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Chemical Sensors with Deep Spatiotemporal Priors

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Abstract: We propose a variational approach to recover concentration from raw fluorescence images of chemical sensors. This allows us to impose prior knowledge regarding the spatiotemporal distribution of the concentration while accounting for the sensor kinetics.

1. Introduction

Chemical sensors are used to measure the properties of specific compounds inside a sample. Some of these sensors emit light upon binding to or unbinding from these compounds, indirectly reporting their concentration. The kinetics of this reversible process dictates the timescale of the reporting. It is therefore critical to account for this kinetics, especially when the concentration of the compound varies at a similar timescale. To illustrate this work, we consider a family of fluorescent reporters that stops emitting light upon binding to H_2O_2 [1].

2. Methods

Let $g(\mathbf{x},t)$, $\mathbf{x}\in\Omega$, denote the (normalized) fluorescence measurements that are recorded during a time interval $[0,T)$ in the domain $\Omega\subset\mathbb{R}^2$ of a sample. The measurements are related to the concentration $c(\mathbf{x},t)$ of a specific compound inside the sample through a reversible first-order binding process. Formally, this can be represented by the ordinary differential equation

$$\frac{g(\mathbf{x},t)}{\mathrm{d}t} = k_{-b}\,(1-g(\mathbf{x},t)) + k_b g(\mathbf{x},t)c(\mathbf{x},t), \tag{1}$$

where k_b and k_{-b} are the binding and unbinding rates, respectively [1].

We sample g and c on a equispaced spatial grid with N points and at $N_t = T/\Delta t$ time points with time step Δt. The samples of g are concatenated into a matrix $\mathbf{G}\in\mathbb{R}^{N\times N_t}$. In practice, we measure the fluorescence images at a larger time step $\Delta t_M = D\Delta t$ with a downsampling factor $D\in\mathbb{N}$. We then obtain the matrix $\tilde{\mathbf{G}} = \mathbf{G}\mathbf{S}_D$ of measurements, where $\mathbf{S}_D\in\mathbb{R}^{N_t\times(N_t/D)}$ encodes the downsampling operation.

In this work, we reconstruct the concentration using a deep spatiotemporal prior [2, 3]. In this framework, the concentration at time $t\in[0,T)$ is the output $\mathbf{c}(\boldsymbol{\theta},t) = \mathbf{f}_{\boldsymbol{\theta}}(\mathbf{z}_t)$ of a neural network $\mathbf{f}_{\boldsymbol{\theta}}:\mathbb{R}^P\to\mathbb{R}^N$ parameterized by $\boldsymbol{\theta}$. The input vector $\mathbf{z}_t = \mathbf{z}_0 + \frac{t}{T-\Delta t}(\mathbf{z}_T - \mathbf{z}_0)$ is a linear combination of two fixed vectors $\mathbf{z}_0,\mathbf{z}_T\in\mathbb{R}^P$. The advantages of this method are twofold. First, a spatial prior is enforced by a classical deep image prior [4, 5]. Second, we enforce temporal regularity on the sequence: a single neural network generates the whole sequence, while the design of the input vectors encodes the temporal proximity of consecutive frames.

To recover the concentration, we optimize the minimization problem

$$\boldsymbol{\theta}^* \in \arg\min_{\boldsymbol{\theta}\in\mathbb{R}^P} \|\mathbf{H}(\mathbf{C}(\boldsymbol{\theta},\Delta t))\mathbf{S}_f - \tilde{\mathbf{G}}\|_1, \tag{2}$$

where $\mathbf{C}(\boldsymbol{\theta},\Delta t) = [\mathbf{f}_{\boldsymbol{\theta}}(\mathbf{z}_0),\mathbf{f}_{\boldsymbol{\theta}}(\mathbf{z}_{\Delta t}),\ldots,\mathbf{f}_{\boldsymbol{\theta}}(\mathbf{z}_{\Delta t(N_t-1)})]\in\mathbb{R}^{N\times N_t}$ is the concatenation of the generated frames of the sequence and $\mathbf{H}:\mathbb{R}^{N\times N_t}\to\mathbb{R}^{N\times N_t}$ solves (1) for the fluorescence using a backward Euler method with step size Δt.

