Utility of Empirical Models of Hemorrhage in Detecting and Quantifying Bleeding

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Situation

Hemorrhage is a life-threatening condition that that, if not **detected** and **treated early**, may lead to **cardiovascular shock**.

Hypothesis & Goal

Machine Learning (ML) approach can be used to build informative models from hemodynamic data records.
Such models could reliably and consistently **detect onset of bleeding**, **estimate bleed rate** and the **amount of blood lost**

Methodology

A. Previously healthy pigs are anesthetized, intubated, ventilated and instrumented with routine invasive **hemodynamic monitoring equipment**.

B. Controlled hemorrhage is induced at a **constant rate of 0 (sham), 5 or 20 mL/min** to a mean arterial pressure of 30-40 mmHg.

C. Multiple **commonly monitored physiologic variables** are collected and used as input of prototype ML system trained to **identify bleed onset**, **bleed rate**, and the **amount of blood lost**.

D. **Training** and **evaluation** of several models are done using **leave-one-subject-out cross validation protocol**. Presented results from **Random Forest** models.

E. In addition, ML models provided descriptions of the **importance** and **impact** of each physiologic variable.

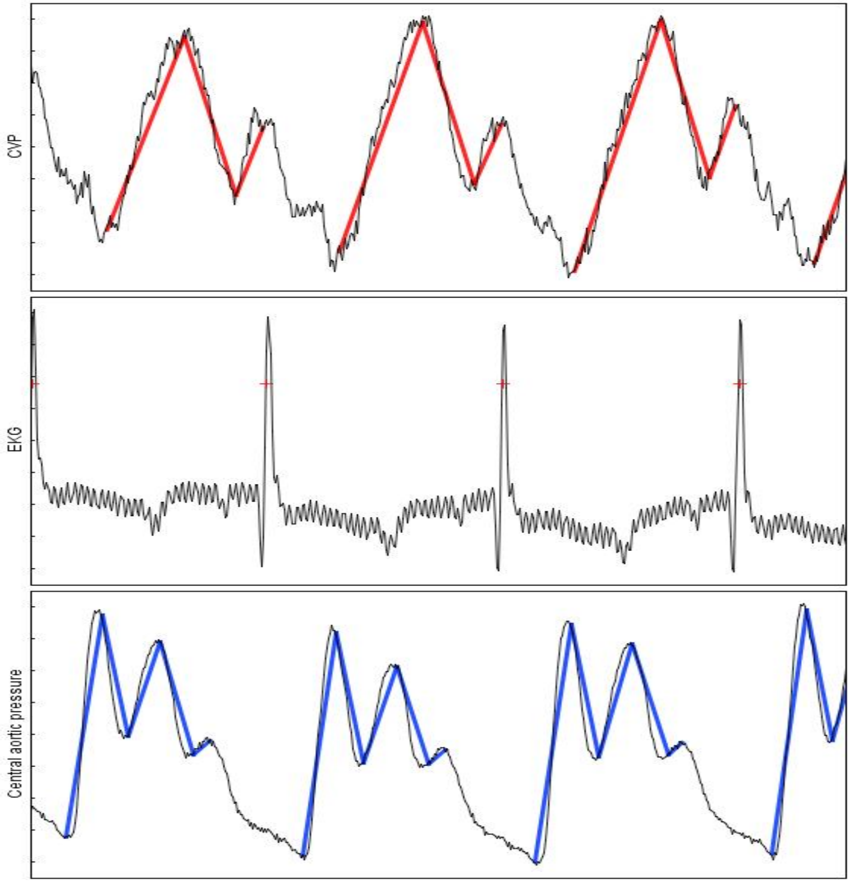
Extracting features

Input

Systolic blood pressure, **diastolic blood pressure**, **mean arterial blood pressure**, **cardiac output**, **stroke volume**, **stroke volume variation**, **pulmonary artery pressure**, **heart rate** are collected every second. **EKG**, **arterial pressure**, **pulmonary pressure**, **CVP**, **CCO**, **SvO2** and **SpO2** are collected 250 times per seconds.

