Self-supervised motion descriptor for cardiac phase detection in 4D CMR based on discrete vector field estimation

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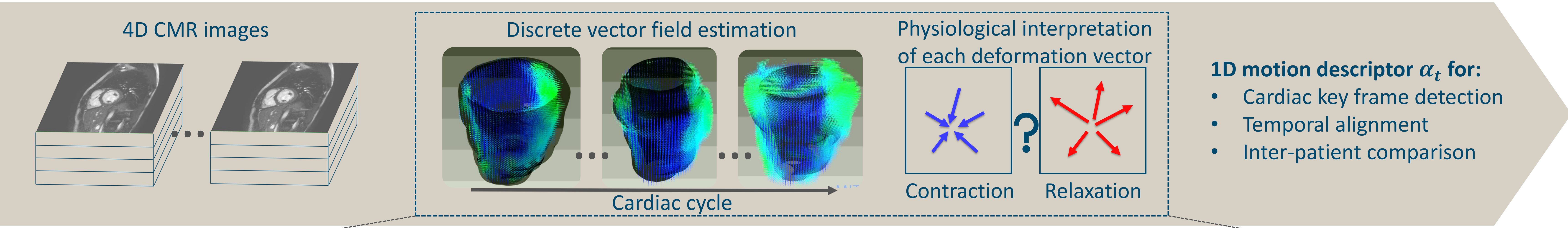
How can we **derive knowledge** about the **cardiac phases** from CMR **without access to any label**?



1D motion descriptor α_t for:
- Cardiac key frame detection
- Temporal alignment
- Inter-patient comparison

Method

What:

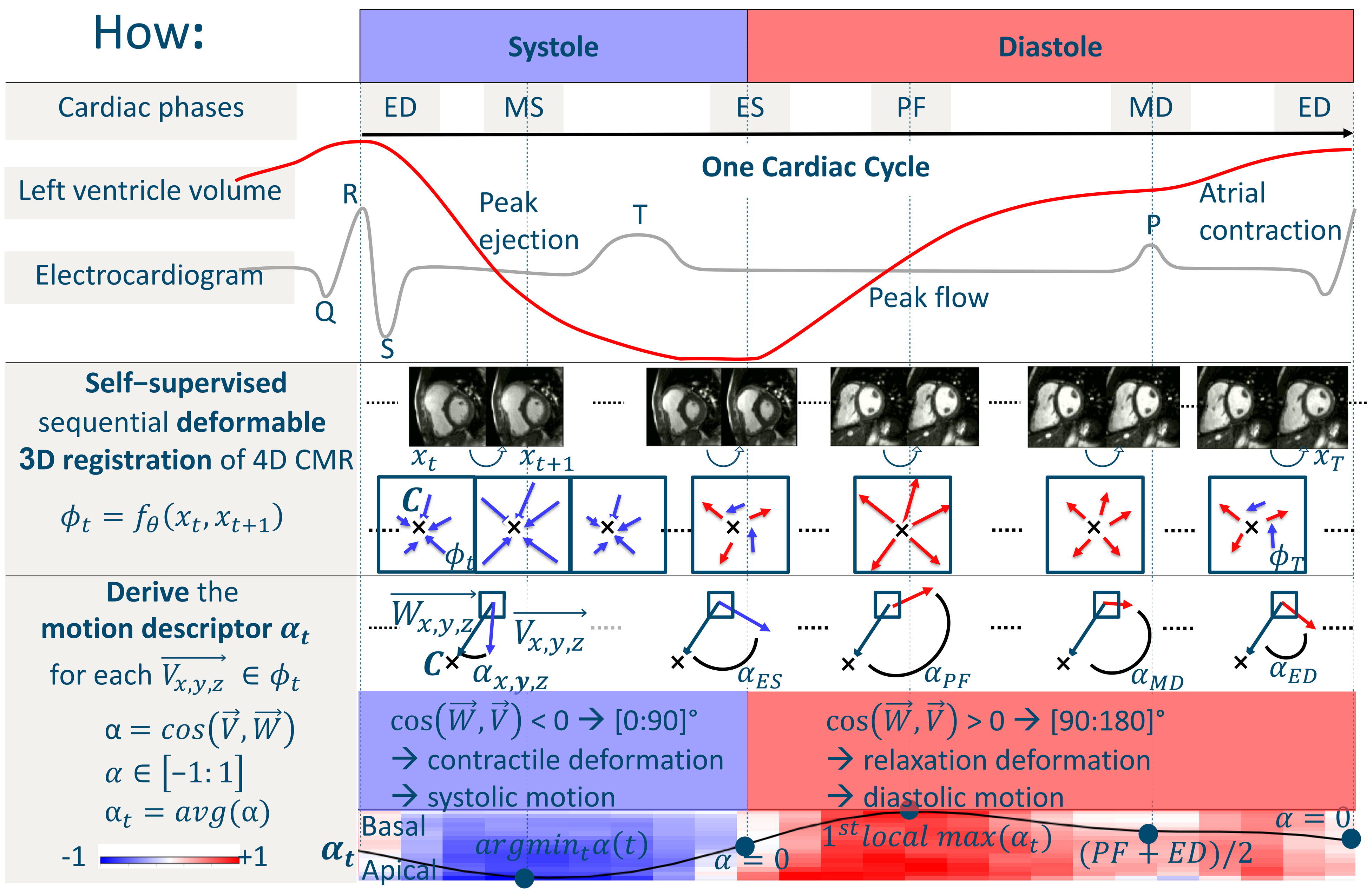
Clinical definition of five relevant key frames
- End of diastole/relaxation (ED)
- Mid systolic peak ejection (MS)
- End of systole/contraction (ES)
- Peak blood flow during diastole (PF)
- Relaxation pause before atrial contraction (MD)

