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Online ICP Forecast for Patients with Traumatic Brain Injury

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Abstract

Traumatic brain injury (TBI) endangers many patients and lays great burden on the neural intensive-care units in the whole world. To improve the outcome of TBI patients, it is desirable to forecast the intracranial Pressure (ICP) so to enable timely or early interventions to control the ICP level. Past research mainly focused on ICP pulse morphology analysis and ICP waveform forecast, but results were not satisfactory. In this paper, to forecast ICP continuous trends, we propose an autoregressive integrated moving average (ARIMA) ICP forecast online application with orders selection predicated on autocorrelation function (ACF) and partial autocorrelation function (PACF). Results show that the accuracy of ICP forecast improves significantly with our forecast model, compared with ARIMA based on Akaike information criterion (AIC) and artificial neural network approach. Besides, the forecast processing time of ARIMA model predicated on PACF and ACF is much shorter than ANN and ARIMA predicated on AIC .

1. Introduction

Traumatic brain injury (TBI) causes heavy neurosurgical critical care workload worldwide. In United States alone, around 1.4 million suffers from TBI annually and nearly 5.3 million live with TBI-related disabilities [1]. Generally, intracranial pressure (ICP) of TBI patients should be kept below 25 mmHg by medical treatment to improve survival rate [1]. As most current commercial neuromonitoring systems cannot predict the ICP, medical interventions are delivered to patients only after clinicians notice sustained and significant ICP trends. Therefore, it is critical to predict the future ICP trends for neuroclinicians to take timely treatment to save the TBI patients. In the past, extensive research has been directed to forecast of ICP hypertension by ICP pulse morphology analysis [2-3] and ICP waveform forecast [4-5], but the results were still not promising. In [2], twenty-four features in five categories (amplitude, time interval, pulse curvature, pulse slope, decay time constant) characterizing the ICP pulse morphology were shown to be useful in predicting ICP elevation. In recent years, discrete wavelet transform based artificial neural network algorithms were also applied to predict the exact ICP waveform, so as to identify the ICP trend [4-5]. However, satisfactory prediction results were reported for only up to three minutes.

In this paper, we propose an autoregressive integrated moving average (ARIMA) ICP forecast application with orders selection based on autocorrelation function and partial autocorrelation function. ICP elevation prediction may be viewed as a binary decision. Our research goes beyond the ICP elevation prediction, because we predict the continuous ICP trends to give a clearer picture and more information for clinicians. When the clinicians notice a dangerous upward trend which may lead to intracranial hypertension, they can then apply corresponding medical treatment according to prevent and control the impending intracranial hypertension. We applied the partial autocorrelation function (PACF) and the autocorrelation function (ACF) [6] in selecting the appropriate orders. We simulated online data streaming from twenty-seven patients' ICP records collected twenty-seven patients' ICP records from National Neuroscience Institute – Tan Tock Seng Hospital. We compared the ICP forecast accuracy of ARIMA model with orders selection on the basis of PACF and ACF and that of ARIMA model with orders selection on the basis of Akaike information criterion (AIC) [7]. Results of Wilcoxon matched pairs signed ranks test show that, the ICP forecast accuracy of ARIMA model with orders selection predicated on PACF and ACF is significantly superior to that of ARIMA model with

orders selection predicated on AIC, at the 5% level (p=0.05). In addition, the processing speed of ARIMA model with orders selection predicated on PACF and ACF is much faster.

To our best of knowledge, no ICP forecast application has been reported with forecast model selection based on visualizable PACF and ACF. In addition, no one has reported satisfactory ICP forecast for thirty minutes range.

2. Methodology

Nonstationarity of ICP

We forecasted the ICP mean of a future window based on the ICP mean extracted from past windows [8]. We divided the past ICP data into many time windows and further segment each time window into several finer sub-windows. Lower resolution is given to the remote data, while higher resolution to the recent data. We then derived the mean of the ICP for each past time window and its sub-windows as features for forecast. We first tested autoregressive moving average (ARMA) algorithm. ARMA worked well on relatively short ICP episodes (e.g, three minutes), which showed that short ICP episodes exhibits some ARMA behaviour. We then identified that ARMA did not work well for long (e.g., thirty minutes) ICP episodes, which were usually non-stationary. We chose ACF and Phillips-Perron unit root test to assess the stationarity, because the result can be quantified and visualized. This point was evidenced by the slowly dying patterns of the autocorrelation function plot of ICP episodes. This was further substantiated by the result that Phillips-Perron unit root test failed to reject the null hypothesis that the ICP is a unit root process with trend. Because the requirement of the data nonstationarity assumption, ARMA is not suitable for longer time horizon forecast.

