DVGardener: An Open-Source Toolbox for Manipulation, Quantification, Generation and Compression of Deformation Vector Fields

Owen Thomas Dillon Ph.D[1], Benjamin KF Lau[1], Hunor Kertesz Ph.D[1] and Prof. Paul J. Keall, PhD[1]
1- Image X Institute, University of Sydney, Australia

AAPM 2024
66TH ANNUAL MEETING & EXHIBITION
JULY 21-25 | LOS ANGELES, CA

IMAGE X INSTITUTE
THE UNIVERSITY OF SYDNEY

Work through this example! Scan here!

Introduction

- **Deformation Vector Fields** (DVFs) are widely used across medical physics where patient motion is a key consideration.

- To help **simplify** projects using DVFs and **harmonize** research around DVFs we developed **DVGardener** as an **open source matlab toolbox** for **analysis, manipulation and compression** of DVFs.

- We created an **example/tutorial** using methods from DVGardener on publicly available 4DCT data taken from The Cancer Imaging Archives [1] performing DIR using the open source Elastix toolkit [2] visualised in 3Dslicer[3], figure 1.

- **The results presented in this poster are from the online tutorial** which addresses typical problems and best practices when using DVFs.

- Please work through the example yourself at

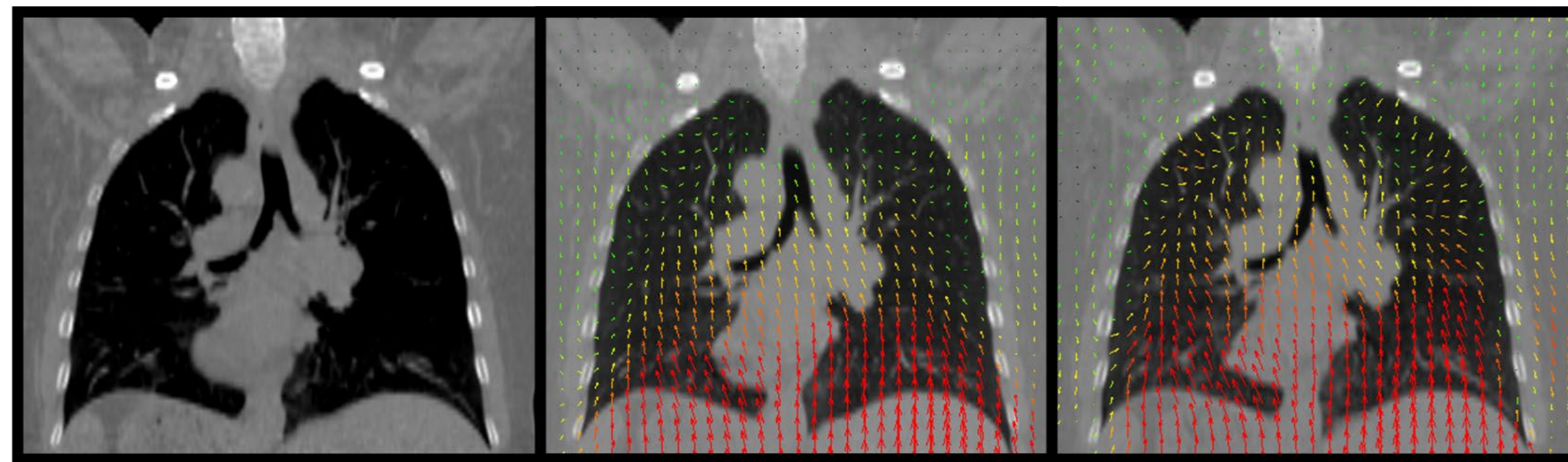 **https://github.com/Image-X-Institute/DVGardener**

Figure 1. exhale image, inhale to exhale registered image, and inhale to exhale via intermediate phases image with corresponding DVFs overlaid. The images are largely the same while the DVFs are qualitatively different.

Quantification

- Standard image comparison metrics e.g. RMSE can be applied to DVFs, however this can obfuscate the **physical meaning of DVF differences** i.e. the distance between tissue placements.

- We compute a residual between DVFs V_a, V_b as $V_{res} = V_a - V_b$.