DL-based discrete vector field estimation
- Learn to approx. the voxel-wise deformation
- Definition of a focus point $C \in \mathbb{R}$ and the location vector $\overrightarrow{W_{x,y,z}}$ based on prior knowledge or self-supervised

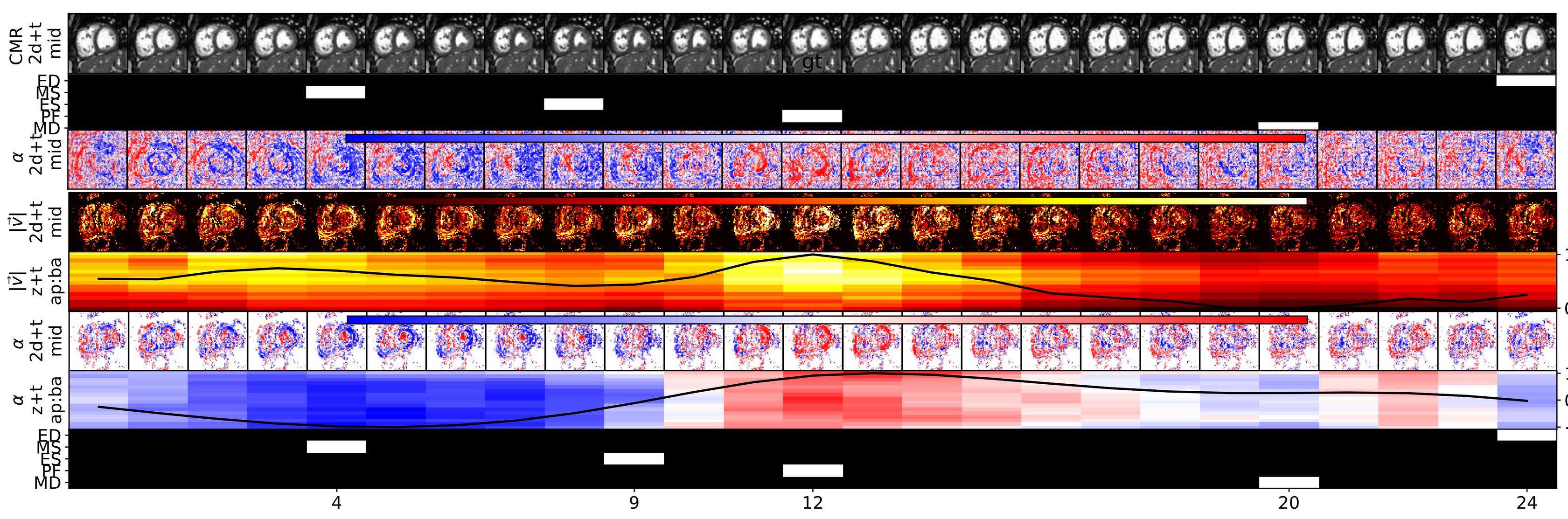
Compare with expected physiological deformation
- $\overrightarrow{V_{x,y,z}}$ towards C → contraction/systolic motion
- $\overrightarrow{V_{x,y,z}}$ away from C → relaxation/diastolic motion

