Predicting Vasospasm after Subarachnoid Hemorrhage Using High-Frequency Physiological Data

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Conflict of Interest Disclosure & Acknowledgement

The co-authors have nothing to disclose with regard to commercial interests.

I do not plan on discussing unlabeled/investigational uses of a commercial product.
Multiple monitoring modalities of brain function and physiology

- ICP
- CPP
- TCD
- PbtO2
- Microdialysis
- Thermal Diffusion
- CBF
- NIRS
- Laser Doppler Flowmetry
- Cortical EEG
- Depth Electrodes

Heterogeneous streams of data
Different sampling rates
Missing data issues
In the time-pressured environment of critical care, providers require a great deal of cognitive fortitude to overcome the vital threshold of gaining even a holistic view of the patient.
Looking for Actionable Knowledge
Purpose of Neuromonitoring = NCC

PREVENT → IDENTIFY → TREAT

1. Assess extent of primary brain injury
2. Detect secondary brain injury – early enough, START RX
3. Measure effect of interventions – STOP RX
4. Prognosticate recovery/outcome
Purpose of Neuromonitoring = NCC

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Vasospasm after Aneurysm Rupture

14.5 per 100,000 in US

Compared to other strokes, younger patients

Substantial burden on health care resources

Long term functional and cognitive disability

Common disease entity (25% patient-days)

Timely interventions for VSP to prevent stroke:

1. **Prediction** scales: resource utilization (intensity of monitoring)

2. First 14 days: **Detect** preclinical or early VSP with TCD
Vasospasm Prediction based on admission CT

Baseline risk score: Fisher, Modified Fisher Scale
Used in clinical care
Advantageous for simplicity

<table>
<thead>
<tr>
<th>Symptom</th>
<th>Infarct</th>
<th>Vessel Narrowing</th>
<th>Reported in Liter.</th>
<th>Scale</th>
<th>Within study</th>
</tr>
</thead>
<tbody>
<tr>
<td>Angiographic VSP</td>
<td></td>
<td>X</td>
<td>50-70%</td>
<td>Fisher</td>
<td>27/41 (66%)</td>
</tr>
<tr>
<td>Delayed Cerebral Ischemia</td>
<td>X</td>
<td>X</td>
<td>19-54%</td>
<td>Claassen</td>
<td>54/276 (20%)</td>
</tr>
<tr>
<td>Symptomatic VSP</td>
<td></td>
<td></td>
<td>20-40%</td>
<td>Modified Fisher</td>
<td>451/1355 (33%)</td>
</tr>
</tbody>
</table>
‘It’s tough to make predictions, especially about the future’ (Danish, unknown)

Comparing two patients:
- Patient with MFS 4 2.2 times more likely to develop VSP than patient with MFS 1

Individual patient:
- 24% of patients with MFS 1 developed symptomatic VSP
Novel sources of data for prediction

Electronic Health Record (EHR)

Continuous Physiologic and Brain Monitors

- Orders
- Procedures
- Phenotype
- Assessments
- Laboratory
- Radiology
- Physiology
- Brain monitors

Are there patterns in high frequency time series data that are informative for VSP classification?

- No hypothesis of what, if any, pattern exists
VSP prediction

Challenges for VSP prediction
- Feature engineering (which variables are discriminative)
- Temporal prediction (how to translate continuous stream into actionable feature)
Random Feature Idea
Random Kitchen Sinks (RKS)

Kernel Learning
\[ f(x) = <w, \phi(x)> \]

Classifier

Project to infinite dimensional space
Create a gram matrix of size nxn
As n increases, becomes computationally challenging

Big Data

Proposed

Randomly Featurize
Project to finite low dimensional space

Linear Machine Training
\[ f(x) = w^T z(x) \]

Classifier

Making RKS temporal

1. Convolution
2. Different downsampling rates
3. Varying temporal lengths for random kernels

Multiply at each time point → take the integral of the multiplications
The higher your convolution, the better the pattern fits your data

Random featurization
extracting features at different scales
to capture time varying characteristics
for different variables
<table>
<thead>
<tr>
<th>Feature Extraction</th>
<th>Derivation Dataset (median AUC of 100 runs)</th>
<th>Validation Dataset (AUC, 95% CI)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PLS</td>
<td>SVM-L</td>
</tr>
<tr>
<td>Age</td>
<td>0.57</td>
<td>0.56</td>
</tr>
<tr>
<td>Sex</td>
<td>0.59</td>
<td>0.59</td>
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<tr>
<td>Hunt Hess</td>
<td>0.58</td>
<td>0.54</td>
</tr>
<tr>
<td>Modified Fisher Scale</td>
<td>0.51</td>
<td>0.53</td>
</tr>
<tr>
<td>Glasgow Coma Scale</td>
<td>0.41</td>
<td>0.43</td>
</tr>
<tr>
<td>Combined Baseline</td>
<td>0.64</td>
<td>0.60</td>
</tr>
<tr>
<td>Diastolic BP</td>
<td>0.56</td>
<td>0.59</td>
</tr>
<tr>
<td>Systolic BP</td>
<td>0.68</td>
<td>0.60</td>
</tr>
<tr>
<td>HR</td>
<td>0.59</td>
<td>0.55</td>
</tr>
<tr>
<td>SpO2</td>
<td>0.59</td>
<td>0.51</td>
</tr>
<tr>
<td>RR</td>
<td>0.57</td>
<td>0.51</td>
</tr>
<tr>
<td>Combined Physiologic</td>
<td>0.73</td>
<td>0.53</td>
</tr>
<tr>
<td>Baseline + Physiologic</td>
<td>0.74</td>
<td>0.55</td>
</tr>
<tr>
<td>mRMR</td>
<td>0.77</td>
<td>0.59</td>
</tr>
</tbody>
</table>
What if our prediction model is a detection model?

CDS based on physiological data:
- Earlier identification of subclinical onset of syndrome
- Reducing time to diagnosis
- Intervening before permanent injury
Conclusions

Higher frequency time series data are superior to lower frequency data for discriminatory feature generation in VSP classification.

“Automateable” monitor data prior to peak VSP period shows promise to provide individualized prediction of VSP.

This might be an informative feature extraction approach with universal subset of physiologic parameters (HR, RR, SBP, DBP, O2 sat).

Syndromes with insidious onset are a peculiar case for data mining experiments.
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