- We compute a *distance image,* figure 2, as

$$I_{dist} = \sqrt{(V_{a,x} - V_{b,x})^2 + (V_{a,y} - V_{b,y})^2 + (V_{a,z} - V_{b,z})^2}$$

- Where where subscripts x, y, z represent x, y, z components i.e. an image of the distance between where V_a and V_b place a section of tissue.

- The distance image can be converted to physically meaningful quantities, figure 3, or further processed to helpful visualisations, figure 4.
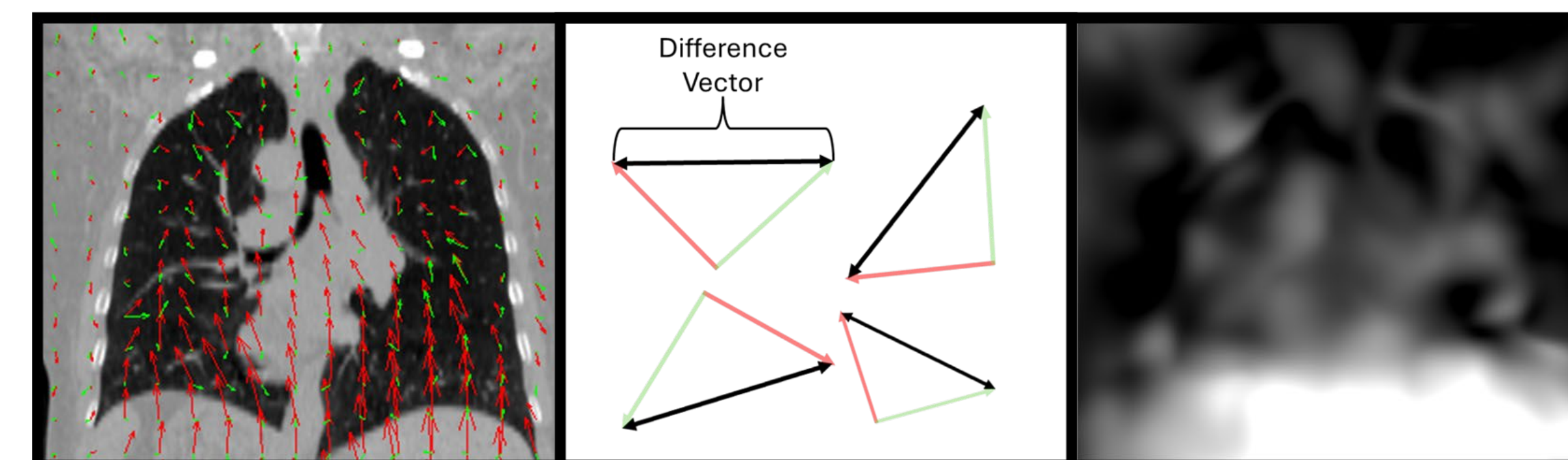

Figure 2: Two similar DVFs overlaid, computing the difference vectors, and the distance image i.e. the length of each difference vector. Note that most of the difference is inside homogenous tissue, where different DVFs produce similar image registrations. Whether this difference matters depends on context e.g. physiological interpretation of motion.

