ESTIMATING FULL-FIELD DISPLACEMENT IN BIOLOGICAL IMAGES USING DEEP LEARNING

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ABSTRACT

The estimation of full-field displacement between biological image frames or in videos is important for quantitative analyses of motion, dynamics and biophysics. However, the often weak signals, poor biological contrast and many noise processes typical to microscopy make this a formidable challenge for many contemporary methods. Here, we present a deep-learning method, termed Displacement Estimation FOR Microscopy (DEFORM-Net), that outperforms traditional digital image correlation and optical flow methods, as well as recent learned approaches, offering simultaneous high accuracy, spatial sampling and speed. DEFORM-Net is experimentally unsupervised, relying on displacement simulation based on a random fractal Perlin-noise process and optimised training loss functions, without the need for experimental ground truth. We demonstrate its performance on real biological videos of beating neonatal mouse cardiomyocytes and pulsed contractions in *Drosophila* pupae, and in various microscopy modalities. We provide DEFORM-Net as open source, including inference in the ImageJ/FIJI platform, for rapid evaluation, which will empower new quantitative applications in biology and medicine.

1 Introduction

Biological tissues are highly dynamic and motion is critical to their form and function [1]. As such, imaging of live samples at high spatiotemporal resolutions and over long term is coming to the fore in revealing a host of dynamic biophysical processes [2]. This emerging domain of imaging, however, is accompanied by new challenges. Namely, the accurate estimation of motion from biological images or videos at the relevant spatial and temporal resolutions, which is required to quantify biophysics. The high throughput of image data, limits in signal-to-noise ratios, and the diversity of biological contrast makes deep learning an attractive prospect to tackle this challenge.

The broad problem of recovering displacement from biological images can be classed in two categories. First, methods that seek to track individual objects over the field of view, such as particle, cell or organism tracking [3]. These methods have received much attention because of the recent advances in super-resolution microscopy at high spatiotemporal scales. They can help reveal biophysics from protein kinetics to collective organism behaviour. Recent methods have utilised deep learning because of its natural affinity for feature identification tasks [3]. Second, methods that seek to estimate the full-field displacement (displacement vector field), i.e., map the local displacement vectors at every spatial location between image frames or videos [4]. In contrast to object tracking, full-field displacement estimation is a necessary step towards quantifying tissue mechanics from the principles of continuum mechanics, which can reveal local forces, deformation and mechanical properties [5]. As such, displacement estimation is critical to many methods in biophysics, for instance elastography (i.e., the mapping of the local mechanical properties in an image, such as using ultrasound, optical coherence tomography or optical microscopy [6, 7]), and in force estimation methods (such as in traction force microscopy or cell stretching [8]). The estimation of full-field displacement has been utilised for

various bio-applications [9, 6, 10, 11, 12, 13, 14, 15]; however, when compared to object tracking, these methods have not been specialised for live-imaging microscopy data.

Accurate estimation of full-field displacement between two image frames is typically carried out using digital image correlation (DIC) [16]. DIC solves the problem of: what displacement field leads to the greatest cross-correlation coefficient between reference and deformed image intensities? This registration procedure assumes that the local image textures are preserved when deformed. Because the solution to this problem is not unique, cross-correlation is maximised iteratively over many small subsets or patches of the images, the deformation of which is typically constrained to some affine transform with enforcement of continuity in displacement [9]. DIC has been developed and utilised primarily for experimental mechanics, such as materials testing and velocimetry, and in computer vision applications, such as image compression and 3D shape reconstruction [17]. Cross-correlation relies on strong image textures; thus, DIC is often enhanced with painting or powder coating of macroscopic samples [6]. While this is rarely feasible for biological samples, DIC has still been an accurate method for full-field displacement estimation, especially in samples that have intrinsically high textural contrast [9, 6]. However, because of the requirement to support sub-pixel accuracy and local deformation, the iterative and subset-based search methods employed in DIC can take minutes for image pairs, and hours or days for videos.

A fast approximation of displacement between two images can be achieved using optical flow (OF), which typically estimates velocity from local spatiotemporal gradients of the image intensity, which must be combined with regularisation, such as of local smoothness, to converge to a unique solution [18]. The development of such methods is an active field of research, with multiple benchmarking efforts in place to keep track of improvements [19, 20]. For example, the Middlebury optical flow challenge currently lists 190 competing methods [19]. Traditional OF methods predominantly rely on the assumption of 'brightness constancy', i.e., that the intensity of the imaged scene does not change, but merely shifts locally in the field of view. OF further struggles with large displacements that exceed the spatial resolution of the moving objects. Thus, OF methods typically excel in rigid image motion with strong image features and gradients, such as in self-driving cars or video compression [20]. However, OF performs poorly in biological images, which typically have lower textural contrast, signal-to-noise ratio and fluctuating intensities. Because of this, DIC is often preferred for biomechanics analyses [9, 6]. Thus, there is a present need for accessible methods that can combine both high accuracy and computational speed.

Deep learning has the potential to address this challenge with a feed-forward scheme that could exceed the speeds of even optical flow methods. A major challenge in this task is that ground truths measurements of displacement are generally unavailable. DIC and OF methods rely on some assumptions in the consistency in intensity or image textures. While the evaluation of performance is typically performed using some benchmark dataset [21] with simulated or model-based approximations of displacements and are assumed to extend to other types of image data. Thus, appropriate metrics and training data consistent with biological images must be generated for any deep learning task. Deep learning has been applied to OF for computer vision, particularly, in simulated and animated graphics [22]. Methods such as the milestone FlowNet [23] achieve powerful OF performance by training on artificial scenes, typically via publicly available datasets. Additionally, several recent works have investigated the use of deep learning for DIC motivated by material testing. Boukhtache et al. [24] have presented StrainNet, a model based on tracking subpixel displacement between images of speckle-painted materials, for instance, in tensile testing. While the StrainNet network was based on the FlowNet architecture, it was instead trained on synthetic images of speckle and a grid-based displacement simulation. The model performed well in estimating microscale deformation of solid material. Yang et al. [25] have extended StrainNet by end-to-end training directly on local strain, enhancing strain sensitivity. Full-field displacement estimation using deep learning, however, has yet to be applied to biological images which often have a broad range of image features, textures and contrast, and can have high-amplitude and localised deformation and strains. As shown in this work, this challenge makes StrainNet and similar materials-testing-inspired networks poorly suited to the task.

In this Paper, we demonstrate an experimentally unsupervised deep learning method for estimating full-field displacement in biological images: meaning that this method can be applied to any biological image pair or video with no prior knowledge of displacement or additional experiments. We refer to our network as: Displacement Estimation FOR Microscopy–'DEFORM-Net'. DEFORM-Net combines images from different modalities, and generates synthetic supervised data consistent with typical power spectral characteristics of biological deformation using fractal Perlin noise, as well as system noise processes that, by design, invalidate the brightness constancy assumptions. We explore various similarity metrics, including perception-based losses, as well as an image correlation based metric using a forward simulation of deformation to improve performance and network generality. DEFORM-Net is evaluated on real microscopy videos of beating mouse cardiomyocytes [26, 27] and pulsating larval epithelial cells (LECs) in *Drosophila* pupae [28]. DEFORM-Net can match and exceed the accuracy of DIC and the speed of OF, with near video-rate inference speed and high spatial sampling. To assist rapid iteration and testing, we provide DEFORM-Net as

open source, including a standalone compiled version for inference and integration with the ImageJ/FIJI platform [29]. Our method is readily adaptable and will empower powerful quantification for dynamic bioimaging challenges.