Visualisation of α_t: slice-wise avg. – colour coded as contraction (blue) and relaxation movement (red) in background. Vol.-wise avg. as interpolated black curve together with a simplification of the physiological rule-set.

How:



Visualisation of α_t for a random patient



- Mid-cavity CMR slice of the model input,
- GT phase labels – only used for evaluation,
- Mid-cavity of α without percentile masking
- Mid-cavity of $|\vec{V}|$ masked by the 70th percentile of $|\vec{V}|$),
- Slice-wise avg. of $|\vec{V}|$ (base2apex) in background. $|\vec{V}|$ as 1D curve (right axis),
- Mid-cavity of α, masked by the 70th percentile of $|\vec{V}|$,
- Slice-wise avg. of α (base2apex) in background. α_t as 1D curve (right axis),
- Predicted phase.

Experiments and quantitative results

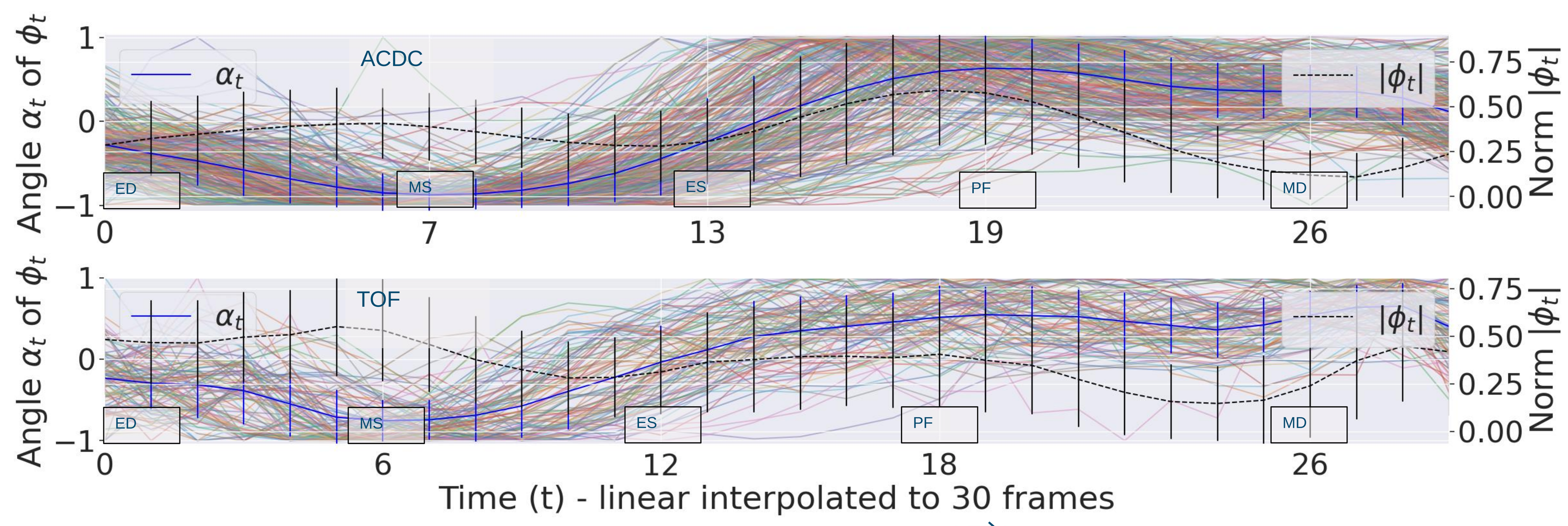
Data	C_n	all	ED	MS	ES	PF	MD
ACDC	*base*	-	1.13 ± 1.82	-	$\mathbf{0.95} \pm 1.29$	-	-
	C^1_{lv}	1.36 ± 1.37	1.13 ± 1.23	$\mathbf{0.97} \pm 0.95$	1.05 ± 1.09	1.87 ± 1.98	1.77 ± 1.59
	C^1_{sept}	1.32 ± 1.21	1.09 ± 1.09	$\mathbf{0.97} \pm 0.83$	0.96 ± 0.87	1.68 ± 1.63	1.91 ± 1.65
	C^2_{vol}	1.56 ± 1.86	1.37 ± 2.01	1.24 ± 1.40	1.19 ± 1.60	1.99 ± 2.14	2.01 ± 2.15
	C^2_{mse}	$\mathbf{1.29} \pm 1.25$	$\mathbf{1.08} \pm 1.26$	1.02 ± 0.94	0.97 ± 0.95	$\mathbf{1.66} \pm 1.56$	$\mathbf{1.73} \pm 1.54$
TOF	*base*	-	1.18 ± 1.91	-	1.21 ± 1.78	-	-
	C^1_{lv}	0.99 ± 0.91	0.81 ± 0.93	1.07 ± 0.79	0.72 ± 0.79	0.90 ± 0.82	$\mathbf{1.46} \pm 1.22$
	C^1_{sept}	$\mathbf{0.95} \pm 0.89$	0.82 ± 0.88	$\mathbf{0.87} \pm 0.72$	0.70 ± 0.76	$\mathbf{0.78} \pm 0.83$	1.58 ± 1.26
	C^2_{vol}	1.02 ± 0.97	0.86 ± 1.04	1.06 ± 0.83	0.76 ± 0.80	0.88 ± 0.90	1.56 ± 1.28
	C^2_{mse}	0.97 ± 0.91	$\mathbf{0.80} \pm 0.85$	0.94 ± 0.76	$\mathbf{0.69} \pm 0.79$	0.85 ± 0.86	1.57 ± 1.27