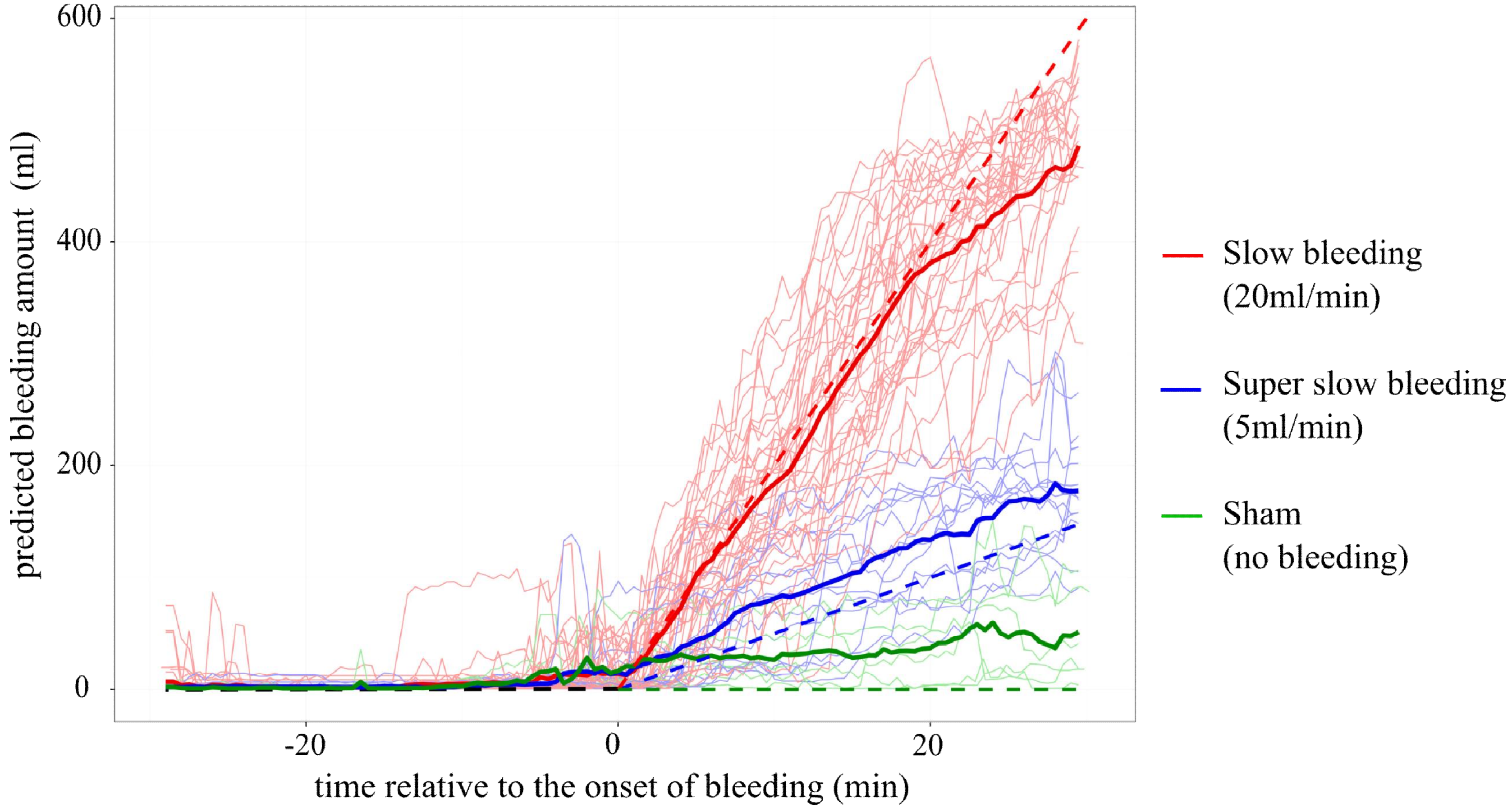
Processing

A large number of features is extracted from raw data. Including various **moving averages** and **moving variances**, **frequency analysis** of the CVP waveform, and **characterization** of both the CVP and arterial pressure waveforms. Tracking of **breathing**.



