Online learning in motion modeling for intra-interventional image sequences

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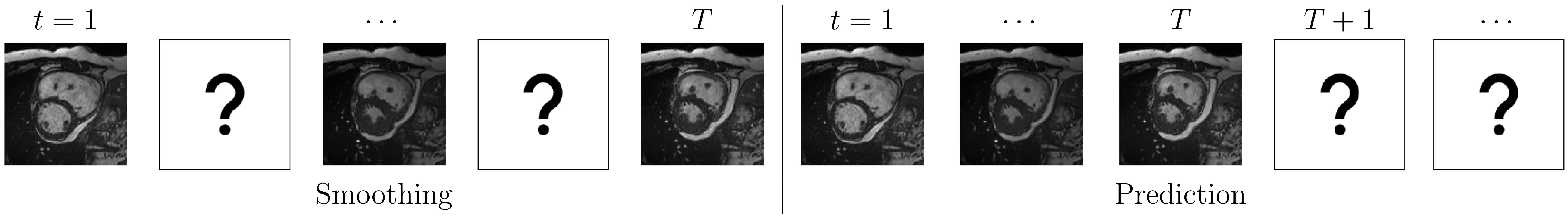
Motivation & Research Goals

Motion modeling, a model with possibility of estimating the motion at previous, current and future times t, is crucial for undersampled intra-interventional imaging [1]. Modeling the motion as the deformable vector field (DVF) enable transferring prior knowledge, like segmentations from a predefine image to the sequence.

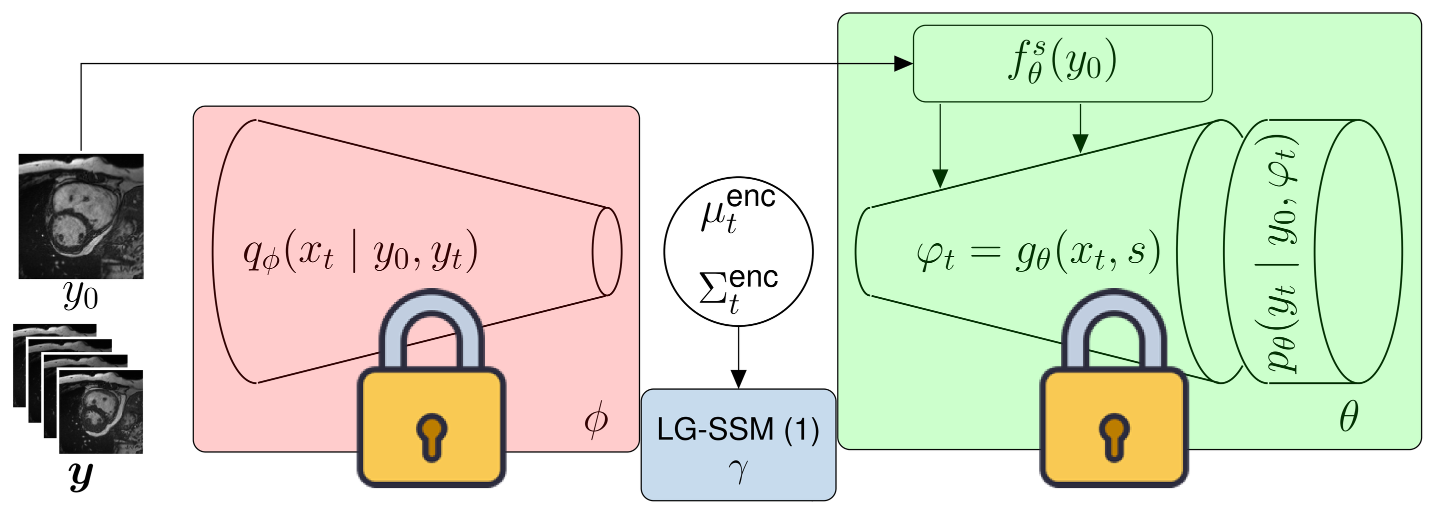


Methods

The motion model [2] is defined in a low-dimensional space as a LG-SSM,

$$z_t|z_{t-1} \sim \mathcal{N}(z_t|Az_{t-1}, Q), \quad x_t|z_t \sim \mathcal{N}(x_t|Cz_t, R), \tag{1}$$