2 Results

2.1 Full-field displacement estimation with deep learning

The problem of estimating full-field displacements from image pairs is illustrated in Figure 1(a–d). This example shows false-coloured widefield fluorescence microscopy images of two consecutive frames, termed as reference (Ref.) and deformed (Def.), from a video of a cluster of spontaneously beating neonatal mouse cardiomyocyte cells. The displacement field between the reference and deformed states has horizontal and vertical (or x and y) components that can be visualised in a vector form, $\mathbf{u} = (u_x, u_y)$, (Fig. 1(c)) or in a phasor form, where $A = |\mathbf{u}|$ and $\phi = \angle\mathbf{u}$, (Fig. 1(d)). The phasor visualisation encodes the displacement magnitude as the value (V) and the angle as the hue (H) in the hue-saturation-value (HSV) colour space. Figure 1(e) shows how this phasor representation can be a convenient means of illustrating the displacement field with a high spatial resolution.

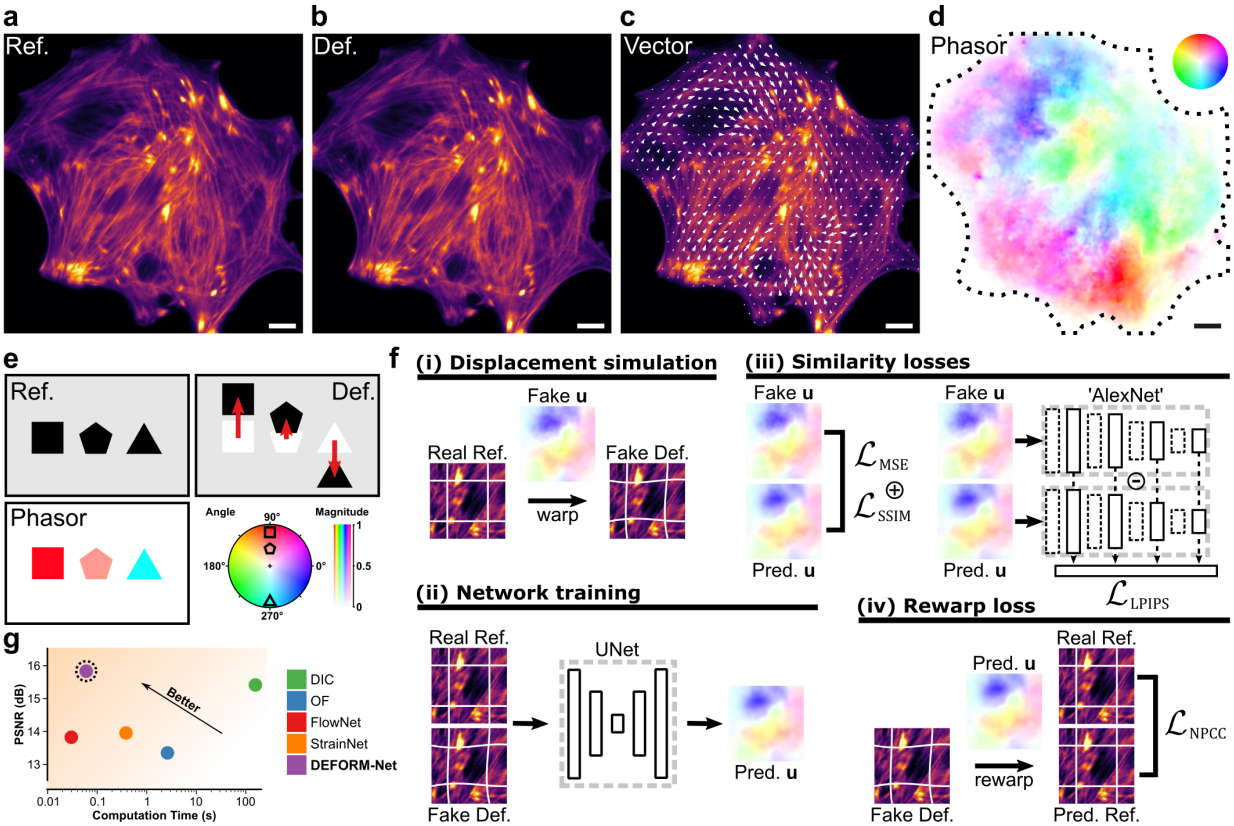

Figure 1: Illustration of full-field displacement estimation. (a) Reference (Ref.) and (b) deformed (Def.) fluorescence microscopy images of mouse cardiomyocytes. The full-field displacement from the reference to the deformed state can be represented by a (c) vector image or (d) phasor plot, where the hue represents the angle and saturation represents the magnitude of the displacement vector. Scale bars are 10 μm. (e) Visual demonstration of the mapping from displacement to colour. (f) Graphical representation of the (i, ii) deep learning method and (iii, iv) loss functions, where $\mathbf{u}$ is the displacement vector field and the terms Real and Fake refer, respectively, to real microscopy data and simulated data. (g) Comparison of the performance displacement estimation methods in real data quantified using the peak signal-to-noise ratio (PSNR).

DEFORM-Net comprises several key components that enable it to estimate an accurate displacement field between input image pairs (Fig. 1(f)). Because ground truths are unavailable in this problem, we simulate realistic displacement fields (Fake $\mathbf{u}$) and use them to generate synthetic pairs of reference (Real Ref.) and deformed (Fake Def.) images for supervised training (Fig. 1(f)(i)). These images are further augmented with noise processes that mimic those in microscopy experiments. This is detailed in the Methods section and evaluated in the later Results sections. We

train an artificial convolutional neural network, based on a U-Net architecture, to transform the image pairs into a predicted displacement field (Pred. $\mathbf{u}$) using several training loss functions (Fig. 1(f)(ii)). First, we implement conventional pixel-wise similarity losses between the predicted displacement field and the simulated ground truth, including the mean-squared error (MSE) and the structured similarity index metric (SSIM) (Fig. 1(f)(iii)). SSIM is a common metric that emphasises matching of perceived textures between image patches and helps counteract the blurring effects associated with absolute error-based estimates [30]. We enhance this with a learned perceptual similarity loss (LPIPS), which is emerging as a powerful image similarity metric based on intercepting intermediate feature maps from pre-trained large-scale classification networks (here, the AlexNet) [31] (Fig. 1(f)(iii)). Finally, we include an unsupervised loss metric based on image correlation that we term as 'rewarp loss' (Fig. 1(f)(iv)). The deformed image is 'undeformed' using the predicted displacement field, estimating the reference image. This is then compared to the real reference image using Pearson cross-correlation (NPCC). As such, no knowledge of the ground truth is required to calculate the rewarp loss. This methodology leads to improved performance in real biological videos compared to previous methods (Fig. 1(g)). We describe these performance values and justify the methodology in the following Results sections, first with simulated supervised test data and then with real experimental data.

