parameters (the weights of the neurons and biases) to learn the dynamic relationships between input and output, so as to minimize the differences between the actual values and predicted values of the output. During the prediction phase (closed loop process, i.e., the predicted output is the feedback to the ANN), a trained ANN uses these learned dynamic characteristics and relationships to predict the mean ($\mu_{Tf(1)}$) of the first future window $T_{f(1)}$, based on a combination of previous mean of the adjacent q past windows ($T_{p(q)}$, … , $T_{p(2)}$, $T_{p(1)}$) and their sub-windows. The predicted mean of the first future window (e.g., mean ($\mu_{Tf(1)}$)) will be used as the feedback to predict its value in the following iterations, as illustrated by the right feedback loop in Fig. 1.

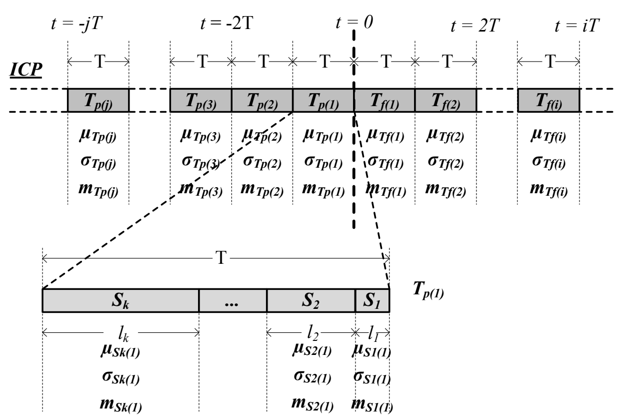

Figure 2: ICP window segmentation and feature extraction

Then, ANN_{NARX}-MFA algorithm moves time reference point forward to the next future window (t = t + T) and updates the identifiers of all the windows. As time window of T has been passed, ANN_{NARX}-MFA algorithm adds in new filtered and cleaned data of immediate past window and proceeds to next round of processing, as illustrated by the left iteration loop in Fig. 1. The whole process iterates until no more new data is available, when the patient is either discharged or relocated for neurosurgery.

Based on the forecast of ICP mean, clinicians can identify when the life-threatening trends (such as ICP elevation) will occur, so that they can prepare for diagnosis and following treatments and allocate necessary manpower and equipments in advance, to prevent or attenuate secondary brain injury, so as to maximize recovery and optimize outcome. They may also choose the suitable medical treatment option based on the ICP forecast from time to time. In this way, not only clinicians save the trouble of simultaneously diagnose, make decisions, and conduct interventions, due to urgency, but also hospitals can allocate necessary manpower and equipments in advance, so as to efficiently utilize such limited and expensive resources.

III. Results and Discussion

A. Relationship Analysis of Features

The mean (μ) represents the average value of ICP for a given period. The standard deviation (σ) represents the stability/variability of ICP for a given period. The slope (m) represents the steepness of ICP elevation for a given period.

In our correlation analysis, no apparent direct inter-relationships exist among mean, standard deviation and slope. Besides, no direct relationship can be found between standard deviation of the window and standard deviations of the segmented sub-windows, or between slope of the window and slopes of the segmented sub-windows. The detailed results are not shown in order to be concise.

Fig. 3 is the scatter plot of ICP mean of the window (μ_T) and the mean of the sub-windows of a sample patients' ICP record obtained with window size of 15 min. Throughout our study, we chose to segment a past window into four sub-windows (i.e., $k = 4$). More sub-windows will be tested in future work. Fig. 3 shows strong positive linear relationship between mean of the window and means of the sub-windows, which implies the means of the sub-windows might be useful for predicting the mean of the future window.

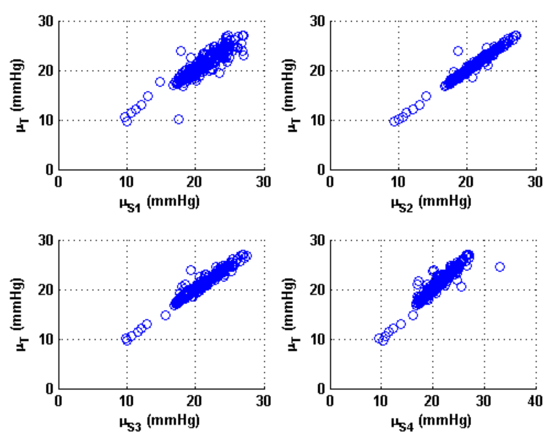

Fig. 3: The relationship between ICP mean of the window (μ_T) and the mean of the sub-windows (μ_{S1}, μ_{S2}, μ_{S3}, μ_{S4}) (T=15 min)

B. Forecast Performance Comparison

We evaluated the forecast performance by coefficient of determination (R^2), mean square error (MSE), and relative absolute error (RAE). In our experiments, the performance of ICP standard deviation prediction and ICP slope prediction is unsatisfactory, because no strong relationship can be found between the standard deviation of the window and the standard deviation of the sub-windows, or between the slope of the window and the slope of the sub-windows. Besides, the performance of ICP mean prediction based on features of standard deviations and/or slopes is also unsatisfactory, because no apparent direct inter-relationships exist among mean, standard deviation and slope. The detailed results are not shown in order to be concise.

