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Spatio-temporal Gaussian processes for separation of ventilation and perfusion related signals in EIT data

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Abstract: Electrical impedance tomography (EIT) is used to measure regional changes in the impedance of the lung tissue caused by changes in either ventilation or perfusion. The separation of these two effects is a longstanding problem with important implications in mechanical ventilation. Unfortunately, previous approaches to perfusion/ventilation separation are not satisfactory. In this work, we introduce a new algorithmic approach, which models both signal components as non-stationary spatio-temporal Gaussian processes (GPs) and we show that the corresponding inference problem can be solved efficiently by exploiting structure in the GP's kernel matrix. More specifically, we enable fast matrix-vector multiplications with the full kernel matrix in a novel variant of a previously proposed scalable GP approach called structured kernel interpolation. We show preliminary results of our method on a first EIT dataset.

I. Introduction

Thoracic electrical impedance tomography (EIT) is a medical imaging modality that measures regional impedance changes within the lung. These impedance changes are mainly caused by ventilation of the lung tissue and to a lesser extent by its perfusion [1]. It was previously suggested, that a separation of these two effects would enable the calculation of regional ventilation-perfusion ratios (V/Q-ratio), which is an important clinical quantity in mechanically ventilated patients [2]. Still, the separation of ventilation and perfusion related signals is a challenging task due to the high difference in amplitudes between the two signals and significant band overlap in their spectra.

Previous approaches have employed pixel-wise Fourier filtering [3], template extraction [4] and principal component analysis (PCA) [2]. Yet, none of the methods has managed to solve the problem to a satisfactory degree – the most promising candidate appears to be the PCA-based approach, which however relies on an initial training phase and a subsequent filtering phase (in which the learned principal components are kept constant). This inherently prevents adaptation to changes in the respiratory or cardiac waveforms over time.

In this paper, we show that the separation of the two pulsatile components in EIT images can be posed as a spatio-temporal GP regression problem using a mixture of non-stationary kernels. As opposed to previous methods, our model does allow to explicitly account for spatial as well as temporal correlation using a concise Bayesian formulation of the source separation task. We show that the corresponding inference can be solved using an iterative structure exploiting GP regression scheme.

II. Material and methods

A Gaussian process is used to encode our prior belief in the distribution of the spatio-temporal EIT data. As a model for the two superposed effects we use the following kernel:

$$\begin{aligned} k_{\mathrm{m}}(\boldsymbol{s},\boldsymbol{s}',t,t') &= k_{\mathrm{vent}}(\boldsymbol{s},\boldsymbol{s}',\phi_1(t),\phi_1(t')) \\ &\quad + k_{\mathrm{perf}}(\boldsymbol{s},\boldsymbol{s}',\phi_2(t),\phi_2(t')) \\ &= k_{\mathrm{vent,SE}}(\boldsymbol{s},\boldsymbol{s}')k_{\mathrm{vent,QP}}\big(\phi_1(t),\phi_1(t')\big) \\ &\quad + k_{\mathrm{perf,SE}}(\boldsymbol{s},\boldsymbol{s}')k_{\mathrm{perf,QP}}\big(\phi_2(t),\phi_2(t')\big), \end{aligned}$$

where $\boldsymbol{s}$ corresponds to the spatial domain (i.e. EIT pixels) and t corresponds to the temporal domain. The spatial correlation is described by a squared exponential kernel (SE) while the temporal correlation is modeled by a quasi-periodic kernel (QP), which is warped through the non-linear functions ϕ_1 and ϕ_2 to account for natural fluctuations in the respiratory and heart rate. The mean of the GP is chosen to be zero: $m(\boldsymbol{s},t) = 0$, and we assume that the measured datapoints are subject to additive Gaussian white noise.

The proposed kernel depends on some free hyperparameters, which can be learned by optimization of the log marginal likelihood. The source separation problem can then be solved by calculating the posterior distribution corresponding to either of the two kernels in the sum [5].

Unfortunately, standard GP inference and log marginal likelihood evaluations are restricted to datasets with at most a few thousand datapoints due to the heavy computational requirements of $\mathcal{O}(n^3)$ involved in computing the inverse and the log determinant of the kernel matrix. Thus, the standard GP solution cannot be applied to typical EIT datasets (with possibly hundreds of thousands of datapoints).

