Basal Strain Estimation using Deep Learning based Deformable Image Registration

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Background

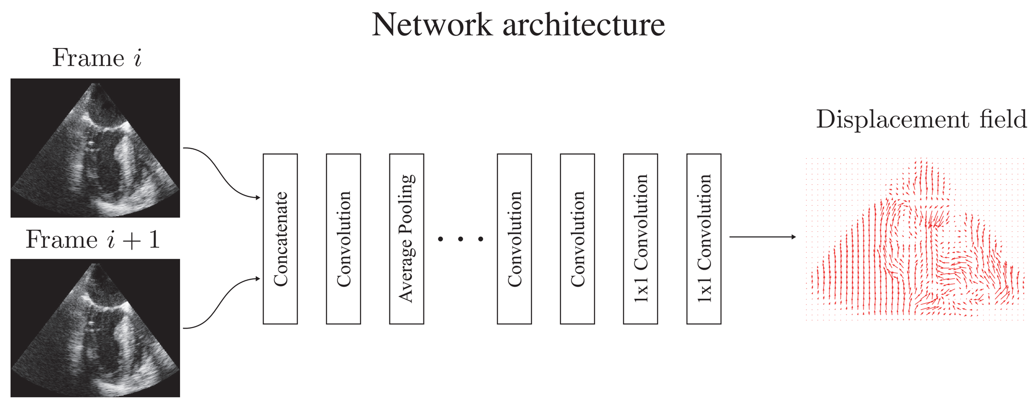
- Patients undergoing cardiac surgery run the risk of serious complications due to reduced cardiac function
- Continuous monitoring of cardiac function is desirable, but requires manual effort with current methods
- Strain/strain rate require manual annotation and large inter-vendor variations cause issues

Aim

Derive non-linear deformation between subsequent images in a TEE sequence to estimate basal longitudinal strain