2.2 Simulating biologically realistic displacements

A major challenge in network training based on supervised learning is the availability of accurate ground truth data. While OF networks, such as FlowNet, employ animated scenes and DIC networks, such as StrainNet, employ the simulation of speckle, we demonstrate that these are insufficient at capturing displacements and image content of biological images, leading to poor performance. Figures 2(a) and (b) show single representative reference frames of analysed image sequences from widefield fluorescence microscopy of mouse cardiomyocytes and confocal microscopy of *Drosophila* LECs, respectively, with the associated displacement field estimated using conventional DIC and OF methods. The implementation details of DIC and OF, along with information about the biological samples, are in the Methods section. We can see that the estimated displacement comprises large scale shifts in various areas of the images, as well as a range of higher spatial frequency variations, both in amplitude and direction. The DIC estimates are of lower spatial resolution to that of OF due to the finite subset size, but are typically regarded as more accurate [17]. While both displacement fields are scaled for visualisation, the displacement in the *Drosophila* cells is approximately eight times greater to that in the cardiomyocytes. The maximum displacement magnitude between frames was approximately 200 nm (2 pixels) in the cardiomyocyte and 1.7 μm (8 pixels) in the Drosophila data. Such large displacements lead to a discrepancy between DIC and OF estimates, likely due to the well-established problem of OF with large displacements [18].

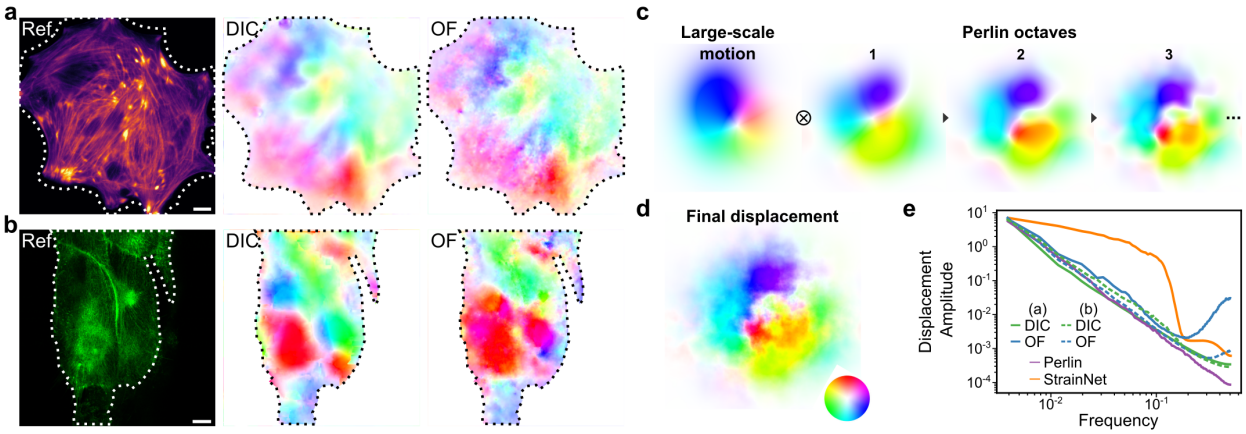

Figure 2: Simulation of realistic displacement fields. (a, b) Reference microscopy images of (a) mouse cardiomyocytes and (b) *Drosophila* LECs with representative displacement fields estimated using DIC and OF methods. Scale bars are 10 μm. (c) Displacement vector field simulation by multiplying random Gaussian large-scale motion with progressively refined fractal Perlin noise. (d) Final simulated random displacement field with controllable spatial power-spectral density. (e) The spatial power-spectral density of displacement amplitudes estimated using DIC and OF from data in (a) and (b) compared to simulated data using Perlin and StrainNet [24] methods.

To capture such properties of biological motion, we propose displacement simulation based on a random fractal Perlin noise process [32]. This is detailed in the Methods section; however, briefly, we first generate large-scale motion using several randomly positioned Gaussian peaks with a random displacement phasor (Fig. 2(c)). We then multiply this with

several 'octaves' of random Perlin noise (amplitude and direction), with each octave possessing progressively refined spatial resolution and reduced energy to generate the final displacement field (Fig. 2(d)). Perlin noise is a procedural noise originally developed as a method to generate realistic image textures [32]. What makes this noise well suited to the task is the precise control of the spatial power spectral density (PSD) of the generated fields, i.e., the energy associated with a particular spatial frequency. Figure 2(e) shows the mean PSD across (n=50) DIC and OF estimates in biological samples in Figs. 2(a) and (b). We immediately see a linear log-log decay of displacement amplitude with spatial frequency consistent between samples and DIC and OF methods. This property of the PSD is often found in natural images, and exploited as an image prior in many reconstruction methods [33]. Our Perlin-based method naturally satisfies this PSD shape. This is an advantage to the grid-based generation method employed in StrainNet [24], which inevitably leads to a hard cut-off response. The inflection in PSD seen in the OF estimates is likely due to the instability in the OF algorithm, which arises when the total displacement exceeds its spatial frequency [18].

2.3 DEFORM-Net outperforms other methods on simulated testing data

We evaluate our displacement simulation and network training method (DEFORM-Net) first in simulated supervised test data. We generate network training data from four different microscopy imaging modalities, presented in Figures 3(a–d). These are: widefield fluorescence, brightfield and differential interference contrast (DICM) microscopies in mouse cardiomyocytes, and confocal fluorescence microscopy of LECs of a *Drosophila* pupa. Specifically, we generate 2,337 frame pairs from randomly cropped regions of interest from video datasets. These frames were randomly partitioned into 1,825 training and 256 validation pairs, as well as 256 frame pairs exclusively used for testing, i.e., unseen by the network training process. All image modalities were used to train a combined model for evaluation in the first instance. While evaluating performance in simulated images is not representative of ultimate performance in real data, we use this for an initial comparison of existing methods.