Later we found that the nonstationarity problem in our ICP signal can be solved by differencing, which suggested that autoregressive integrated moving average (ARIMA) forecast model is suitable for our thirty minutes horizon ICP forecast. In patients' ICP data collected, we did not observe significant seasonality by PACF test and ACF test [6], so seasonal autoregressive integrated moving average algorithm (SARIMA) is not advised. Hence, we consider autoregressive integrated moving average (ARIMA) algorithm for forecasting. We also attempted to predict the ICP using linear regression approach. However, the negative R^2 (R^2=1-SS_{err}/SS_{tot}) yielded suggested that linear regression approach does not fit with our ICP forecast application.

ARIMA differencing order selection

As mentioned above, we solved the nonstationarity problem in our ICP signal by differencing, which was verified by the result of the ACF and Phillips-Perron unit root test. Usually, the nonstationarity was not significant in the first order differenced ICP data. If the nonstationarity can still be observed in the ACF of first order differenced ICP data, we can take higher order differencing on the ICP data, until the differenced data passes the Phillips-Perron unit root test and slowly-dying pattern cannot be observed. Because the evolving trends in ICP vary from time to time, we implemented an algorithm shown in Fig. 1 to select the appropriate differencing order d for our ICP forecast application. Generally, we found that first order or second order differencing was enough to transform our data to be stationary for forecasting.

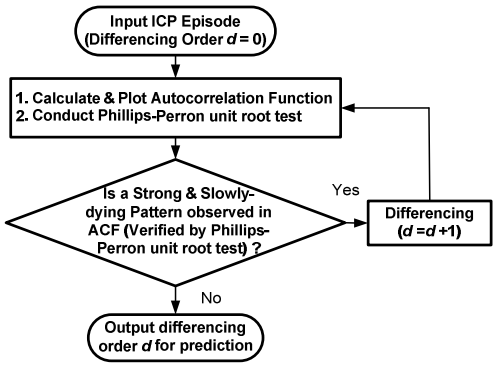

Figure 1: Flow chart of differencing order *d* selection algorithm

ARIMA autoregressive order and moving average order selection

Besides differencing order d, an appropriate ARIMA model also consists of another two orders: autoregressive order p and moving average order q. By the appropriate differencing order d obtained, we differenced the data of a particular ICP episode so that we can identify appropriate autoregressive order p and moving average order q from PACF and ACF of the differenced data.

The process of selecting autoregressive orders (p, q) of the d-th order differenced ICP data is depicted in Fig. 2. If the PACF of the d-th order differenced ICP data cuts off after lag p, and there is no significant lag in ACF of the d-th order differenced ICP data, the d-th order differenced ICP data can be modelled as a p-th

order autoregressive process. If the ACF of the *d*-th order differenced ICP data cuts off after lag *q*, and there is no significant lag in PACF of the *d*-th order differenced ICP data, the *d*-th order differenced ICP data can be modelled as a *q*-th order moving average process. As shown in Fig. 3, if the PACF of the *d*-th order differenced ICP data becomes very small in absolute value after lag *p*, and the ACF of the *d*-th order differenced ICP data becomes very small in absolute value after lag *q*, the *d*-th order differenced ICP data can be modelled as a (*p*, *q*)-th order autoregressive moving average process [6].

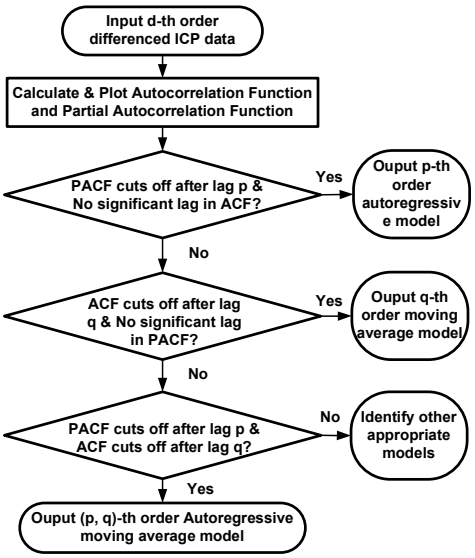

Figure 2: Flow chart of autoregressive order *p* and moving average order *q* selection algorithm

After finding appropriated orders (*p*, *d*, *q*) of ARIMA, we input the *d*-th order differenced ICP data into autoregressive moving average (*p*, *q*) sub-process. The output predicted was also *d*-th order differenced ICP, so we need to conduct *d*-th order integration to complete autoregressive integrated moving average (*p*, *d*, *q*) process in order to obtain the final ICP forecast data.