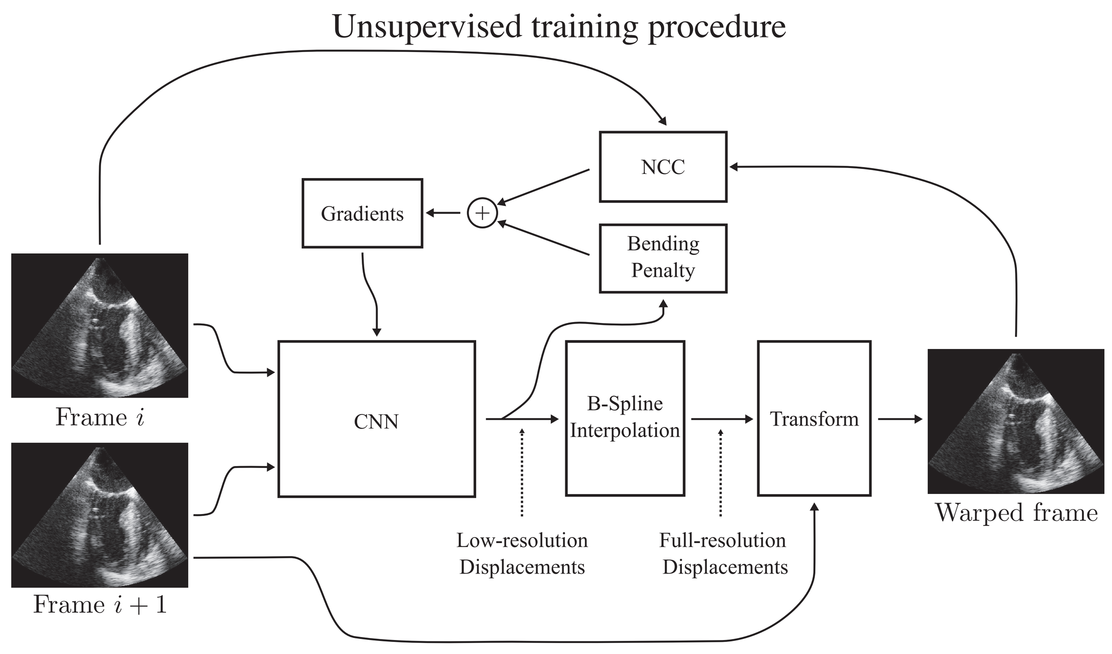
Method

Network architecture



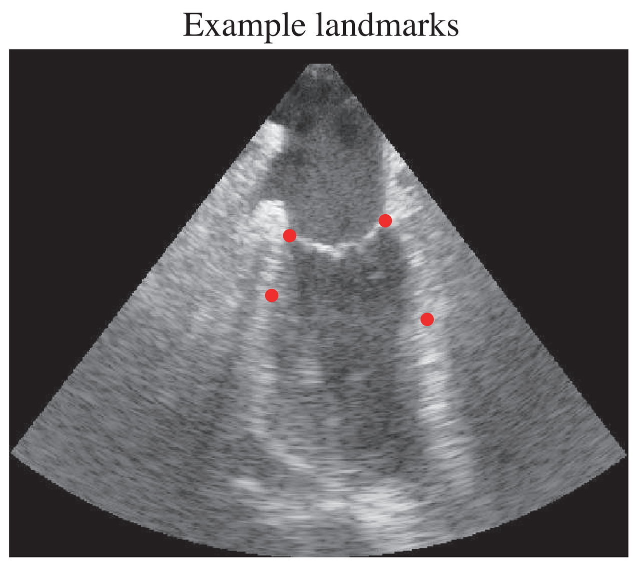
- Continuation of the work of De Vos et al.[1]
- Fully convolutional network estimate low-resolution displacements in x and y directions
- Number of alternating convolutional and pooling layers can be adjusted to achieve desired downsampling
- B-spline interpolation used to upsample and achieve full-resolution displacement field estimates D^d

Unsupervised training procedure



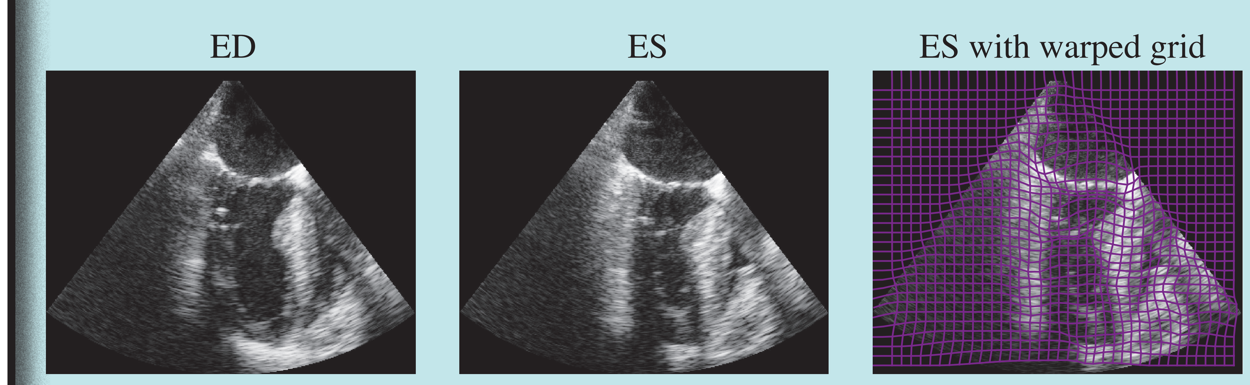
- Unsupervised training scheme maximizing similarity between consecutive frames
  $I_i(x,y) \approx I_{i+1}(x + D^d_x(x,y), y + D^d_y(x,y))$
- Normalized cross-correlation used as similarity measure:
  $$\frac{1}{WH}\sum_{x,y}\frac{1}{\sigma_i\sigma_{i+1}}\left(I_i(x,y)-\mu_i\right)\left(I_{i+1}(x,y)-\mu_{i+1}\right)$$
- Bending penalty introduced as regularization term to ensure global smoothness:
  $$P = \lambda\sum\sum_{x,y\in I}\left(\frac{\partial^2 \vec{D}^d}{\partial x^2}\right)^2+\left(\frac{\partial^2 \vec{D}^d}{\partial y^2}\right)^2+2\left(\frac{\partial^2 \vec{D}^d}{\partial xy}\right)^2$$
- Strain estimated on each side by following the displacements of four landmarks on the myocardium
- Implementation in Python using the Tensorflow library