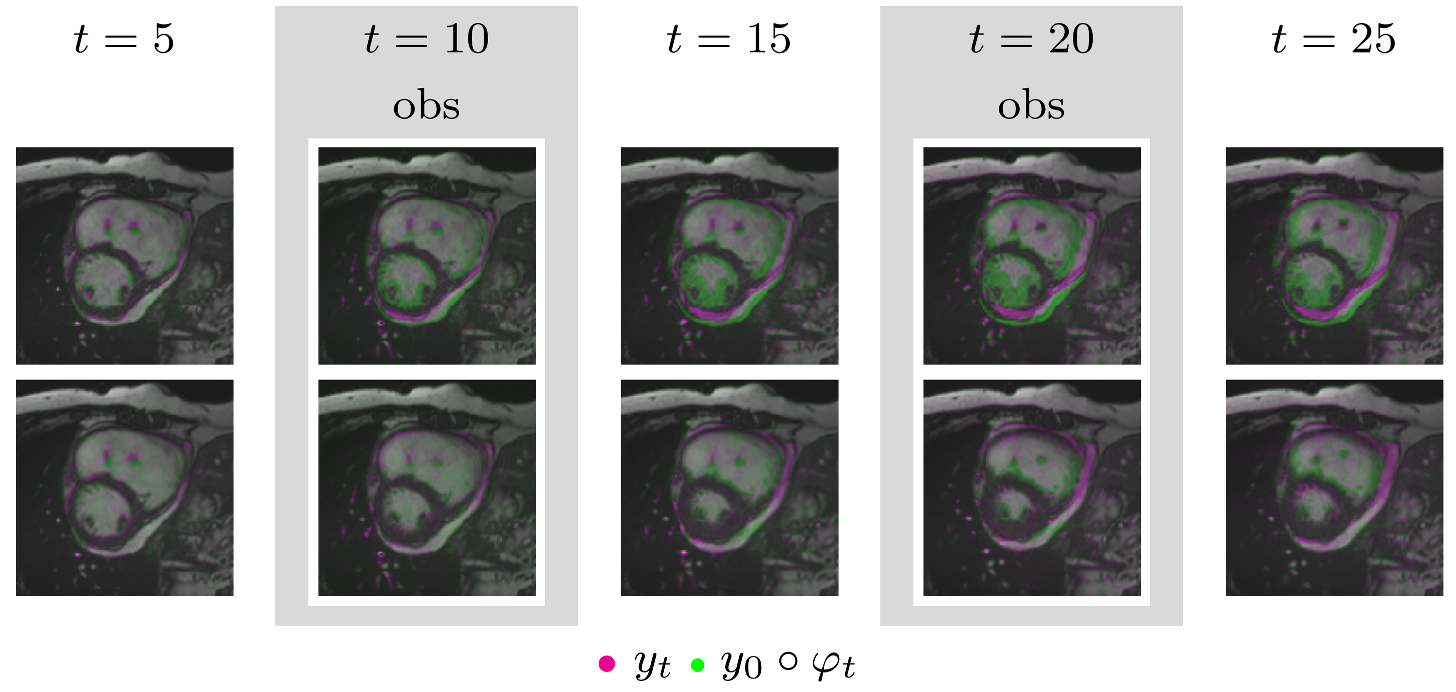
with analytical solutions to the inference problems. We can train the dimensionality reduction and the LG-SSM simultaneously using variational inference with the LG-SSM as a prior for a VAE, and improve the LG-SSM by maximizing the exact log-likelihood online [3], for new unseen sequences, i.e.,

