GANcMRI: Cardiac magnetic resonance video generation and physiologic guidance using latent space prompting

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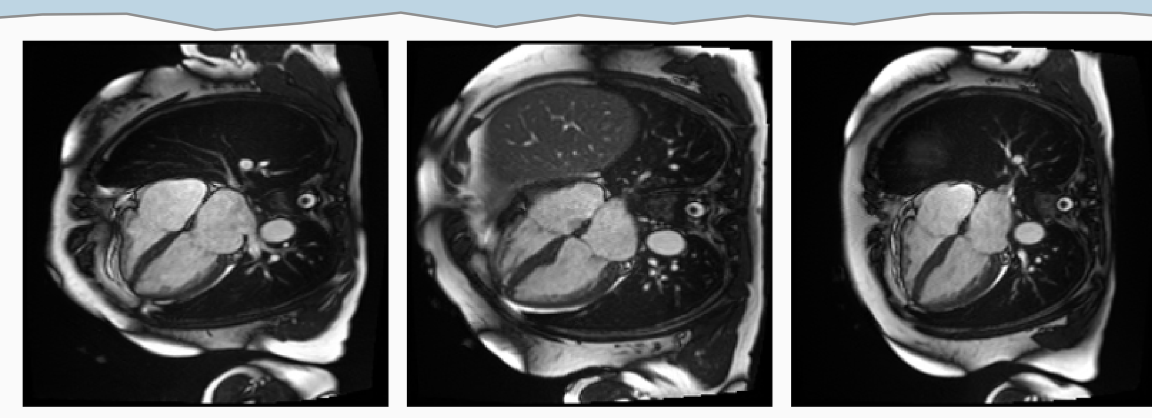
Motivation

- Cardiac MRI is expensive and lengthy.
- Limited publicly available cMRI datasets
- Traditional reconstruction techniques don't utilize previously collected data