[1] → C based on anatomical GT knowledge

[2] → C based on more generic information (unsupervised)

- Comparison with supervised (base) and four different focus points C.
- Two multi-disease/-centre/-scanner short axis CMR datasets (100 patients, ACDC cohort [1] and 278 patients with Tetralogy of Fallot (TOF) [2]).

Qualitative results



- Per-cohort avg. of α_t (blue/left axis) and of $|\vec{V}|_t$ (black/right axis)
- Temporal aligned, resampled avg. phase indices (x-axis)
- Please note: $\alpha_t < 0$ → systolic and $\alpha_t > 0$ → diastolic frames.

Conclusion

- Efficient reduction of a **3D+t deformable vector field,** derived from plain CMR, into a **1D motion descriptor**, in a **self-supervised** manner.
- Application of this descriptor to the task of **cardiac phase detection**.
- Significantly (p<0.001) **outperformed the supervised base** and **equal to the inter-observer** error, while **no labels required**.
- Code and additional labels are publicly available [3].

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[1] Bernard, O., …, Heng, P., et. al.: Deep Learning Techniques for Automatic MRI Cardiac Multi-Structures Segmentation and Diagnosis: Is the Problem Solved? IEEE Transaction on Medical Imaging 37(11), 2514-2525 (2018). https://doi.org/10.1109/TMI.208.2837502
[2] Sarikouch, S., …, Mir, T.S., et. al.: Impact of Gender and Age on Cardiovascular Function Late After Repair of Tetralogy of Fallot. Circulation: Cardiovascular Imaging 4(6), 703-711 (2011). https://doi.org/10.1161/circimaging.111.963637
[3] https://github.com/Cardio-AI/cmr-phase-detection

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