Low-Complexity Tracking of Neurological State using Manifold Learning

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ABSTRACT

We present recent results on tracking and denoising of quasi-periodic biosignals, and their application in the detection of critical patient states. In particular, we present an efficient method for tracking neurological state using a dimensionally-reduced non-linear manifold of routinely measured physiological and neurological signals, such as intracranial pressure (ICP), transcranial doppler (TCD), and electrocardiogram (ECG).

MANIFOLD LEARNING

If continuous quasi-periodic biosignals can be segmented and normalized into consecutive pulses or beats, denoted as $x_i \in \mathbb{R}^n$, then the goal of manifold learning is to learn a low-dimensional subspace representation of these signals, denoted as $s_i \in \mathbb{R}^m$, such that pulses that are similar in the time-domain representation are also close in the dimensionally-reduced ($n < m$) subspace representation. This can be achieved by minimizing the measure:

$$\epsilon = \sum_{i,j=1} (s_i - s_i)^2 \cdot W_{i,j} = 2\, S^T\, L\, S$$

where W is a graph with edges $W_{i,j}$ reflecting the similarity between pulses x_i and x_j, $L = D - W$ is the graph Laplacian, and D is a diagonal matrix storing the column sums of W. The optimal S can be obtained by finding the largest k generalized eigenvectors λ of the eigen-problem: $W\, S\, = \lambda\, D\, S$.

Moreover, we can constrain the learning of the manifold to incorporate clinically-relevant priors by modifying the edges of the graph W to reflect a non-linear measure of similarity between the pulses. In Figure 1, for example, we compute a 3D embedding of ICP signals that incorporates ICP pulse morphology, its average value, and a time-index relative to a critical state (intracranial hypertension).

LOCALIZATION AND RECONSTRUCTION

A graph representation of data enables relevant variations in signals to be more easily quantified.

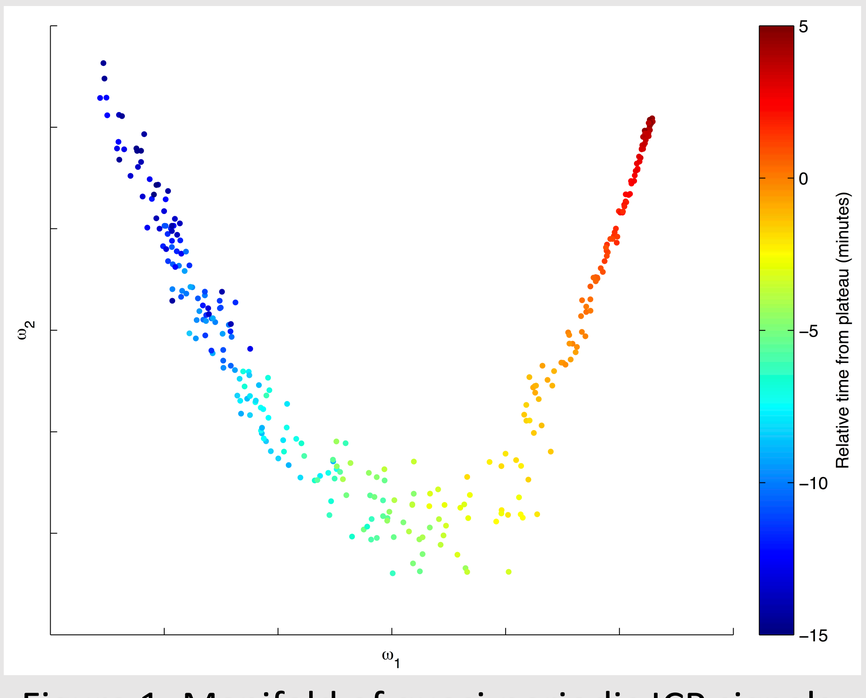


Figure 1: Manifold of quasi-periodic ICP signals.