- Within DVGardener we can compute distances over the entire image, a masked ROI, specific structures or specific surfaces of structures – each relevant to different applications, figure 3.
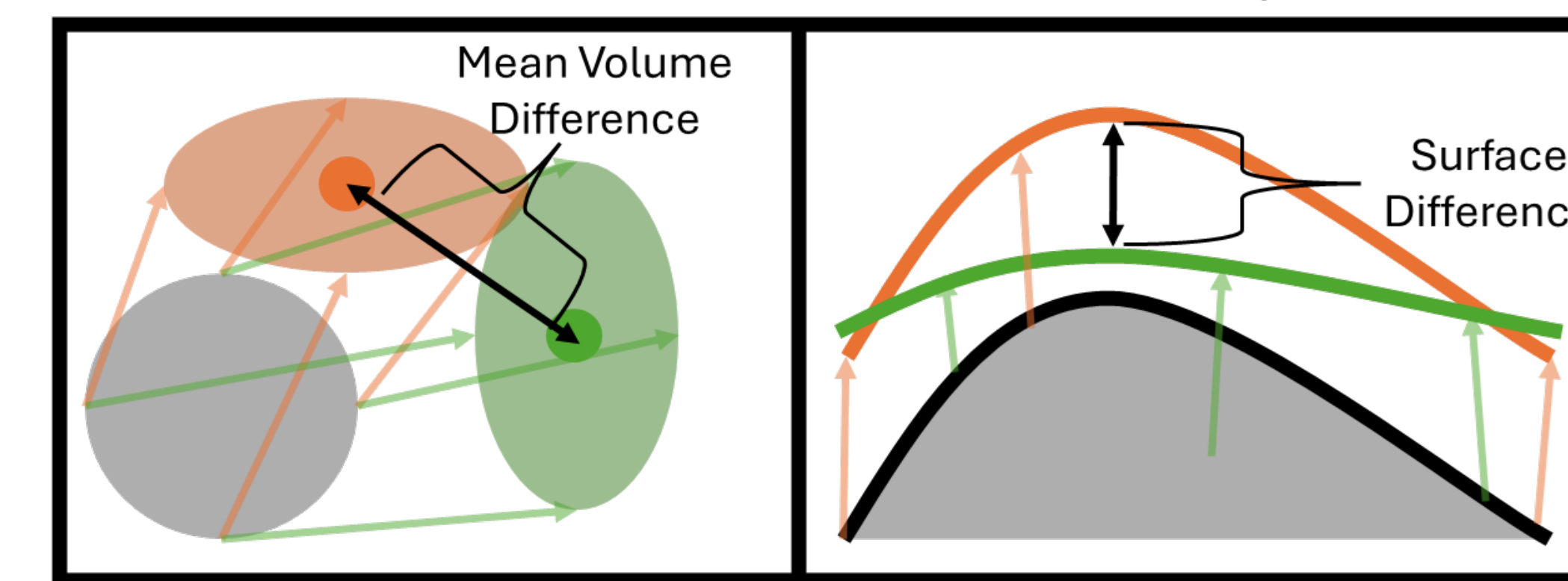

Figure 3: Volume difference and surface difference for e.g. calculating how a structure moves vs how a structure changes shape.
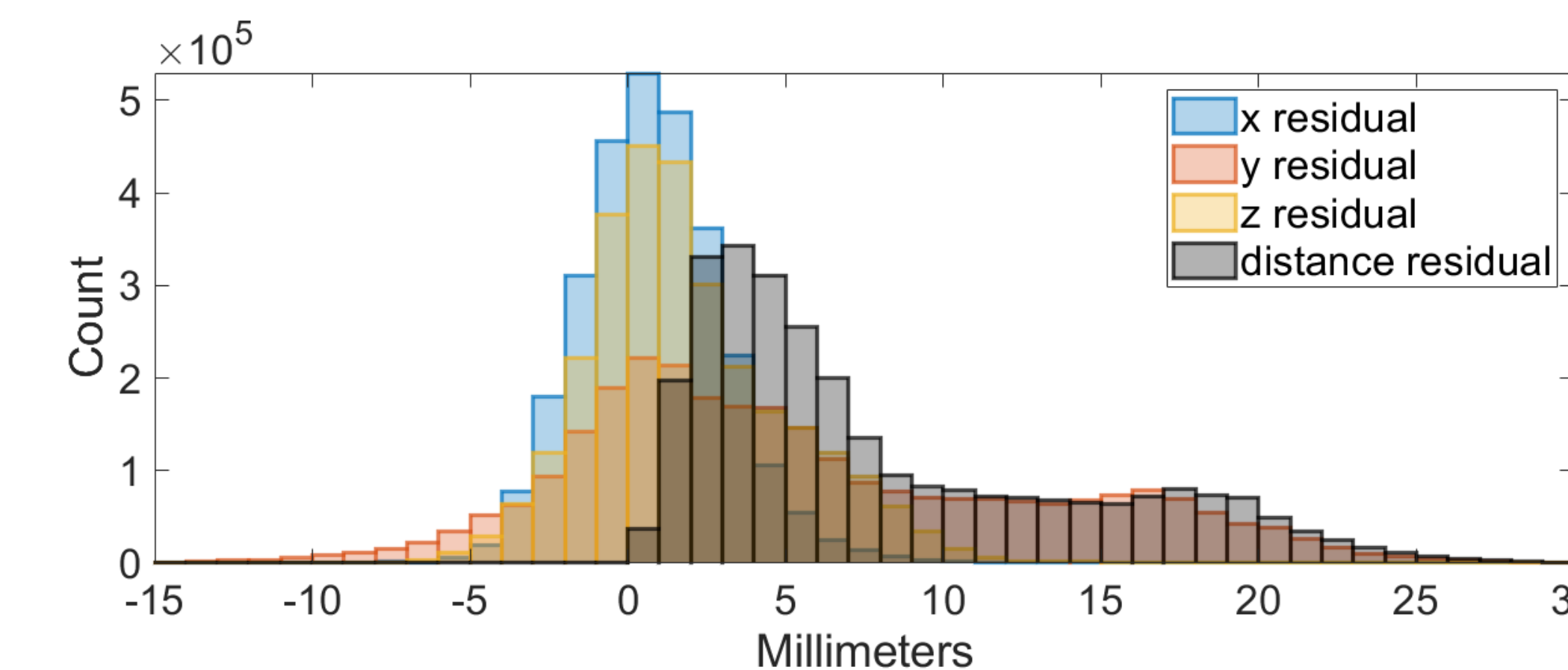

