Comparison of Representation Learning Techniques for Tracking in time-resolved 3D Ultrasound

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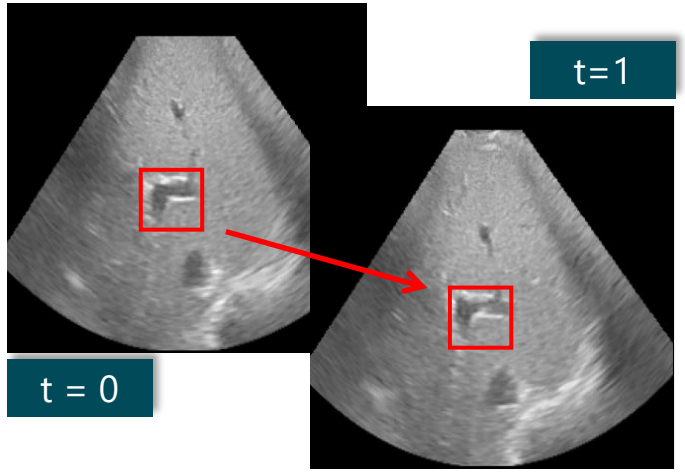
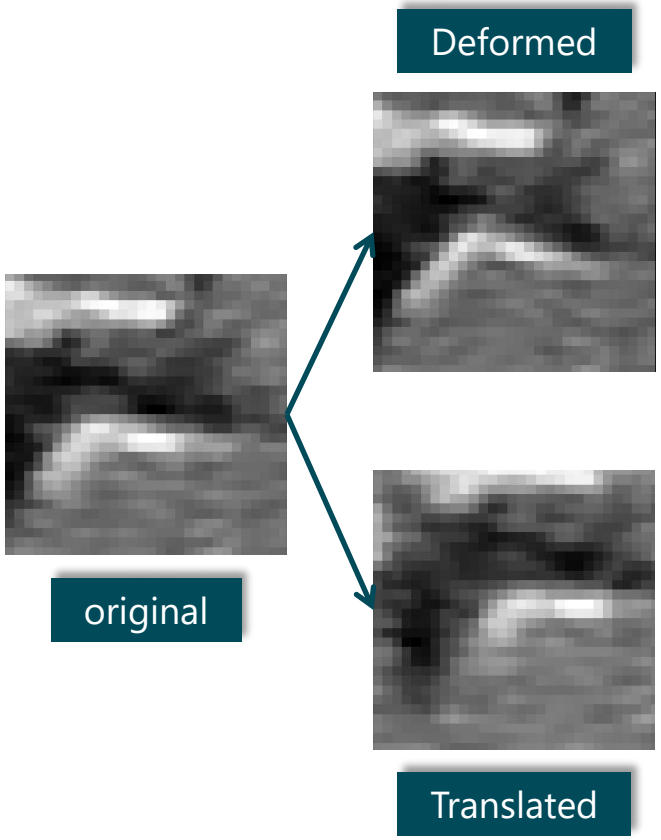
Preparing US Data



- Tracking in 4D Ultrasound is challenging
- Location and shape of targets change
- Approach: Representation Learning in US patches



- Long-term 4D Liver Ultrasound dataset
- Consider Deformations and Translations
- Deformation is simulated using data augmentation
- Generated test data:
  - 10 x 50 Deformations
  - 10 x 50 Translations

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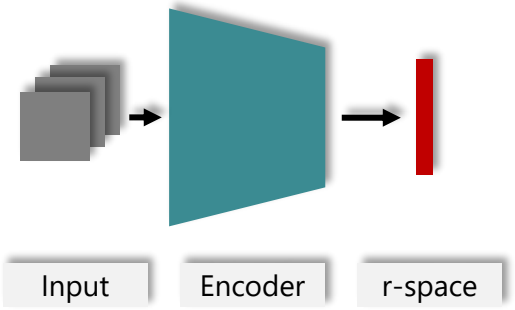
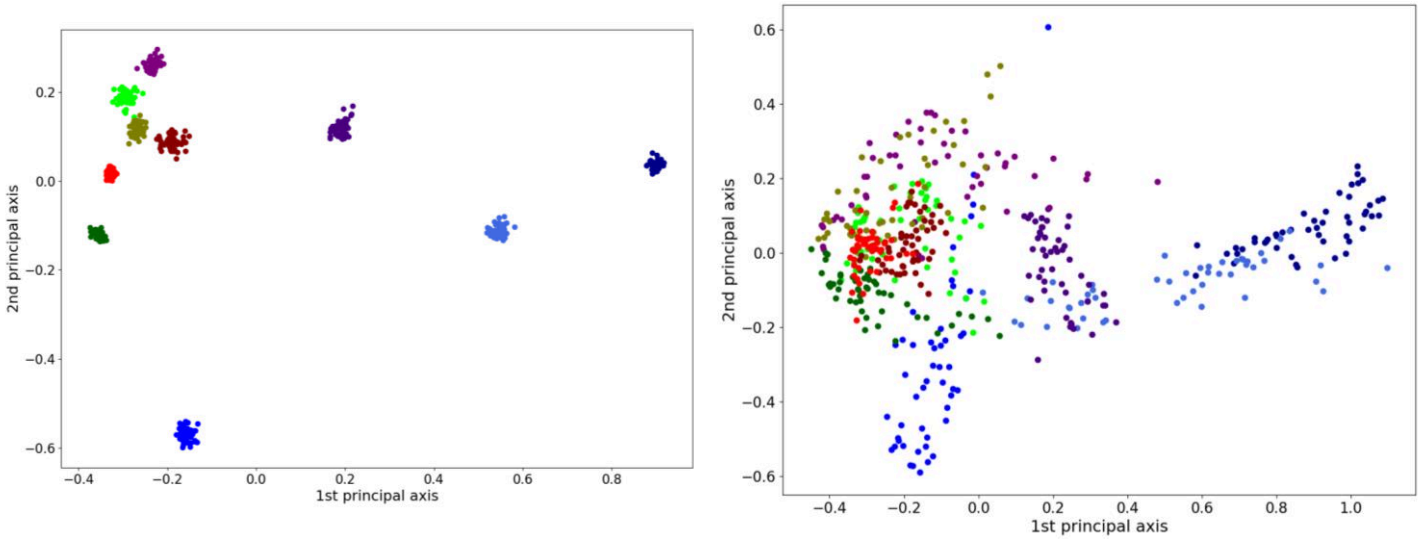
Mapping US Patches into Representation Space



- Mapping patches into representation space
  1. Conventional autoencoder (cAE)
  2. Variational autoencoder (VAE)
  3. Sliced-Wasserstein autoencoder (SWAE)
- AEs are trained using long-term US dataset



Two principal Components of r-space of Deformations (left) and Translations (right) generated by conventional autoencoder.

- Consider Translations and Deformations separately
- Clustering in r-space using k-means algorithm

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Clustering in Representation Space

Data Type	Auto-encoder	Precision	CH score
Deformation	cAE	1.0	1197
	VAE	0.8	60
	SWAE	1.0	2385
Translation	cAE	0.6	28
	VAE	0.5	8
	SWAE	0.7	33

- Metrics
  - Precision: Rate of correct clustered samples
  - Calinski-Harabasz (CH) score: Rate between intra- and inter cluster dispersion
- Clustering performance depends on
  - Type of autoencoder
  - Kind of motion
- Clustering of deformed patches is more effective than transformed patches – promising for target tracking
- Results indicate that SWAE is promising for Tracking

- In Future study Tracking in r-space of SWAE will be performed