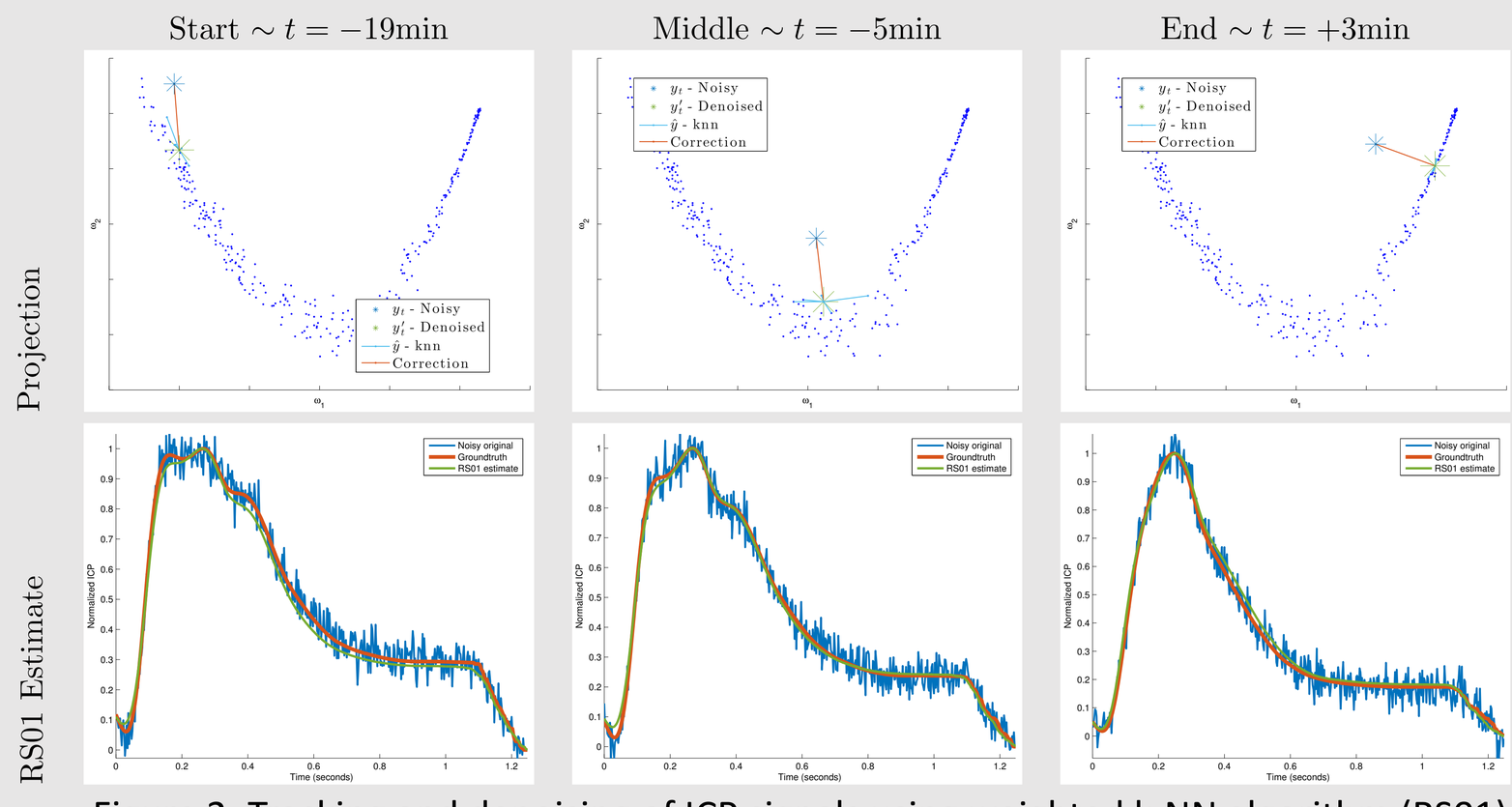


Figure 2: Tracking and denoising of ICP signals using weighted k-NN algorithm (RS01).

TRACKING AND PREDICTION

With an appropriately-chosen weighting function, the semantic ordering of projected pulses can be exploited to perform low-complexity tracking and high-accuracy prediction of critical patient states.

For example, ICP can be predicted using low-order auto-regressive moving-average (ARMA) models:

$$\hat{s}_{k+1} = \sum_{i=0}^{M} \alpha_i s_{k-i} + \sum_{j=0}^{N} \beta_j p_{k-j}$$

$$\hat{x}_{t+1} = f^{-1}(\hat{s}_{k+1})$$

where $M, N \leq 30$, and $f^{-1}(\cdot)$ denotes an inverse mapping. These are preferable to higher-order controllers, which often suffer from instability.

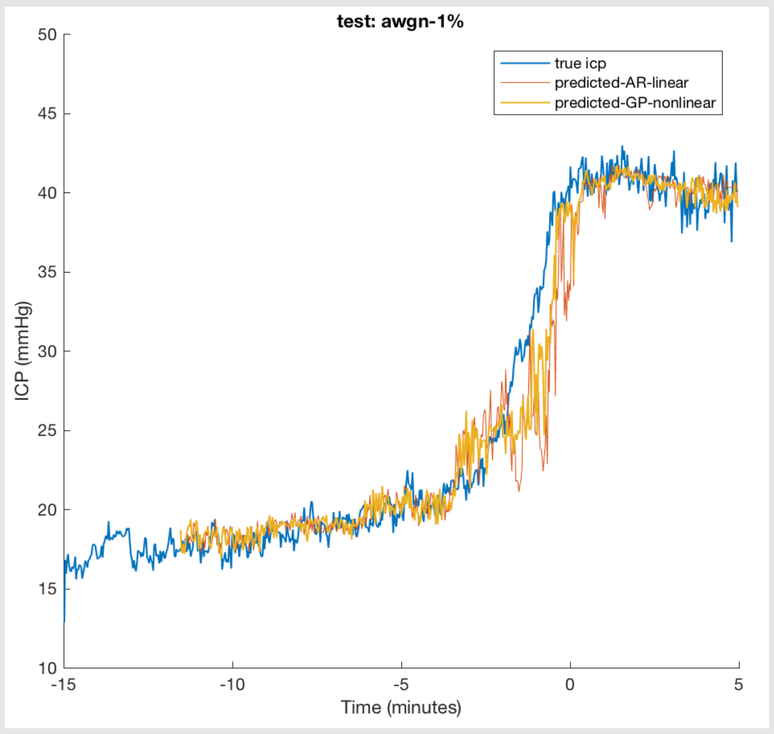


Figure 3: Prediction of ICP 5-min ahead in time with $\geq 90\%$ relative accuracy in value.

CONCLUSION

Our experiments demonstrate that critical patient-states can be predicted with high-accuracy several minutes prior to their onset by continuously tracking high-dimensional biosignals on on low-dimensional manifolds. This subspace representation of data enables the realization of stable, intuitive, and ultimately visualizable, low-complexity algorithms that can aid clinicians in real-time prognosis and risk-abatement tasks.