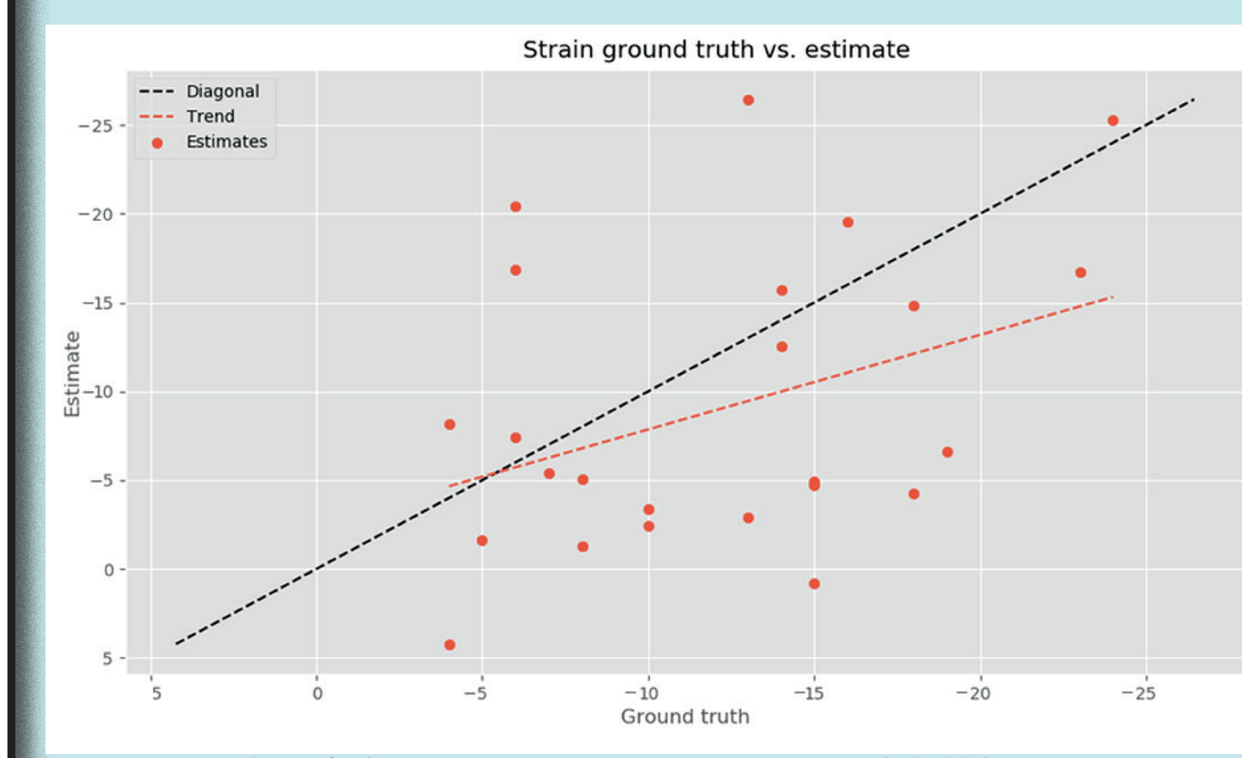
Example landmarks

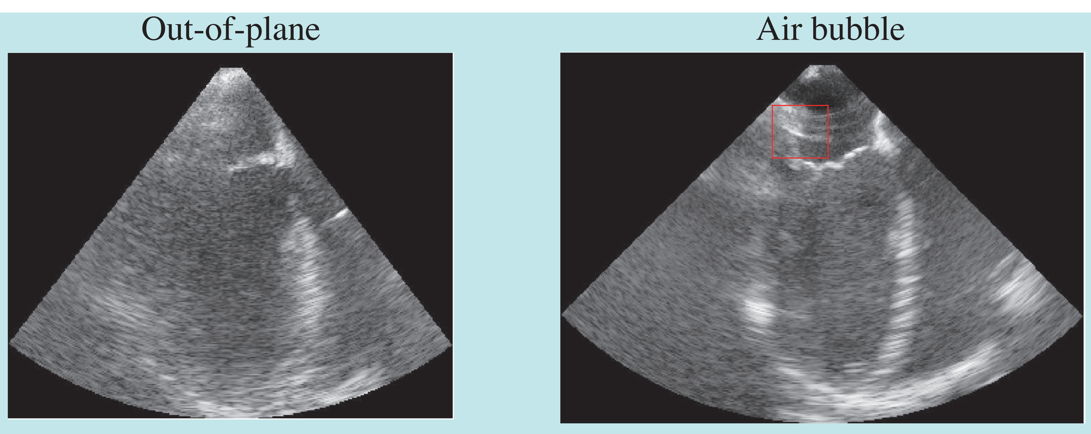


Results and Discussion

- Inspection of the warped grids shows that the displacement estimates are reasonable in most cases
- Strain estimation achieves a mean difference of 7.25% (± 4.56%) when compared to expert annotations performed with standard clinical software (GE Echopac 202.53)
- High degree of underestimation indicates too much downsampling or regularization
- Noisy samples give unpredictable estimates
- Out-of-plane movement and air bubbles ”traps” tracker leading to bad estimates
- Filtering approaches (Kalman, Exponential moving average) did not improve robustness
- Robustness could be improved by daisy-chaining networks, incrementally estimating displacements (work in progress)
- Inference time is slow, ~230ms between frame pairs
- Moving processing currently done in Python to the Tensorflow runtime could decrease inference time
- To fully automate the procedure, automatic detection of the landmarks must be implemented







Acknowledgements
Espen Holte, Bjørnar Grenne and Håvard Dalen acquired the clinical data. The work was supported by ”Operating Room of the Future” at St. Olavs Hospital and ”CIUS - Center for Innovative Ultrasound Solutions” at NTNU

References

[1] B.D. de Vos, F.F. Berendsen, M.A. Viergever, H. Sokooti, M. Staring and I. Išgum, “A deep learning framework for unsupervised affine and deformable image registration,” Medical image analysis, vol. 52, pp. 128– 143, 2019.

Conclusion

- A fully convolutional network was implemented to estimate frame-to-frame displacements
- Unsupervised training makes data gathering less time-consuming
- Displacement and strain estimation works as expected in low noise samples, but more noise degrades performance
- Remaining work includes automatic detection of landmarks and improving robustness