Figure 4: Histograms of DVF differences in each component and the distance image communicate the scale of the discrepancy.

Compression

- In the case of our $512 \times 149 \times 512$ CT example the DVFs are **458MB files**. The compressed representations are **0.11MB files** while capturing 92% of the DVF to submillimetre accuracy, figure 6.

- While DVFs may have an underlying low dimensional representation e.g. B-spline components, other methods such as Demons or via AI [5] may not.

- By analogy to JPEG compression, we express the DVF in terms of discrete cosines. The discrete cosine transform is linear and computationally efficient allowing for straightforward manipulation.
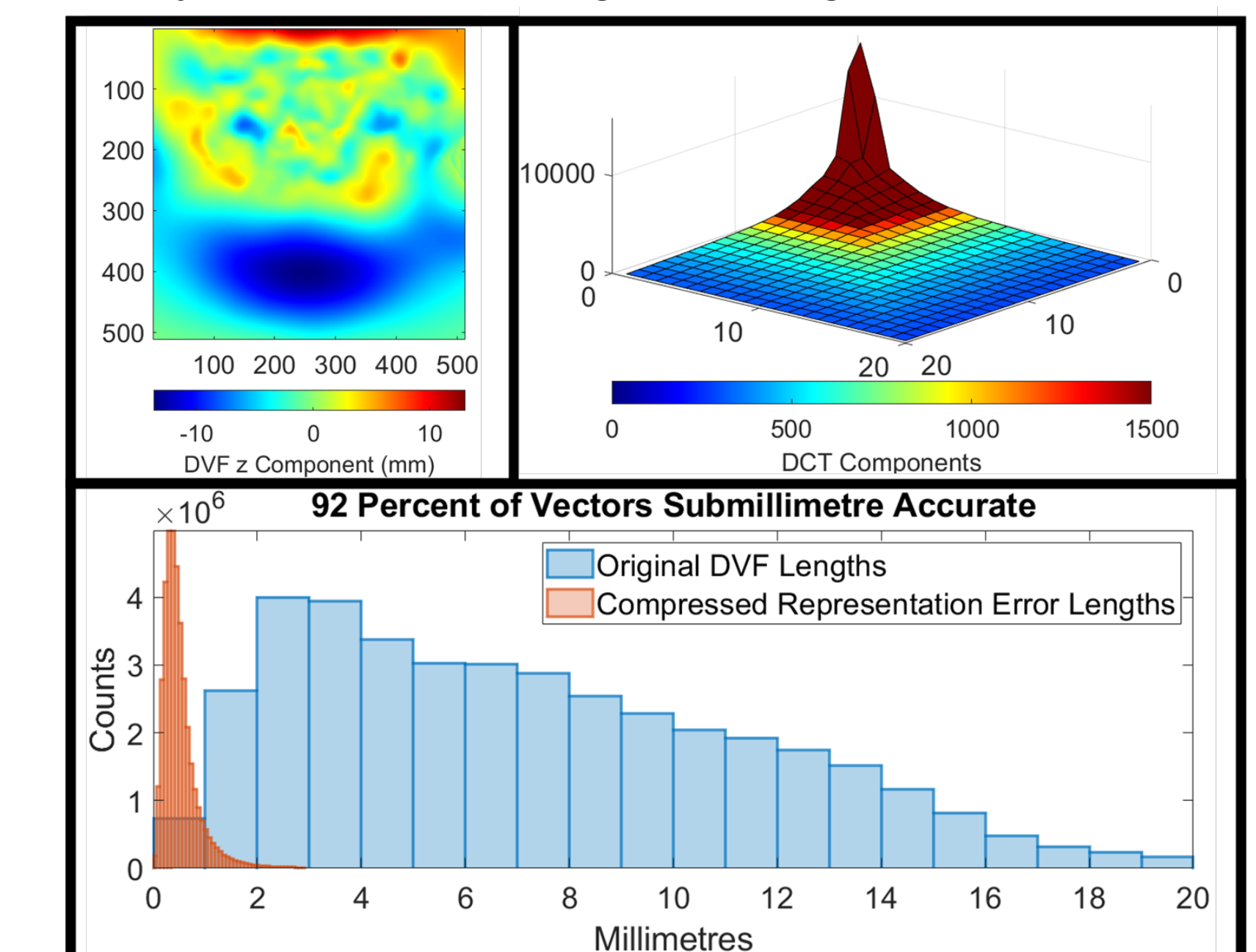