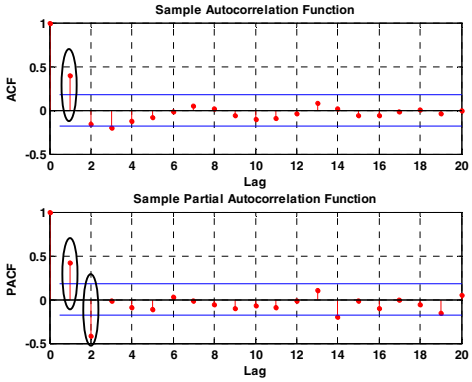

Figure 3: Selecting *p* and *q* by ACF and PACF

3. Results and Discussion

We simulated online ICP signal streaming from twenty-seven patients' ICP records collected from NICUs of National Neuroscience Institute - Tan Tock Seng Hospital, Singapore between 2009 ~ 2010. Patients underwent multi-modality monitoring with continuous recording for at least forty eight consecutive hours were included in our study. The ICP was measured invasively using a fibre-optic intraparenchymal gauge (Codman and Shurtleff, Taynham, MA). All the continuously monitored neurophysiological readings were sampled and recorded for every ten seconds on a Philips IntelliVue system. All medical records were anonymized and the study received ethics approval from the Institutional Review Board.

The raw ICP monitoring data collected from NICUs were usually contaminated by a considerable amount of artifacts. These artifacts indicate rapid and dramatic ICP oscillations, which are advised by neuroclinicians to be physiologically impossible. These artifacts not only trigger false alerts in neuromonitoring systems but also severely affect the accuracy of short-term ICP forecast. We detected all the artifact episodes by empirical mode decomposition method, because it does not affect the original characteristics of ICP signal [9]. We imputed the ICP values of artifact episodes by median filter. The patients' ICP records may also contain missing values, because of probe displacement, patient movement, neurosurgical intervention or human errors. We cleaned the ICP data by discarding the missing values.

After artifact removal and missing data cleaning, we forecasted the future thirty-minutes ICP mean. The performance accuracy is measured by coefficient of determination (R-squared (R^2)) and relative absolute

error (RAE). The R^2 (R^2=1-SS_{err}/SS_{tot}) is defined to be one minus the ratio between the sum of squares of residuals and the total sum of squares. The RAE ($RAE = \sum_{i=1}^{n} |P_i - T_i| / \sum_{i=1}^{n} |T_i - \overline{T}|$) is defined to be the ratio between the sum of the absolute values of residuals and the sum of the absolute values of the difference between each target value and the mean of all target values. Both R^2 and RAE measure how well the forecast model can predict the future outcomes.

We then compared the ICP forecast accuracy of ARIMA model with orders selection predicated on PACF and ACF and that of ARIMA model with orders selection predicated on Akaike information criterion (AIC) [7]. The results were summarized in Table 1.The mean and the standard deviation (Std) of the R-squared (R^2) of the ARIMA model with orders selection based on PACF and ACF are 0.898 and 0.082, respectively. In comparison, the mean and the standard deviation of the R^2 of the ARIMA model with orders selection predicated on AIC are 0.712 and 0.244, respectively. Results of Wilcoxon matched pairs signed ranks test show that, the ICP forecast accuracy of ARIMA model with orders selection predicated on PACF and ACF is significantly superior to that of ARIMA model with orders selection predicated on AIC, at the 0.05 p-value level.

We also compared the performance of ARIMA approaches with exogenous input artificial neural network artifical neural network (ANN) approach [4]. As shown in Table 1, ARIMA based on AIC is inferior to ANN in accuracy by 11.4% ((0.712-0.804)/0.804). The accuracy of ARIMA based on PACF and ACF is higher than that of ANN by 11.7% ((0.898-0.804)/0.804).

Table 1: Forecast Performance comparison between ARIMA on PACF and ACF and ARIMA on AIC (comparison with other methods)

Method	R^2 Mean	R^2 Std	RAE Mean	RAE Std	t (sec)
ARIMA PACF and ACF	0.898	0.082	0.254	0.109	0.002
ARIMA on AIC	0.712	0.244	0.394	0.167	1.723
ANN	0.804	0.170	0.352	0.124	0.667

Another important performance index for online forecast is the average processing time per each forecast *t*. As shown in Table 1, the average processing time of ARIMA model predicated on PACF and ACF is 0.002 sec, which is much faster than ANN and ARIMA on AIC.

4. Conclusions

Forecasting continuous ICP trends for patients with traumatic brain injury can greatly facilitate doctors to make timely treatments in order to save those patients from death. Motivated by urgent need and significant impact, we presented an ICP forecast application of the ARIMA model with orders selection on the basis of ACF and PACF. Forecast experiment results showed that the ICP forecast accuracy of ARIMA improved significantly with orders selection predicated on ACF and PACF, compared with ARIMA based on AIC and ANN. Besides, the average forecast processing time of ARIMA model predicated on PACF and ACF is much shorter than that of ARIMA predicated on AIC and that of ANN.

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