INTRACRANIAL PRESSURE OF PATIENTS AFTER SEVERE TRAUMATIC BRAIN INJURY: A PILOT STUDY FOR LETHALITY ESTIMATION FROM TIME SERIES

Michal Teplan[1], Ivan Bajla[1], Roman Rosipal[1], Martin Rusnák[2]

[1]Institute of Measurement Science, Department of Theoretical Methods,

Slovak Academy of Sciences, Bratislava, Slovakia

[2]Department of Public Health, Trnava University, Trnava, Slovakia

Abstract

Intracranial pressure (ICP) belongs among relevant physiological parameters that are advised to be monitored at emergency units with patients after severe traumatic brain injury. However no advanced tools in a form of alarm based on ICP time series were developed. Procedure for assessment regarding actual degree of lethality is presented. ICP time segments and its derived features are applied into Gaussian mixture model in order to form vital and lethal clusters. From consecutive processing of time evolution of posterior probabilities a monitoring tool for each patient is built. New form of alarm may attract attention of medical stuff in order to adopt appropriate intervention for patients' stabilization.

Keywords

intracranial pressure, time series segment features, gaussian mixture model, multivariate feature clustering, alarm function

Introduction

Measurement of ICP values over time period for patients with severe traumatic brain injury (TBI) represents an additional information source that could help to manage the patients' therapy in critical states during their hospitalization. Few papers describe attempts to analyse ICP waveforms from continuous monitoring [1-4]. For our pilot study a set of clinical records of ICP for 45 patients in the period of maximally 10 days were available. Within these data 34 records belonged to those patients who had survived and had been discharged from the intensive care unit in a stabilized state. The basic idea of how to utilize these data for making reliable clinical decision in every moment of the development of patients' health conditions is to explore a possibility of clustering time series segments of the records into clusters characterizing vital or lethal prognoses. Due to the various clinical limitations, the ICP recording was discretized into one-hour interval characterized by maximum value within this interval. The starting time of the ICP measurements varied for individual patients and for surviving patients the maximal duration of the ICP measurement was set to 10 days (240 time instants). The clinical protocol also leads to occasional discontinuity in the ICP recording caused by necessity to disconnect a patient for the time of examination at another clinical department. The remedy for all of such missing values has been made by linear interpolation of data.

Methods

Segmentation of ICP time series and construction of feature spaces

The ICP time series (Fig. 1, part A), acquired each hour, can be regarded as a collection of ICP values, x_1, x_2, ..., x_T, or as a T-dimensional vector $\boldsymbol{x}$ of real values. All ICP vectors (available in our case up to T = 240) constitute our sample set. It should be emphasized, that there is an essential difference between a conventional task of classification of any time series (or discrete bio-signals) and the task specific for our situation. Obviously, the attribute of vitality or lethality (two classes of the whole ICP

records) of the available ICP time series is known, however, what we are interested in, is a question, whether there exists a structure within a set of time segments of a whole ICP record or segments derived from it, which would provide useful auxiliary information on patient vitality prognosis in any time instant of the ICP values monitoring. The idea is that such a type of information could help the clinician to make a decision on necessary consecutive steps in any moment of patient treatment. Thus, we can consider a window with a pre-defined length w that can be slided along each ICP record generating a group of local segments of the ICP time series. It is reasonable to collect all obtained segments into a common data set for the whole ICP training sample set, and search for some clusters in this set (ideally one which represents segments characteristic for vital records, and another one representing "lethal" segments).

Various data clustering methods exist [5-7] in order to solve this task. After preliminary clustering experiments with segments of the length w = 6, 12, 18, 24, we found out that taking into account time segments of the ICP records independently of time, the obtained vital/lethal data clusters were strongly overlapped. Therefore we decided: i) to substitute (elementary) segments of ICP records by the segments of the ICP records which represent the parts with identical beginning (in the first measured instant) and variable length, that is vector $\boldsymbol{s}_k = (x_1, x_{2,\ldots,} x_k)$, where k = 18, 19, ..., 240; ii) instead of taking into account the original ICP values, to define appropriate "interval" feature vectors for each segment [8, 9]. The following features have been defined for the components of the vector $\boldsymbol{s}_k$:

1. maximum value,
2. mean value,
3. a ICP curve variability,
4. feature based on the length of a ICP curve,
5. covariance coefficient,
6. autocorrelation coefficient.