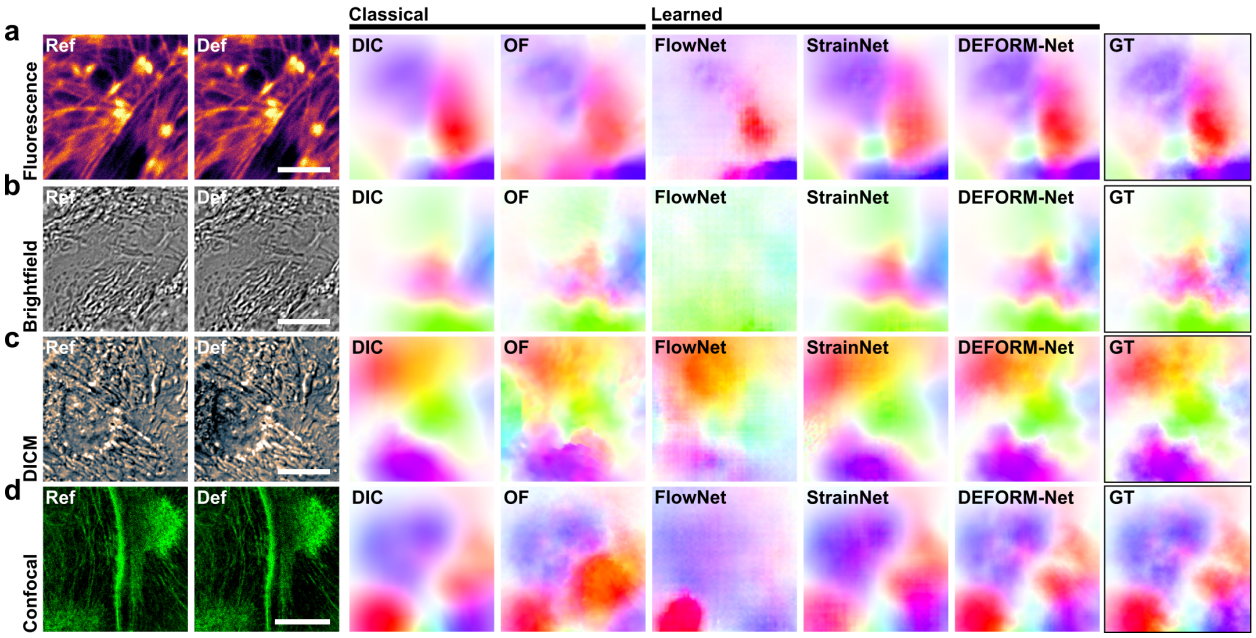

Figure 3: Visual comparison of methods in different imaging modalities and contrast in simulated data. (a–d) Representative microscopy images and estimated displacement fields of (a–c) mouse cardiomyocytes and (d) *Drosophila* LECs using widefield fluorescence, brightfield, differential interference contrast (DICM) and confocal fluorescence microscopies. Scale bars are 10 μm.

Figure 3 compares the performance of classical and learned methods in a representative image randomly selected from the testing set for each modality. Specifically, we perform conventional DIC using 'ncorr2' software [34] and OF using a pyramidal TV-L1 solver [35], which were chosen because they output the highest accuracy estimates compared to other common open-source methods for this data (see Methods). We compare this to FlowNet, which is a major milestone in learned OF, as a benchmark, as well as StrainNet, which was demonstrated for DIC in materials testing. The original StrainNet network (trained on artificial speckle) performed poorly; thus, for a fair comparison, we have retrained StrainNet with the images used in this work, but simulated with the grid-based approach scaled to the higher

displacement amplitudes seen in the images. Because StrainNet relies on separated generation of displacements at various resolutions, the training set expanded to over 20,000 image pairs and was trained for 6× longer. FlowNet, however, was not retrained as it relies on the use of animated graphics datasets. Like conventional OF, it is expected that it can be applied indiscriminately to all data.

Visually comparing the different methods to the ground truth (GT), we see that DIC outputs an accurate but substantially blurred estimate. OF, however, produces higher spatial resolution outputs with several sections in the images that fail to match the GT. FlowNet performs overall poorly, especially in images with low image contrast and high noise (Figs. 3(b) and (d)). While StrainNet estimates are adequate compared to DIC, DEFORM-Net substantially improves the estimate quality, especially in terms of spatial resolution. Notably, StrainNet has directly implemented the FlowNet network architecture (FlowNetF), which included a multiscale loss in the decoder side. We found that this architecture did not provide an appreciable benefit to a conventional U-Net; however, it added substantial training overhead in terms of memory and training time.

We then assessed the performance of various error metrics (Tab. 1). Specifically, we use peak signal-to-noise ratio (PSNR) as $10 \cdot \log_{10}(1/\mathrm{MSE})$, such that a higher value corresponds to better performance for all metrics. Notably, as it is a log-scale metric, a 3-dB variation in PSNR corresponds to a two-fold variation in accuracy. DEFORM-Net outperforms all other methods on all loss metrics, including those of DIC. Importantly, the inference time per frame is substantially improved over classical methods. Much faster OF methods could be implemented; however, the slower pyramidal and iterative method was required to achieve satisfactory performance in biological images. While FlowNet is the fastest, it evaluates a 4× sub-sampled output compared to other methods; StrainNet utilises an identical inference graph to FlowNet without subsampling, for a more direct comparison. All learned methods, however, breach the limiting two-minute processing time of DIC.

Table 1: Performance statistics of displacement estimation methods in simulated data. Data is presented as mean value and standard error of mean in brackets ($n = 50$). Highest performance values within standard error bounds are highlighted in bold. PSNR: peak signal-to-noise ratio; SSIM: structured similarity index metric; LPIPS: learned perceptual image patch similarity.

Method	**PSNR** (dB)	**SSIM** (/100)	**LPIPS** (/100)	**Rewarp** (/100)	**Time** (s)
DIC	24.6 (0.2)	68.6 (0.7)	92.6 (0.4)	97.1 (0.3)	128.6 (0.3)
OF	19.9 (0.3)	34.8 (1.4)	87.1 (0.7)	95.6 (0.5)	2.62 (0.01)
FlowNet	18.3 (0.2)	14.3 (0.8)	82.2 (0.8)	86.5 (1.0)	**0.028 (0.0007)**
StrainNet	19.5 (0.3)	55.5 (1.7)	89.0 (0.7)	92.8 (0.8)	0.389 (0.0006)
DEFORM-Net	**26.5 (0.2)**	**73.7 (0.5)**	**96.4 (0.2)**	**98.0 (0.2)**	0.068 (0.0008)

2.4 DEFORM-Net outperforms other methods on microscopy data

We next evaluate DEFORM-Net on real experimental data. Because there is no access to independent ground truth data, we must consider alternate means of assessing performance. Naively, we can consider the 'rewarp' metric, whereby when a deformed image is 'undeformed' using an accurate estimate of displacement, it should correlate well to the reference image. Figure 4(a), however, illustrates a major challenge in using correlation as a metric of accurate displacement. Consider the displacement of a set of points between two frames. It is reasonable that for a small enough subset, there may be several possible displacements that lead to a high local correlation in intensities. Only when the subset size is sufficiently large to describe a unique set of image features, will the estimate likely possess a global maximum that corresponds to the true displacement field. We see this issue arise when using the 'rewarp' metric to assess performance.

Evaluating real experimental image frames of the *Drosophila* video (n=50) using the ground-truth-free rewarp metric showed that, unexpectedly, DIC performs overall the worst (Fig. 4(b)). The scenario of evaluating rewarp loss on a pixel-subset scale leads to the following property: an accurate displacement estimate improves rewarp loss, however, a good rewarp loss does not indicate an accurate displacement estimate. This idea of some constancy in intensity values during displacement is common to DIC and OF, and their solutions differ in the method of regularisation and constraints that make it converge to a globally accurate solution. Thus, it is unsurprising that all methods intrinsically perform well in this loss, despite producing different estimates.