Table I: ICP mean forecast performance comparison for coefficient of determination (R^2), mean square error (MSE), and relative absolute error (RAE) (results are shown in $\mu \pm \sigma$ format)

Metric	Model	T=15 min	T=30 min	T=45 min
R^2	ANN_{NARX}-MFA	0.93 ± 0.05	0.81 ± 0.11	0.56 ± 0.25
	ANN_{NAR}	0.88 ± 0.07	0.73 ± 0.15	0.43 ± 0.32
	ARMA	0.76 ± 0.10	0.61 ± 0.16	0.28 ± 0.25
MSE	ANN_{NARX}-MFA	0.88 ± 0.58	3.26 ± 1.96	8.12 ± 4.72
	ANN_{NAR}	1.73 ± 0.99	4.79 ± 2.63	10.25 ± 5.95
	ARMA	4.46 ± 1.89	7.28 ± 3.19	12.91 ± 8.96
RAE	ANN_{NARX}-MFA	9% ± 3%	24% ± 11%	49% ± 23%
	ANN_{NAR}	15% ± 5%	33% ± 16%	69% ± 27%
	ARMA	32% ± 8%	49% ± 15%	85% ± 13%

Table I shows the ICP mean forecast performance comparison. Experimental results showed that ANN_{NARX}-MFA algorithm consistently outperforms the ANN_{NAR} algorithm in performance comparison of coefficient of determination, mean square error, and relative absolute error, because additional feature (mean) obtained from finer sub-windows help to catch the subtle changes of ICP trends. This verifies the effectiveness of decomposing the whole window into sub-windows to obtain features in making predictions on future windows. Experimental results also showed that, for various window sizes, ANN algorithms are superior to traditional ARMA algorithm for in prediction accuracy, which implies that ANN algorithms are better than ARMA algorithm in learning long term dynamic relationships.

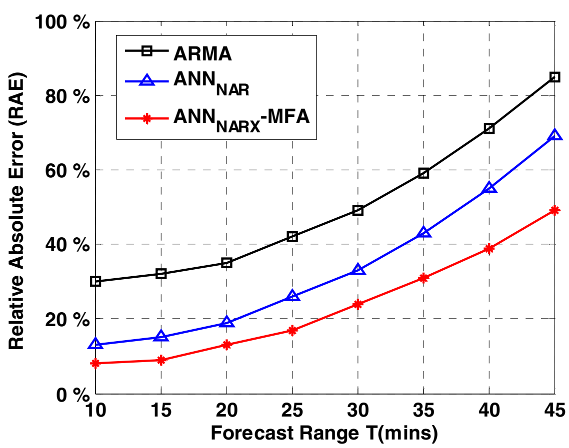

Figure 4: ICP Mean Prediction Accuracy vs. Forecast Range T

Fig. 4 shows the comparison of ICP mean prediction relative absolute error (RAE) for different forecast range T. Results indicates that the ICP mean prediction accuracy of all three algorithms degrades as forecast range increases from 10 mins to 45 mins, this is because the longer the prediction horizon is, the more difficult it is to catch the ICP trends. Results also showed that features extracted from window segmentation consistently improve the prediction accuracy for various forecast range. This demonstrates the ability of our proposed algorithm to predict ICP mean for both short time horizon and medium time horizon. The predicted results for short time horizon are useful for clinicians to identify the optimal medical treatment and the concentration for certain medicine, whereas those for long time horizon are useful for clinicians to prepare for critical interventions and surgeries.

IV. CONCLUSION

We presented an artificial neural network based mean forecast algorithm (ANN_{NARX}-MFA) for forecasting ICP mean, based on features extracted by window segmentation. Results also show that, for ICP mean prediction, our proposed algorithm outperforms the autoregressive moving average model in prediction accuracy. The ANN_{NARX}-MFA algorithm may be extended to forecast of the mean of other neurophysiological signals, based their own features, or based on the correlations among different neurophysiological signals. Based on the ICP forecast, clinicians not only may choose the suitable medical treatment option, but also can prepare for treatment and required resources to save the trouble and maximize the outcome.

ACKNOWLEDGEMENT

The authors would like to acknowledge the research support from the staff in Neuro-Intensive Care Units of National Neuroscience Institute - Tan Tock Seng Hospital Singapore for collecting medical data.

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