Thus, we experimented with a 6-dimensional feature space.

Gaussian mixture model for ICP time series clustering

Linear or quadratic discrimination analyses resulted in poor classification of the ICP-based features into vital and lethal classes. However, visual inspection of a lower dimensional space created by the first two components of the principal component analysis method applied to the extracted features indicated the existing cluster character of the ICP-based features. It appears that for such a data distribution, Gaussian mixture model (GMM) may be an appropriate quantitative model of multivariate cluster-based data fitting. We used the Matlab-based (Mathworks, version R2012b) toolbox Netlab [10] to implement GMM and to explore various situations of the ICP data clustering. Outcomes with various numbers of clusters (n = 2, 3, …, 7) were explored. The following procedure was used for labelling of each GMM cluster either by the lethality or vitality label. Let's denote by L/V the ratio between all used lethal (L) and vital (V) segments originated from lethal and vital patient records. Similarly, we denote by L_m/V_m the same ratio of the two types of segments in each obtained cluster Cm. Then, if $L_m/V_m > L/V$ we label the cluster C_m as lethal L', L'', ... otherwise as vital V', V'', ... The same is valid for a greater number of clusters. We have accomplished a cross-validation scheme called leave-one-out principle, in which data from one patient are left as a testing data representing a new patient with unknown prognosis (actually the ground truth for us at the same time), while the ICP-based features of the remaining 44 patients were used for training; that is building the corresponding GMM clusters. Having found the GMM clusters for the chosen number of clusters, values of posterior probabilities can be computed for every data point - sample. These probabilities reflect the degree to which the given data point belongs to each GMM cluster. Based on the time evolution of these probabilities for each patient a characteristic curve can be constructed and the level of expected vitality or lethality can be derived.

Development of an alarm function

As stated above, based on GMM clusters posterior probabilites a lethality or vitality monitoring system can be constructed. Since these probabilities are related to clusters whose labelling to lethal or vital was related to the overall ratio of samples belonging to vital and lethal patients, it is necessary to correct them by the corresponding ratios (of credibility) $L_m/(L_m+V_m)$ in each cluster (clusters L', L'', ... and V', V'', ... in Fig.1, part B). To get the overall characteristic, all posterior curves were summed over all lethal and vital curves separately. The resulting summed posterior curves for the lethal (L*) and vital (V*) clusters are plotted in Fig.1, part C. We investegated different heuristics for the construction of the so-called lethality/vitality expactation function and we have chosen the one we consider to posses the most appropriate behaviour. This expactation function was computed as subtracting the L* and V* curves. Based on the specific medical experience a treshold value can be set and an alarm will be triggered if the expectation function exceeds this treshold (Fig. 1, E).