To overcome this challenge in validation, we consider an independent method of validation by manually tracking the displacement of local features using the ImageJ manual tracking functionality. Using this method, we have manually generated 4 sets of trajectories that are visually accurate from the raw videos. Each trajectory comprises 87 coordinate points corresponding to each consecutive frame pair in the entire video. We then compare the displacement with that of the corresponding estimate in the nearest pixel for each method, and evaluate the MSE of their distance metric. The

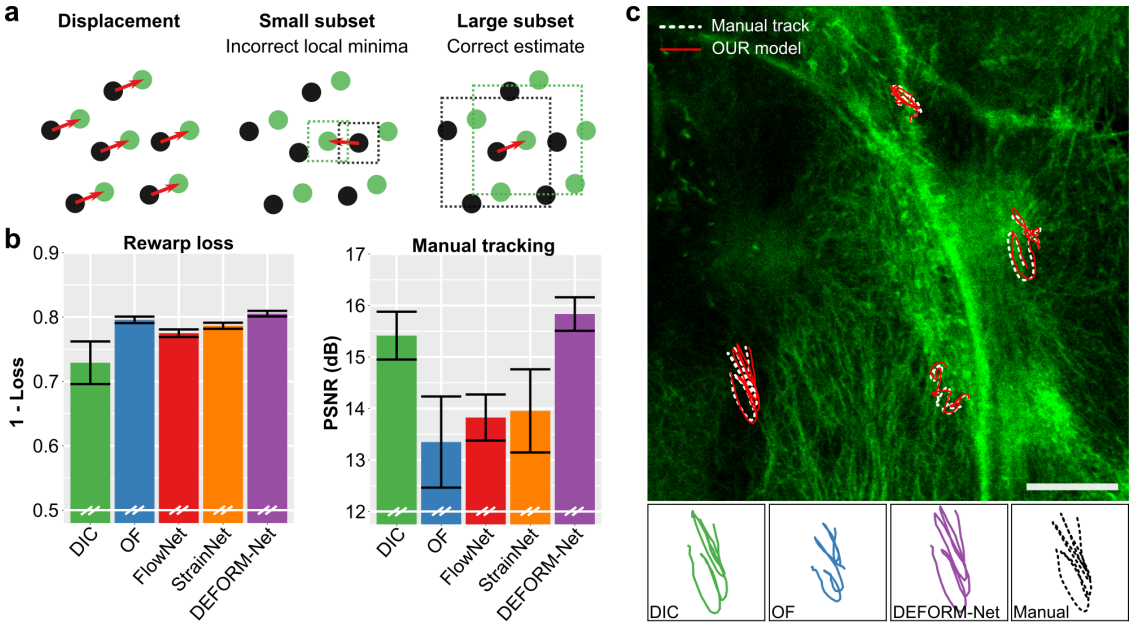

Figure 4: Performance evaluation in real displacement data. (a) The challenge of using image intensity correlation as a metric for displacement. (b) Method performance evaluated using the intensity correlation-based rewarp metric (n = 50) compared to manually tracked (n = 4) displacements. Error bars are standard error of mean. (c) Visualisation of manually tracked displacements in a *Drosophila* microscopy video. Insets compare displacement tracks evaluated using various methods. Scale bar is 10 μm.

MSE for each frame and track are averaged and converted to the log-scale PSNR for comparison. Figure 4(c) shows example trajectories using such a method, with statistics shown in Fig. 4(b). We see that the performance in real data is similarly high for DIC and DEFORM-Net compared to other methods, in line with expectation based on the simulated tests. We focus our evaluation of videos of *Drosophila* LECs, which exhibit the largest relative displacement, and thus highest ease of manual tracking. We use this manual-tracking-based metric for further evaluations.

2.5 Including microscopy-informed noise in training data is essential

A major part of the performance of DEFORM-Net is the added treatment of image intensity noise. It is well-known that, compared to natural macroscopic scenes, biological images are often challenged by many sources of noise, such as from poor biological contrast, background noise or poor sensitivity of instruments. Beyond random noise that follows a Poisson process, which is added to our training data, additional large-scale fluctuations in intensity can invalidate the brightness constancy assumption in OF methods.

Figures 5(a) and (b) illustrate this issue in images of *Drosophila* LECs. The DIC vector image shows a pattern of pulsatile motion in a developing pupa. The red circle marks an area of converging displacement and the red band highlights an area where an optical occlusion in the tissue shadows the fluorescence signal captured by the confocal scan. The OF estimate, however, shows a different direction in the displacement vectors. Compared to manual tracking, Figure 5(c) shows that DIC estimates are more accurate, which we use as the baseline. This can be confirmed by inspecting the full video. The poor performance of OF is likely because the intensity between frames are not consistent. In fact, this is common to fluorescence imaging due to photobleaching, fluctuation in the fluorescent background, and variations in the absorption and scattering of light in a living tissue.

To test accuracy and generality, we train a DEFORM-Net model with data comprising only the multimodal cardiomyocyte images (excluding any *Drosophila* images) and added 5% Poisson noise. Naively, we would like our model to be applicable to all images with a use-case similar to that of DIC or OF. However, Figure 5(d) shows that the output of such a network exhibits similar artefacts as that in OF, suggesting that this network learns some similar properties of brightness constancy to OF models. To account for variations in intensity, we introduce another noise which we term as 'intensity modulation' noise. Specifically, we introduce additive large-scale and low-spatial-resolution noise, also modelled using our Perlin noise process (but with fewer octaves), with a maximum peak size of 10% of the image dynamic range. This introduces visible modulations in image intensity in the reference and deformed training images.