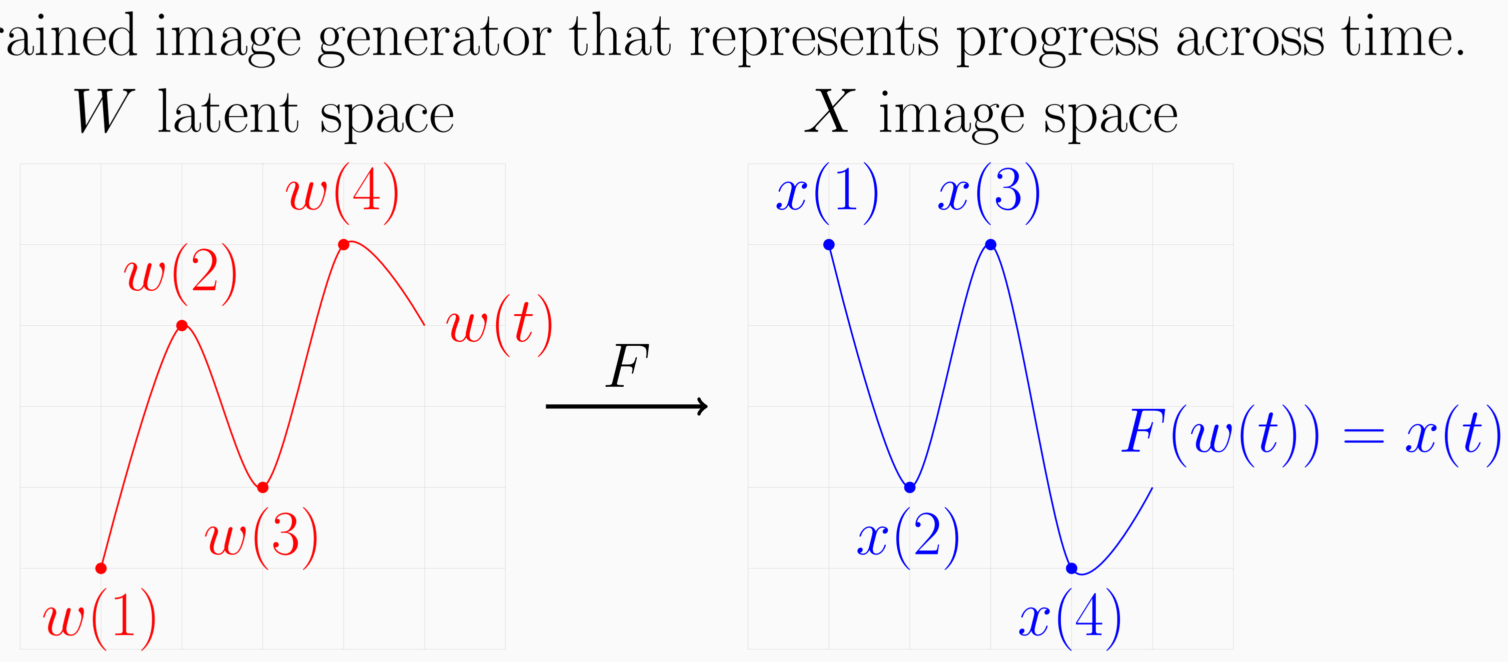


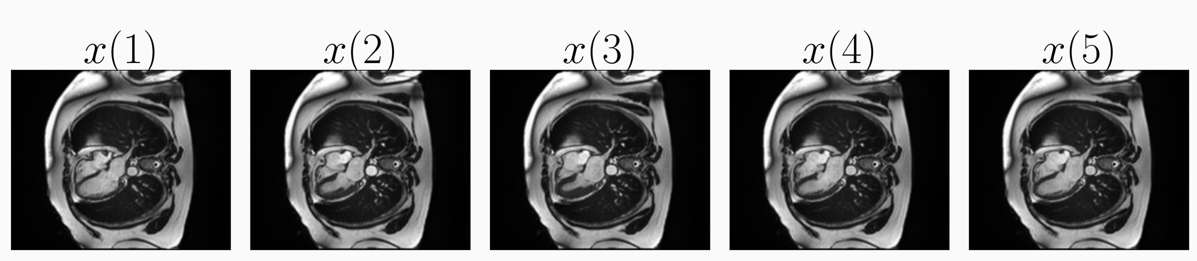
Conditional cMRI video generation

Demo

Methods

We train StyleGAN2 on $\sim$ 2M frames of cardiac MRI from the UK Biobank. We formulate video generation as the problem of finding a trajectory through the latent space of a pretrained image generator that represents progress across time.





We develop two methods for modeling this trajectory. Both methods rely on a projector, $P(\cdot) : X \to W$, that finds a latent vector corresponding to the real image using gradient descent.

ED-to-ES:

$$k_{ED\to ES} = \frac{\sum_{j=0}^{N} P(ES\_frms[j]) - P(ED\_frms[j])}{N}$$

Where N is the number of videos, ES_frms is a list of ES frames, ED_frms is a list of ED frames, and $ED\_frms[j]$ and $ES\_frms[j]$ are from the same video.

Frame-to-Frame

$$k_{i\to i+1} = \frac{\sum_{j=0}^{N} P(videos[j][i+1]) - P(videos[j][i])}{N}$$

Where $videos$ is a list of videos, and $videos[j][i]$ is the i-th frame from the j-th video.

To fix the sharp transition, we fit a PCA model $PCA(\cdot)$, computing 32 principal components of the dataset $K = \{k_{1\to 2} \dots k_{i\to i+1} \dots k_{49\to 50}\}$, and use this pretrained model to update our frame-to-frame trajectories:

$$k'_{i\to i+1} = k_{i\to i+1} - PCA^{-1}(PCA(k_{i\to i+1}))$$

Physiological Guidance

Following a similar idea, we model the trajectory such that if we move along it the phenotype value in the corresponding image will increase.

$$k_{low\to high} = \frac{\sum_{l=0}^{L} high\_latents[l]}{L} - \frac{\sum_{s=0}^{S} low\_latents[s]}{S}$$

$high\_latents$ correspond to the images where the measured phenotype has high quantity and $low\_latents$ has low.

Results

Synthetic single frame cMRI images are indistinguishable from the real ones

When presented with side-by-side comparisons of fake and real cardiac MRI (cMRI) frames, a clinical cardiologist identified the fake image as real in 60% of the cases, based on an evaluation of 100 pairs.