Figure 6: DVF components, 20×20 largest DCT components, and histogram of raw DVF components vs residual error of compressed form.

Generation

- Can generate novel DVFs V_j via gaussian sampling
$$V_j = F w_j + \mu_V$$

Where F is a filter encoding level of smoothness and locally acceptable amplitude, w_j is a white noise vector and μ_V a mean e.g. DVF to perturb.

- Can treat existing library of DVFs (e.g. all phase-to-phase registrations) and sample among those via PCA
$$V_j = \sum_{k=1}^{r} \sigma_k u_k w_{j,k}$$

where σ_k, u_k are singular values and singular vectors up to rank r and $w_{j,k}$ is a white noise scalar.

- Methods also apply to compressed representation for use in constrained memory applications e.g. AI training.

- Enforce consistency e.g. if $V_{1,2,3}$ is composite DVF from image 1 to 2 to 3 and $V_{1,3}$ is the DVF from image 1 to 3 we can enforce residual consistency
$$V_{1,2,3}^{rc} = V_{1,2,3} + V_{res} = V_{1,2,3} + (V_{1,3} - V_{1,2,3}) = V_{1,3}$$

and update the intermediate DVFs as
$$V_{1,2}^{rc} = V_{1,2} + \frac{1}{2} V_{res}, \; V_{2,3}^{rc} = V_{2,3} + \frac{1}{2} V_{res}$$

with higher physiological accuracy [4]. Example in figure 5.

- Alternatively apply approximate consistency by weighted average affine scaling
$$V_{1,2,3}^{waas} = \hat{a} V_{1,2,3} + \hat{b}$$
$$\hat{a}, \hat{b} = \min_{a,b} \left\{ \|V_{1,2,3}^{waas} - V_{1,2}\|_2 + \lambda \|(a-1) + b\|_2 \right\}$$