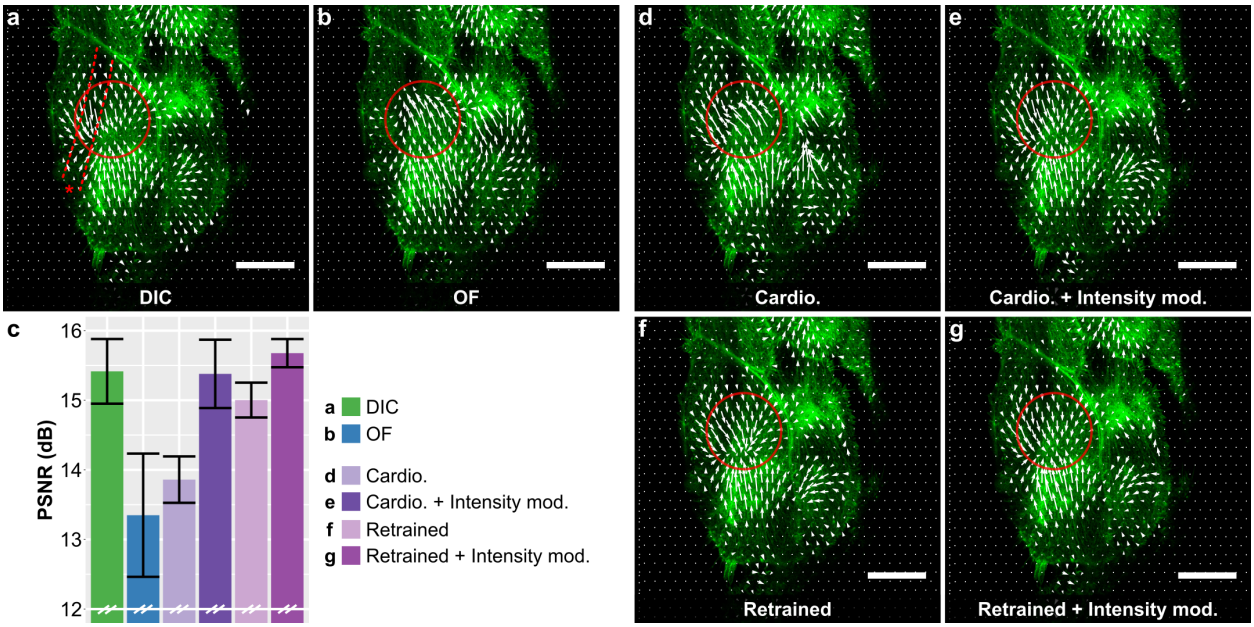

Figure 5: The role of noise and retraining in generalisation of network performance. (a–b) Displacement vectors from a single frame from a video of cells in a *Drosophila* pupa evaluated using conventional (a) DIC and (b) OF methods. (c) Accuracy of methods compared to manual tracking. Error bars are standard error of mean. (d–g) Displacement vectors from networks trained using different methods: (d) cardiomyocyte data only; (e) cardiomyocyte data only with intensity modulation noise; (f) retrained on *Drosophila* images; and, (g) retrained on *Drosophila* images with intensity modulation noise. Scale bars are 20 μm.

Interestingly, when trained with such data, even excluding any images of *Drosophila* pupal cells, the performance is substantially enhanced to match that of DIC (Fig. 5(e)).

By retraining DEFORM-Net with data that includes the *Drosophila* images, the overall performance increases substantially for the Poisson noise-only case (Fig. 5(f)). However, retraining only has a marginal improvement when intensity modulation noise is included (Fig. 5(g)). This performance (Fig. 5(c)) suggests that intensity modulation noise is important for enhancing network generalisation, perhaps more so than the breadth of training images, and has thus been implemented in all other evaluations in this work.

2.6 Combining supervised and unsupervised losses enhances generalisation

DEFORM-Net comprises several training loss functions to enhance its performance and generality. Here, we describe the selection of the losses and their utility with respect to performance metrics in simulated and real data. Table 2 lists the performance metrics of each loss in models with various combinations of training loss functions. We compare a baseline model that utilised the conventional MSE and SSIM losses only against those with added rewarp loss or LPIPS loss, as well as the combined model with all losses included. These are also benchmarked against the conventional DIC and OF methods. The performance is evaluated using the PSNR, SSIM, LPIPS and rewarp metrics in simulated testing data, as well as in real *Drosophila* image frames compared to manual tracking (Manual PSNR). We also evaluate performance of each model when *Drosophila* images are specifically excluded from training (Cross-domain PSNR) to test generalisation.

The baseline model performs adequately in all metrics and matches, for most part, the performance of DIC. When trained with the relevant *Drosophila* data (Manual PSNR), it outperforms DIC in real data. However, when faced with data outwith that used in training (Cross-domain PSNR), this advantage is lost. Interestingly, with the addition of rewarp loss, the PSNR error in simulated testing data is improved substantially. Naively, we may assume that training with MSE loss should maximise PSNR ($\propto 1/\text{MSE}$). However, because rewarp loss is unsupervised and describes an apriori physical property of the data, it likely helps the network avoid overfitting, and thus, improves performance when evaluated in unseen testing data. Despite this, this benefit is not conferred immediately to the performance in real data. Alternatively, the addition of LPIPS loss to the baseline model has little impact on the network performance.

Table 2: The role of training loss functions on performance evaluated on both simulated and real displacement data. Highest performance values within standard error bounds are highlighted in bold.

Method	**PSNR (dB)**	**SSIM (/100)**	**LPIPS (/100)**	**Rewarp (/100)**	**Manual PSNR (dB)**	**Cross-domain PSNR (dB)**
DIC	24.6 (0.2)	68.5 (0.6)	92.6 (0.4)	97.1 (0.3)	15.4 (0.5)	15.4 (0.5)
OF	19.9 (0.3)	34.8 (1.4)	87.1 (0.7)	95.6 (0.5)	13.3 (0.9)	13.3 (0.9)
Baseline	24.4 (0.2)	**77.4 (0.4)**	95.4 (0.3)	96.8 (0.3)	**15.7 (0.2)**	15.4 (0.5)
Rewarp loss	**26.3 (0.2)**	73.3 (0.5)	95.8 (0.3)	**97.9 (0.2)**	**15.6 (0.4)**	15.3 (0.1)
LPIPS loss	24.9 (0.3)	75.2 (0.5)	**96.3 (0.2)**	97.0 (0.3)	15.3 (0.1)	15.4 (0.3)
Combined loss	**26.5 (0.2)**	73.7 (0.5)	**96.4 (0.2)**	**98.0 (0.2)**	**15.8 (0.3)**	**16.0 (0.3)**

Interestingly, when both rewarp and LPIPS losses are included in a combined model, the performance is substantially enhanced in the cross-domain scenario. Specifically, this indicates that generalisation is improved when only limited training data is available. Based on the previous performance of the rewarp metric compared to manual tracking, we can see that rewarp loss can be challenged by the presence of local minima. This will likely result is substantial high-spatial-frequency local displacements in the estimate that would not be present in the simulated ground truth data. The added LPIPS loss likely focuses its attention on these details, while MSE or even SSIM losses are known to not be sensitive to such high-frequency content [31]. While the baseline model is adequate at meeting the DIC challenge, we have utilised the combined model for all other demonstrations in this work.

2.7 Demonstration of DEFORM-Net

Figure 6 illustrates the utility of DEFORM-Net in quantifying motion in biological videos of beating cardiomyocytes and pulsating *Drosophila* LECs. Figure 6(a) shows a regular cardiac beating cycle, evaluated as the mean of the displacement amplitude in the field of view over the 15-second video. Neonatal cardiomyocytes exhibit spontaneous synchronised beating. Insets in Fig. 6(a)(i) and (ii) show displacement vectors at time points associated with the primary and secondary peaks in the displacement amplitude revealing a pattern of partial relaxation succeeded by a smaller contraction. Studying the spontaneous beating of neonatal cardiomyocytes and the intercellular communication between neighbouring cells provides invaluable insights into cardiac activity, intrinsic pacemaker activity, and developmental signalling pathways [36]. Understanding these fundamental mechanisms not only elucidates the normal functioning of the developing heart but also offers critical avenues for research into various diseases and potential therapeutic interventions. The full video is available as a Supplementary Movie S1.