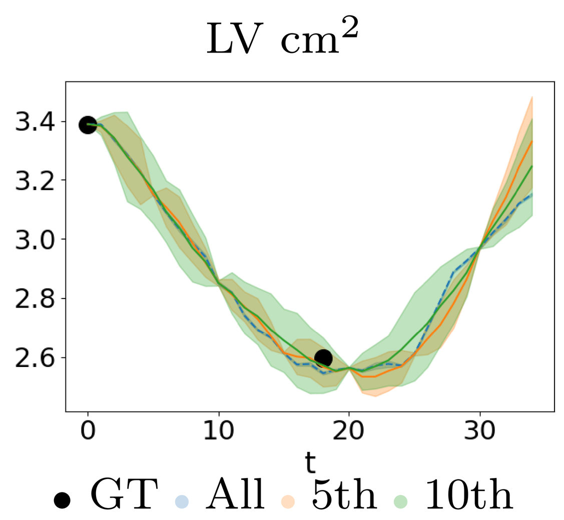


$$\log p(\boldsymbol{y} \mid y_0) \geq \mathbb{E}_{q_\phi(\boldsymbol{x}|y_0,\boldsymbol{y})}\left[\log \frac{p_\theta(\boldsymbol{y} \mid y_0, \boldsymbol{\varphi})}{q_\phi(\boldsymbol{x} \mid y_0, \boldsymbol{y})} + \mathbb{E}_{p_\gamma(\boldsymbol{z}|\boldsymbol{x})}\left[\log \frac{p_\gamma(\boldsymbol{x}, \boldsymbol{z})}{p_\gamma(\boldsymbol{z} \mid \boldsymbol{x})}\right]\right], \quad \max_{\gamma_t} \log p_{\gamma_t}(x_{t-N:t}) = \max_{\gamma_t} \log \prod_{k=t-N}^{t} p_{\gamma_t}(x_k \mid x_{k-1}).$$

Smoothing (Pre-trained model 15 ms)

Overlay of true sequence (magenta), and $\varphi_t = 0$, on top, and our estimation given every 10th sample, on bottom (green).