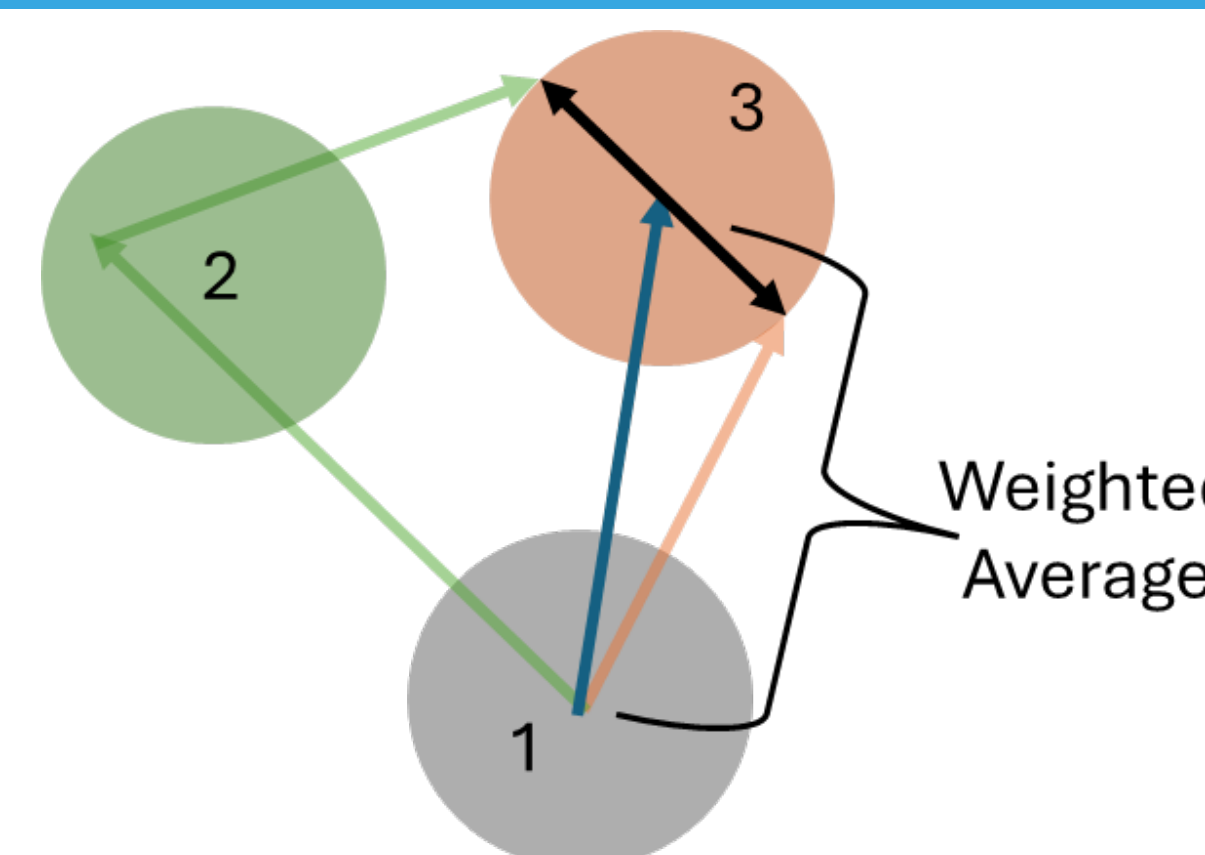Where a, b are scalars and λ controls the weighting.

Figure 5: Higher physiological accuracy can be achieved by combining DVFs that should represent the same motion e.g. 1 to 2 to 3 and 1 to 3 should meet.

Weighted Average

References

1. Hugo, G. D., Weiss, E., Sleeman, W. C., Balik, S., Keall, P. J., Lu, J., & Williamson, J. F., 2016. Data from 4D Lung Imaging of NSCLC Patients (Version 2) [Data set]. The Cancer Imaging Archive.

2. Klein, S., Staring, M., Murphy, K., Viergever, M.A. and Pluim, J.P., 2009. Elastix: a toolbox for intensity-based medical image registration. *IEEE transactions on medical imaging*, 29(1), pp.196-205.

3. Fedorov, A., Beichel, R., Kalpathy-Cramer, J., Finet, J., Fillion-Robin, J.C., Pujol, S., Bauer, C., Jennings, D., Fennessy, F., Sonka, M. and Buatti, J., 2012. 3D Slicer as an image computing platform for the Quantitative Imaging Network. *Magnetic resonance imaging*, 30(9), pp.1323-1341.

4. Kipritidis, J., Woodruff, H.C., Eslick, E.M., Hegi-Johnson, F. and Keall, P.J., 2016, April. New pathways for end-to-end validation of CT ventilation imaging (CTVI) using deformable image registration. In *2016 IEEE 13th international symposium on biomedical imaging (ISBI)* (pp. 939-942). IEEE.

5. Balakrishnan, G., Zhao, A., Sabuncu, M.R., Guttag, J. and Dalca, A.V., 2019. Voxelmorph: a learning framework for deformable medical image registration. *IEEE transactions on medical imaging*, 38(8), pp.1788-1800.

Contact Info