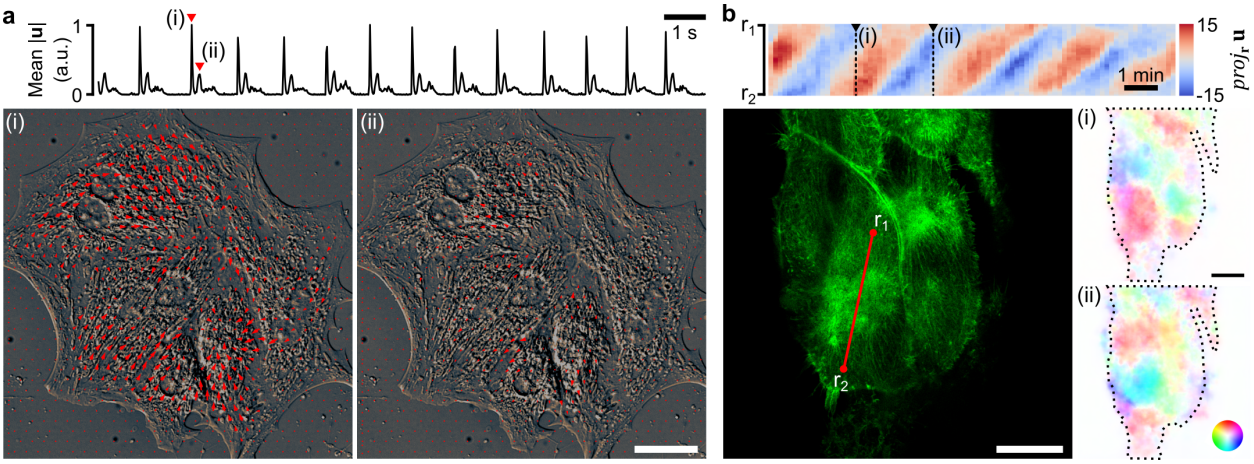

Figure 6: Demonstration of full-field displacement estimation. (a) Beating mouse cardiomyocytes imaged with DICM show a regular beating pace from the mean displacement magnitude across frames. Snapshots of displacement field vectors are from (a)(i) primary and (a)(ii) secondary peaks. (b) Displacement projected along the $r_1 r_2$ vector from a video of a pulsating *Drosophila* LEC. Insets show the displacement phasor maps at frames (b)(i) and (b)(ii). Scale bars are 20 μm.

Figure 6(b) shows the pulsatile motion in a *Drosophila* LEC as a projection of the displacement field along the line indicated by points r_1 and r_2. This line plots a trajectory of wave-like motion along the cell's long axis. Insets in

Fig. 6(b)(i) and (ii) show displacement phasor plots from two time points. Such pulsed contractions are important in *Drosophila* development because they are involved in the apical constriction of LECs, which precedes their programmed cell death during metamorphosis, when larval tissues are replaced by adult tissues [28]. Understanding pulsed contractions will provide mechanistic insights into congenital conditions caused by defective contractility, for example, neural tube disorders, such as spina bifida [37]. The full video is available as a Supplementary Movie S2.

3 Discussion

DEFORM-Net can be a powerful method for accurate and rapid estimation of displacement in biological images that combines the accuracy of DIC with rapid and high-resolution feed-forward inference of deep learning. Conventional DIC and OF methods are routinely used for advanced biological analyses [6, 9, 10, 11, 12, 13, 14]. There, the problem of displacement estimation is typically void of independent validation and, further, is dependent on the nature of image contrast and the displacement, with no trivial estimates of accuracy. Because of this, the general wisdom suggests that one should select a method that produces outputs that are consistent with the motion intuitively observed in the images. Typically, the user will select the method and optimise available parameters to achieve a desired speed and artefact-free displacement estimates. In the same way, we foresee that DEFORM-Net could be used with some selection of pre-processing and the model. We have evidenced that DEFORM-Net can perform well in generalisation, i.e., on data that it has never seen before. Specifically, we demonstrate equivalent performance (evaluated by comparison to manual tracking) in confocal microscopy videos of pulsating *Drosophila* pupal cells by DEFORM-Net that was trained on neither any *Drosophila* images nor any confocal microscopy scans, suggesting good cross-domain as well as cross-sample performance (Table 2).

To facilitate rapid dissemination, we provide DEFORM-Net as open source (see Methods section). Because training new models can be a challenge both in the requirement for advanced hardware and expertise, we also provide the capacity to perform rapid inference with pre-trained models through a compiled executable through a command-line interface or using the ImageJ/FIJI platform [29]. For this, we further make available several key models from this paper and the associated datasets. Additional details on the software is included in the Supplementary Information.

DEFORM-Net performs well with limited training data. Specifically, we have used 1,738 frame pairs from three 15-second mouse cardiomyocyte videos to train a model that performed well in cross-domain and cross-sample *Drosophila* videos. If retraining is required, such experimentally unsupervised datasets are reasonable to acquire in a single or few sample scans, e.g., solely the data that is desired to be analysed. This suggests that no additional experimental time may be required to train the model. Further, one may combine existing data with new sample frames for combined multi-domain training, as we carried out in this work.

The fractal Perlin noise simulation of displacement fields is a critical part of DEFORM-Net and its improved performance compared to StrainNet and FlowNet methods. The PSD of the simulated displacement fields can be tailored to that expected in the real data. However, further improvements may be gained by introducing some PSD regularisation in the training loss functions, which can be important priors in biological data [38]. Specifically, the PSD of the network output can be constrained to match that of natural images [33]. The rewarp and LPIPS losses further provide options for more natural and physics-based regularisation of network training. Rewarp loss is not globally optimisable because of local minima, especially at higher spatial resolutions. Naively evaluating the rewarp metric on the low spatial resolution components of displacements did not improve performance (data not shown). In DIC, such metrics are regularised by analysing patches and constraining the local deformation to a set of affine transforms [34]. While this could be adapted to the loss function, its evaluation would be substantially slowed as this is the critically slow component of the DIC method.

Alternatively, perceptual networks and the derived loss functions are an exceptionally interesting prospect for this task [31]. Qualitatively, human observation can track a greater range of motion between overlapped image frames, even in areas where DIC and OF fail, likely utilising a breadth of image contrast, texture and feature identification abilities. Thus, displacement estimation tasks could be enhanced by transforming input data to new perception-based representations, or by combining several networks that excel at complementary tasks. The field of learned OF methods is flourishing with many new advances that can be investigated for DEFORM-Net. While we have not exhaustively compared our network performance to the immediate state of the art in learned OF, FlowNet still remains as an important recent benchmark with only marginally poorer performance to the current leading methods in that area. However, in our work we have observed that such methods are ill-suited to the domain of biological images because of the routine violation of the brightness constancy assumption as well as several other such sources of noise.

4 Conclusion

We have presented DEFORM-Net, a deep-learning method for estimating full-field displacement between biological images or video frames. DEFORM-Net outperforms conventional DIC and OF methods as well as learned DIC, StrainNet, and OF, FlowNet, methods in typical microscopy data that is challenged by poor sample signal, low contrast and background noise. This performance was afforded by the random fractal Perlin-noise simulation with a controlled PSD matching natural displacements as well as the addition of intensity noise and several training loss functions. The trained models exhibited good performance on videos of beating mouse cardiomyocytes and pulsating *Drosophila* LECs, including in cross-domain and cross-sample scenarios, suggesting good generalisation. We present DEFORM-Net as open source with inference implemented in the ImageJ/FIJI platform, towards rapid evaluation across many applied problems in biology and medicine.

5 Methods

5.1 Simulating full-field displacement with fractal Perlin noise

The simulated displacement fields are generated in two stages. First, several two-dimensional Gaussian peaks are placed at randomised locations and combined additively. Specifically, we generate six peaks, while their location, magnitude and standard deviation are randomly sampled from independent Gaussian distributions.