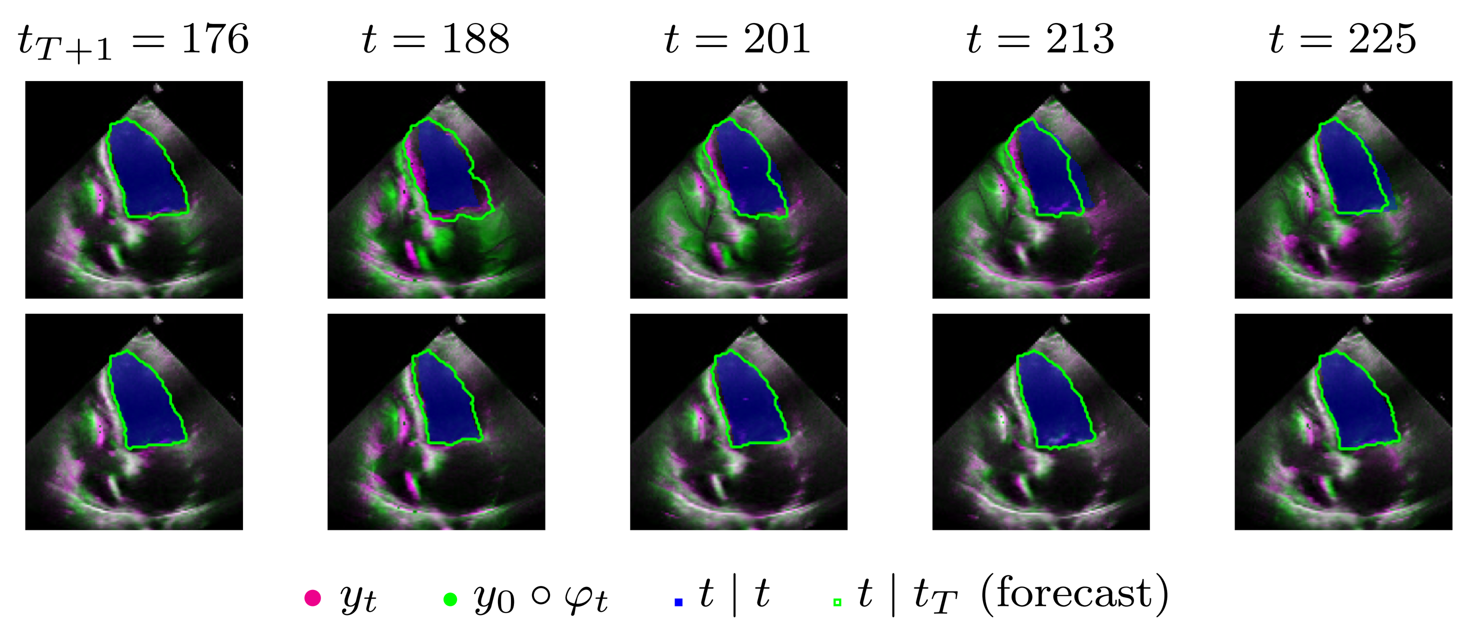


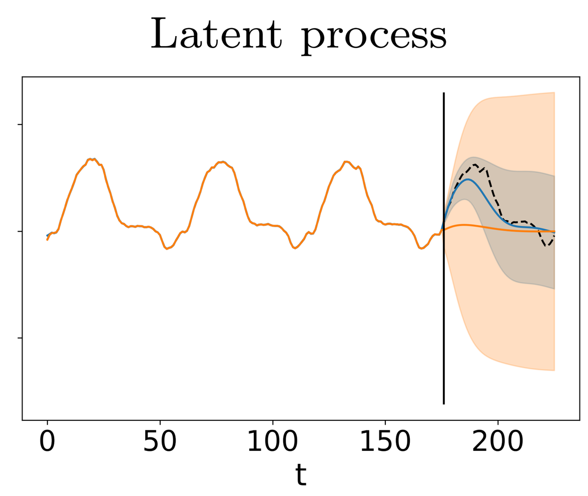
Overall result.

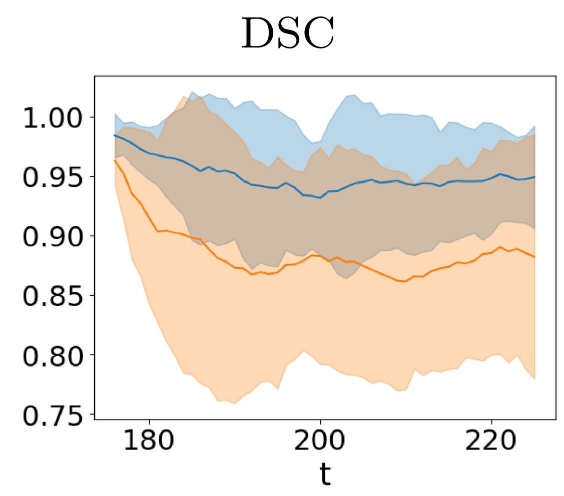
	DSC		
	RV	LV-Myo	LV-BP
SyN	0.79	0.72	**0.86**
Our	**0.80**	**0.82**	0.84
Our 5th	0.80	0.81	0.84
Our 10th	0.79	0.80	0.83

Prediction (Online-trained model 75 ms)

Overlay of true sequence (magenta), and pre-trained model, on top, and online-trained, on bottom (green).







Pre-trained vs. Online

Overall result.

	$\log p_\gamma(x_{T:T+H})$	RMSE $(x_{T:T+H})$	DSC $(\varphi_{T+25\|T})$
Pre-trained	-10.5	7.04	0.81
Online	$\mathbf{-6.3}$	**5.54**	**0.85**

Conclusion

- The model performs similar registration accuracy as well-established registration methods, even in unobserved timesteps.
- Patient-specific motion adaptation is possible by updating a subset of the model parameters online.

References

[1] Real-time motion management in MRI-guided radiotherapy: Current status and AI-enabled prospects. E.Lombardo, J.Dhont, D.Page, et al. Radiotherapy and Oncology 2023

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[3] Real-Time Convex Optimization in Signal Processing. J.Mattingley, S. Boyd. IEEE Signal Processing Magazine 2010.

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