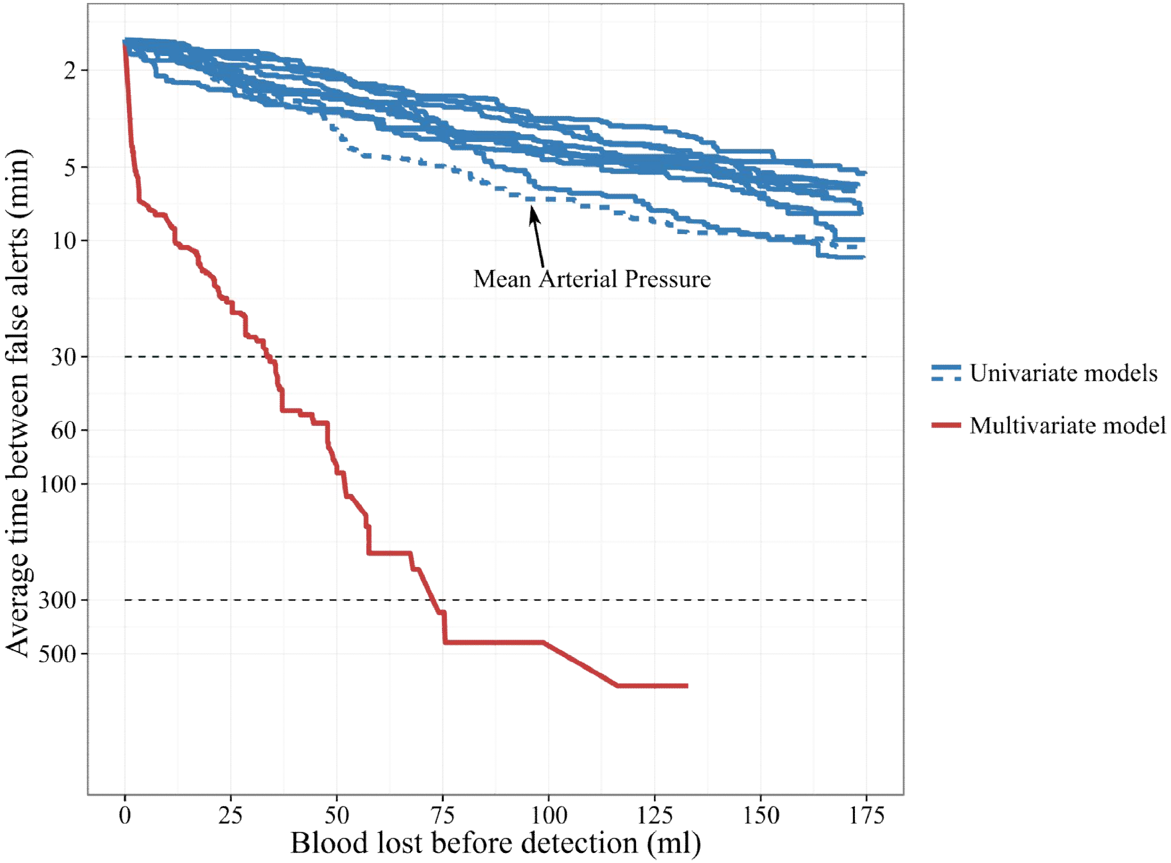
This plot shows an example of one of our features. Here, you can see the characterization of CVP and Central aortic pressure waveform by polygons fitting.

Predicted bleeding amount



This plot shows the **predicted bleeding** for each pig individually (thin lines) and by group (large lines). Dotted lines represent the ground truth that our model try to predict.

Evaluation of bleeding detection



This plot is (called AMOC) shows the relation between the **amount of blood lost before detection** (x axis) and the **average time between two consecutive false alerts** (y axis). The optimum point of this plot in the bottom left corner.

Our technique is represented in red. Detectors based on each vital sign individually are represented in blue.

As an example, the plot tells you that our technique is able to detect bleeding in average after 75mL of blood lost (3.75 min with a bleeding of 20 mL/min) , while generating a false alert every 450 min (every 7.5 hours).

With similar time before detection, using direct vital signs leads to generate a false alert every 5 min.

Estimated importance of derivative features

The impact of each vital sign and each featurization is measured.

Rank	Vital	High level featurization	Gain
1	CVP	averaging + trend over time	.382
2	CVP	waveform shape + trend over time	.136
3	Sys BP	averaging + trend over time	.135
4	Pulmonary Pressure	averaging + trend over time	.101
5	Pulse Pressure	averaging + trend over time	.084
6	Pulmonary Pressure	averaging + trend over time	.080
7	CVP	waveform shape + trend over time	.0778
8	CVP	frequency analysis+ trend over time	.0550
9	CVP	waveform shape + trend over time	.0469

This table shows the impact of each vital sign and each featurization in our detector. Only the top 9 vitals+features are shown.

We observe the CVP to be very informative. It is not the raw value of CVP that matter, but values derived from it. “averaging + trend over time” refers to on of the many of our features that characterize the evolution of CVP over time.

Other important vitals are the Systolic blood pressure, pulse pressure and pulmonary pressure.

The impact of raw vital sign value is very low and would be at the bottom of this table (not represented). The conclusion is that featurization of vital sign is essential.

Conclusion

- Machine Learning (ML) can be used to enable **efficient** and **robust detection**, **tracking** and **characterization** of bleeding.

- ML based tools could also be used to inform the **understanding** of physiological responses to bleeding.

- **Vital featurization** and **personalized features** are the essential for good performances.