3. Results

We used a diffusion equation to simulate the propagation of the compound of interest in a leaf-like sample. The concentration propagates rapidly along the veins and slowly elsewhere. The fluorescent measurements are simulated from the concentration with a reaction equation, downsampled with $f = 5$, and corrupted with Poisson noise.

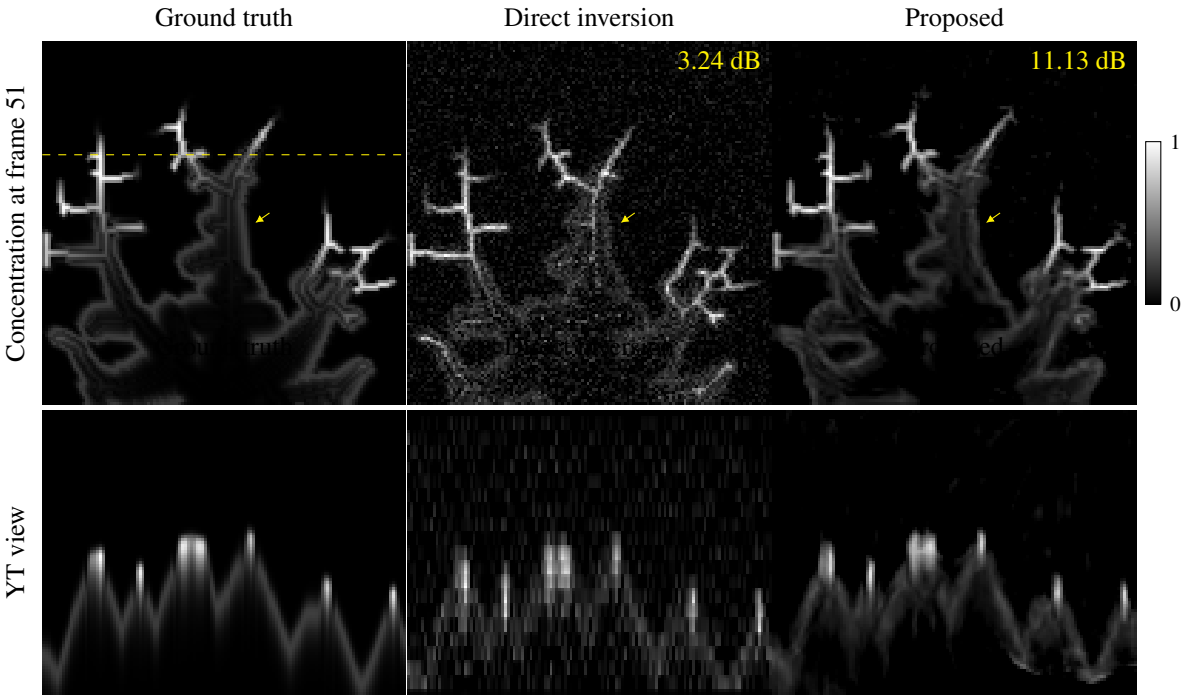

Fig. 1. Concentration profiles. Top row: XY view of the concentration at frame 51. Bottom row: YT view of the concentration at $Y = 40$ (indicated by the dashed line). For each method, the signal-to-noise ratio of the whole sequence is indicated in the top right corner in the first row.

Figure 1 shows the concentrations estimated by a direct inversion of (1) in comparison with our proposed method. The direct inversion entails an exponential smoothing of the measurements in time. As a result, it is sensitive to noise, especially in the non-vascular region, where the concentration is low. By contrast, the deep spatiotemporal prior mitigates the artifacts resulting from noise, and the areas where the propagation is slow are well recovered. The signal-to-noise ratios computed for each reconstruction confirm our visual inspection (3.24 versus 11.13dB).

4. Conclusion

We have proposed a variational formulation with a deep spatiotemporal prior to recover the concentration of a compound from noisy fluorescent images of chemical sensors. Our results suggest that such a framework allows us to accurately recover the spatiotemporal profile of concentration in spite of the noise and the downsampling.

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