Frame-to-frame video generation outperforms other approaches

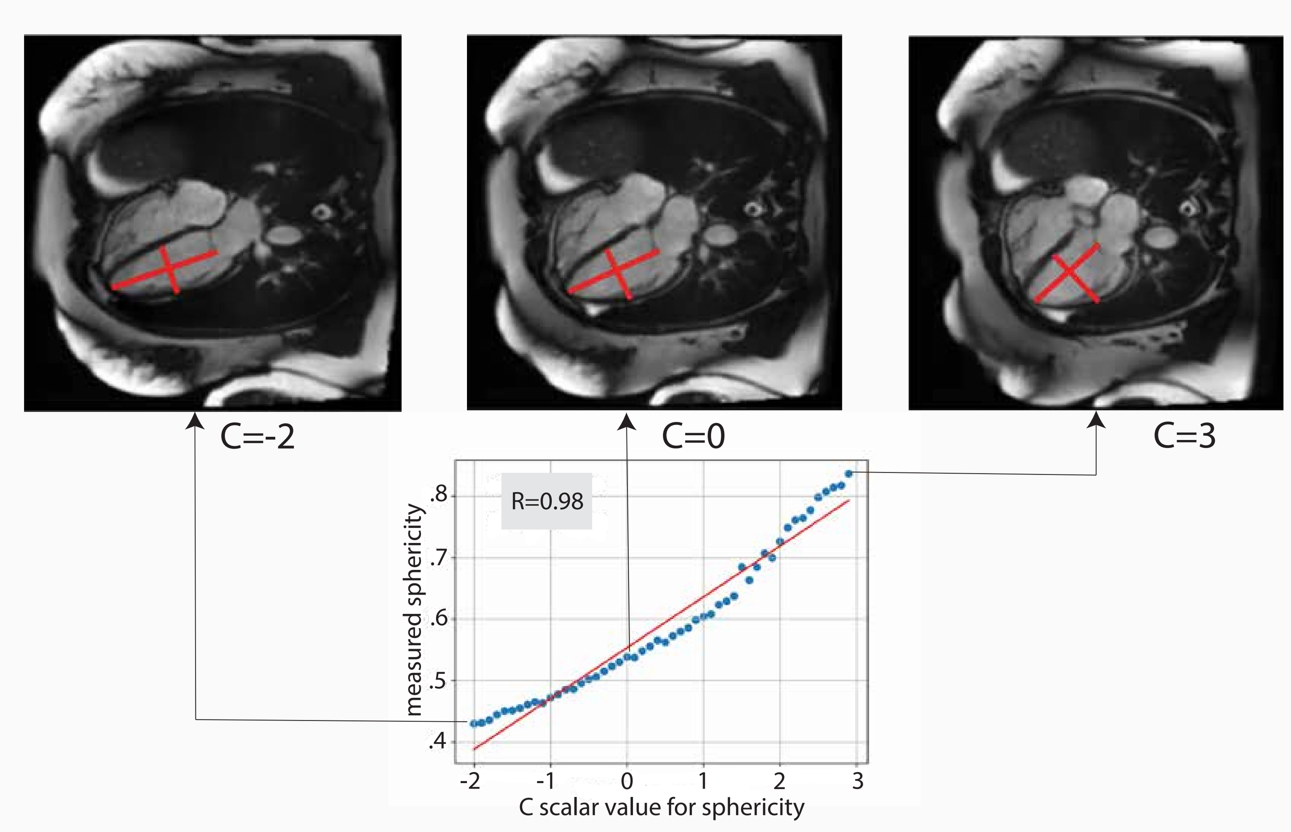
Frechet Video Distance (FVD) was computed between each two pairs of distributions:

	Real	ED-to-ES	F-to-f
Real	4.01	301.83	283.53
ED-to-ES		35.28	95.16
Frame-to-frame			8.81

The cardiologist rated the Frame-to-Frame as the highest in quality, but he could still differentiate it from real.

GANcMRI accurately reflects physiologic adjustment

We perform pearson R test between the step size along phenotype trajectory and the actual phenotype value of the synthetic images corresponding to the modified latent vector. $R = 0.98$ and p value $= 7.8 \cdot 10^{-35}$ for sphericity index, and $R = 0.89$ and p value $= 6.9 \cdot 10^{-18}$ for lv area.



Impact

- Generate large anonymous cMRI datasets
- Pre-surgical modeling and using learned latent space to gain new insights in cardiac diseases
- Education
- ML-based ctemporal-resolution can reduce cMRI scan time by enabling the capture of low-resolution images with fewer k-space lines