II.I. Warped structured kernel interpolation

Different approaches to scalable GP inference have been introduced in the literature – one such method is the structured kernel interpolation (SKI) [6], which imposes Toeplitz and Kronecker structure on the kernel matrix via a set of equispaced/grid-structured inducing points. This leads to an approximate form for the full kernel matrix:

$$K_{X,X} \approx W K_{U,U} W^T \coloneqq K_{\mathrm{SKI}},$$

here, X denotes the set of input points (in this case, the spatio-temporal values of the EIT data) and U denotes the set of inducing points. The matrix $K_{U,U}$ is structured (Kronecker and Toeplitz structure) and the interpolation matrix W can be constructed as a sparse matrix, thus enabling very fast matrix-vector multiplications (with quasi-linear $\mathcal{O}(n)$ complexity). This allows to efficiently solve the inference problem and to compute the log marginal likelihood via iterative methods [6, 7]. SKI was shown to scale to possibly millions of datapoints.

Unfortunately, in standard SKI, Toeplitz structure cannot be exploited in the proposed kernel due to its summation structure and due to the non-stationarity of the warping functions ϕ_1 and ϕ_2. Therefore, based on SKI, we introduce a novel approximation to the non-stationary kernel used in this paper, which we call warpSKI. We propose to use two sets of non-equispaced inducing points $\widehat{U}_1 = \Phi_1^{-1}(U_1)$ and $\widehat{U}_2 = \Phi_2^{-1}(U_2)$, where Φ_1^{-1} and Φ_2^{-1} denote the application of the inverse of the two warping functions to all points in the equispaced/grid-structured inducing points sets U_1 and U_2. We proceed to specify the full approximate form of the proposed kernel:

$$K_{\mathrm{m}\,X,X} = W_1 K_{\mathrm{perf}\,U_1,U_1} W_1 + W_2 K_{\mathrm{perf}\,U_2,U_2} W_2,$$

here, W_1 and W_2 are sparse weight matrices constructed to interpolate between the input points X and the warped inducing points $\widehat{U}_1$ and $\widehat{U}_2$, respectively. As in standard SKI, the two kernel matrices have Kronecker and Toeplitz structure, thus allowing for fast matrix-vector multiplications with the full kernel matrix. As in standard SKI, iterative methods can be applied to solve the inference and to evaluate the log marginal likelihood in quasi-linear time.

III. Results

The considered EIT dataset of a spontaneous breathing neonate is from [8]. We use the first 215 frames to train our model and as a measure of training success we predict the next frame and evaluate the prediction error (using normalized root-mean square error). The phase warping functions ϕ_1 and ϕ_2 are determined directly from the data – the respiratory phase was extracted from a pixel belonging to the left lung, the cardiac phase was extracted from a pixel between the two lungs. The total number of input points is $n = 699\,825$. The two non-equidistant inducing point sets $\widehat{U}_1$ and $\widehat{U}_2$ are used to impose Kronecker and Toeplitz structure on the kernel matrix. For the hyperparameter optimization, it can be beneficial to use hyperpriors and fix some of the hyperparameters (based on prior knowledge about the data) to guide the optimization. Here we optimize for the variances σ_{vent}, σ_{perf}, the length-scales of the spatial kernel $l_{\mathrm{vent,SE}}$, $l_{\mathrm{perf,SE}}$ and the length-scales of the time domain $l_{\mathrm{vent,SE\,QP}}$, $l_{\mathrm{perf,SE\,QP}}$ with regularizing lognormal hyperpriors on all of the length-scales. The remaining hyperparameters were set to fixed values based on prior knowledge about the data.

All calculations were done on an INTEL Core i7-6700K CPU. The optimization of hyperparameters took ~9 hours and the subsequent perfusion-ventilation separation was calculated in 159.1 seconds. The nRMSE on the test frame was 0.176, indicating a good model fit. Fig. 1 shows the result of the successful source separation on the considered dataset.

IV. Discussion and conclusions

We have introduced a novel solution to the EIT perfusion-ventilation separation problem using a Gaussian process model. The validity of the method was demonstrated on one dataset. As opposed to previous methods, our model offers a concise Bayesian formulation for both temporal and spatial structure in the data. As yet, the learning of hyperparameters is still too expensive for practical use – this problem might be solved by restricting the hyperparameter search to a finite set of predefined hyperparameter configurations (corresponding to some known breathing types). In the future, we plan to evaluate our method on more datasets and compare it to the previous PCA-based approach.

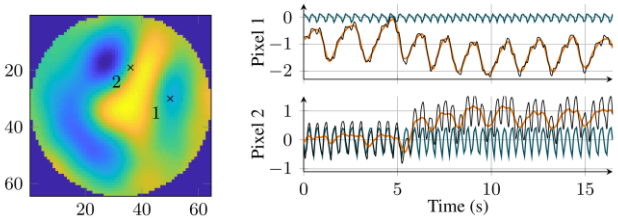

Figure 1: Result of EIT perfusion-ventilation separation. Time traces correspond to the marked pixels and include measured signals (black), the posterior mean of perfusion related signals (green) and the posterior mean of ventilation related signals (orange).

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