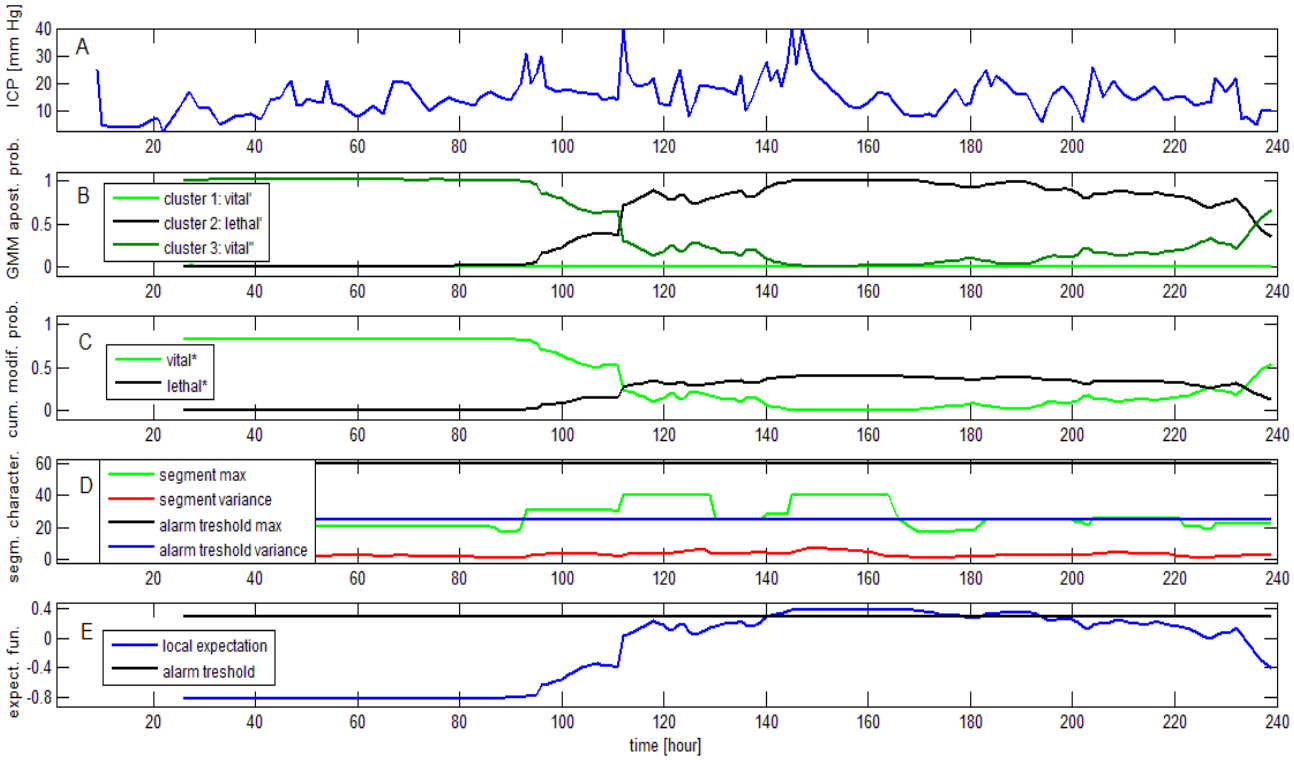

Fig. 1: Single lethal subject. A: ICP time series, B: posterior probabilities for each of three clusters, C: cumulative modified probabilities for joint vital and joint lethal clusters, D: Segment characteristics with conventional type alarm approach, E: local expectation function (subtraction of the two curves from C) serving for a new type of alarm signalization.

Results

Using the GMM with 3 clusters we were able to successfully recognize lethal status in seven out of the ten subjects that exited already in the unit of emergency care. Another two lethal patients were correctly reclassified with the GMM utilizing 7 clusters. One lethal patient was classified as vital but visual inspection revealed that this subject's ICP could represent an outlier when visually compared with the other lethal ICP records.

An example of correctly classified ICP patterns is presented in Fig. 1. Displayed ICP time series (part A) do not manifest any clear characteristics of the risk regarding patient status. The conventional approach of ICP reading in real time conditions by clinicians is represented in part D, where two main alarm features are presented: A patient is usually considered as endangered, if either the maximum values of ICP rises above certain critical level (in our case threshold set to 60 mm Hg) or the values are very unstable, i.e. in case of increased variability (threshold set to 25 mm Hg).

Our newly developed alarm is connected to expectation function Fig. 1 part E. The patient's risk curve with the part where it crosses the alarm threshold was computed in several consecutive steps; including utilized posterior probabilities for each of the 3 clusters from the GMM (part B) and cumulative modified probabilities computed separately for all lethal and vital cluster probabilities (part C).

Conclusion

Although the outcome from this preliminary study is based on a limited set of patients, the proposed approach to ICP data analysis is encouraging for useful application in automatic assessment of patients' risk of lethality. After further, more detailed investigations, we believe the proposed method may appear helpful for clinicians in real setting at intensive care units while dealing with patients after severe head injuries.

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Mgr. Michal Teplan, PhD.
Department of Theoretical Methods
Institute of Measurement Science
Slovak Academy of Sciences
Dúbravská cesta 9 84104, Bratislava, Slovakia

E-mail: michal.teplan@savba.sk
Phone: +421 259104537