Second, the large-scale displacements are combined with fractal Perlin noise [32], a type of smooth pseudo-random pattern, the appearance of which is often likened to clouds. This introduces small-scale variations which closely match the displacement distributions observed within our microscopy images. Conveniently, we utilise the open `perlin_numpy` [39] package for this. Briefly, the generation procedure for fractal Perlin noise is as follows: a grid is defined, the scale of which determines the scale of the variations in the noise. A random unit vector, known as the gradient vector, is generated at each grid node. For each point in the field, the four closest grid nodes are considered. The dot product between each node's gradient vector and the displacement vector of the point from the node is calculated. Then, the final noise value is obtained by smoothly interpolating between these four results, based upon the distance between the point and each node. The interpolation function used should have stationary points at the grid nodes, as this leads to the noise values equalling zero at each node, binding the scale of noise variations to the grid scale. Fractal noise is created by adding many layers of Perlin noise, referred to as 'octaves'. Each octave's magnitude and grid spacing are scaled down from the previous by factors known as the 'persistence' and 'lacunarity', respectively.

The parameters used for large-scale noise and fractal Perlin noise generation were chosen based on a visual match to the DIC and OF estimates in biological data. The exact values may be inspected in the `perlin_generator` module of the supporting open-source code (See Methods Section 5.4).

5.2 Generation of supervised training data

Training DEFORM-Net requires input images in the reference and deformed configuration, as well as the corresponding displacement field to evaluate the supervised training losses. To generate this set of data, we used individual frames from real microscopy videos. For each image pair, a randomly cropped area (here, 512×512 pix) from a real frame was used as the reference image, with the corresponding grid spatial coordinates, $I_R(x, y)$. Then a simulated displacement field, $\mathbf{u}(x, y) = u_x(x, y)\hat{\mathbf{x}} + u_y(x, y)\hat{\mathbf{y}}$, is used to deform the reference image to a simulated deformed image, I_D. This is achieved by evaluating the reference image at new transformed coordinates: $(x', y') = (x - u_x, y - u_y)$, i.e., $I_D(x, y) = I_R(x', y')$. Because (x', y') are subpixel coordinates, we used two-dimensional interpolation based on a bivariate spline approximation over a rectangular mesh. This procedure was repeated for each image frame in the real microscopy videos, and the final data was randomly shuffled and partitioned into exclusive training, validation and testing subsets (exact image numbers are provided in the relevant Results sections). The training data was used for training, loss evaluation and backpropagation, while the validation data was used to visualise convergence. Testing data was used for all evaluations in the results with no influence on the training process.

5.3 Network architecture and loss functions

DEFORM-Net uses a 7-level U-Net autoencoder [40], which outputs full-resolution $W \times H \times 2$ displacement estimates (one for the x and y displacement component), where W is the number of pixels in $x-$direction and H is the number of pixels in $y-$direction. The reference and deformed frames are concatenated and input as a $W \times H \times 6$ tensor. This is to support 3-channel RGB colour images; however, greyscale images were used in this instance because all

biological data were single-intensity images. The number of input channels does not appreciably increase inference or training times, as the first convolutional layer transforms the input to a set 64 channels regardless.

DEFORM-Net was trained using a desktop computer equipped with an NVIDIA GTX 1080Ti GPU and an Intel Xeon W-2145 CPU. Training took approximately 5 hours for 300 epochs and 1,825 frame pairs with 512 $\times$ 512 pixels each.

A combination of supervised training loss functions were used to train our final model, each based upon comparing the estimated displacement fields to the simulated ground truth, including: (1) the Mean Squared Error (MSE), (2) the Structural Similarity Index Measure (SSIM) [30], and (3) the Learned Perceptual Image Patch Similarity (LPIPS) [31]. In addition to these, (4) an unsupervised 'rewarp' loss was used.

(1) MSE loss evaluates the mean squared error of the Euclidean distance metric between the network output and the ground truth:

$$\mathcal{L}_{\text{MSE}} = \frac{1}{N}\sum_{i=1}^{N} \left\| \mathbf{u}_{\text{pred.},i} - \mathbf{u}_{\text{fake},i} \right\|_2^2 , \tag{1}$$

where $\mathbf{u}_{\text{pred.}}$ and $\mathbf{u}_{\text{fake}}$ are the network outputs (predicted) and simulated (fake) displacement fields, respectively (Fig. 1(f)). This loss is typical in many deep learning-based displacement estimation methods [23, 24, 41], despite not accurately reflecting several critical aspects of image quality, such as the level of blurring or noise [42]. The MSE is also commonly referred to as the endpoint error (EPE) when evaluated on vector values, such as displacements.

(2) SSIM is frequently used as a metric designed to perceptually compare larger scale features within images [30, 42]. It aims to capture structural differences, such as those arising from blurring or noise, independent of changes in image brightness (which represents displacement magnitude in our case). This is achieved by splitting the input images into patches for comparison (here, 11-pixels wide), rather than only considering corresponding individual pixels. The SSIM is most commonly written as a product of three components:

$$\text{SSIM}(a,b) = \frac{\sigma_{ab}}{\sigma_a \sigma_b} \cdot \frac{2\bar{a}\bar{b}}{\bar{a}^2 + \bar{b}^2} \cdot \frac{2\sigma_a\sigma_b}{\sigma_a^2 + \sigma_b^2} , \tag{2}$$

where

$$\bar{a} = \frac{1}{N}\sum_{i=1}^{N} a_i , \quad \bar{b} = \frac{1}{N}\sum_{i=1}^{N} b_i , \quad \sigma_a^2 = \frac{1}{N-1}\sum_{i=1}^{N}(a_i - \bar{a})^2 ,$$
$$\sigma_b^2 = \frac{1}{N-1}\sum_{i=1}^{N}(b_i - \bar{b})^2 , \quad \sigma_{ab} = \frac{1}{N-1}\sum_{i=1}^{N}(a_i - \bar{a})(b_i - \bar{b}) .$$

For conciseness, we refer to two data patches as a and b. For the case of comparing displacement fields, we evaluate SSIM loss as a combination of SSIM of the x and y displacement components, i.e.:

$$\mathcal{L}_{\text{SSIM}} = 1 - \text{SSIM}(\mathbf{u}_{\mathbf{x},\text{pred.}}, \mathbf{u}_{\mathbf{x},\text{fake}}) + 1 - \text{SSIM}(\mathbf{u}_{\mathbf{y},\text{pred.}}, \mathbf{u}_{\mathbf{y},\text{fake}}) . \tag{3}$$

The first component of SSIM (Eq. (2)) is the correlation coefficient, the second measures the luminance similarity, and the third measures the contrast similarity. After being calculated for each patch, the SSIM scores are averaged across the image. The SSIM is normalised to [-1, 1], with higher scores indicating greater similarity between images. Therefore, for use as a loss function, the SSIM is subtracted from one. The SSIM implementation was based on previous work [43].

(3) LPIPS is emerging as a powerful loss that aligns with human estimates of image similarity [31]. To compute it, first, a small pre-trained AlexNet model [44] is evaluated upon corresponding patches of the input images. For each pixel within these patches, the feature embeddings produced by each layer of the network are normalised channel-wise and weighted using a learned vector. At each layer, the l_2 distance between the resultant vectors originating from each patch is computed, and then averaged across all layers and pixels to give an overall patch score. The final metric is the mean score of all image patches. As with the SSIM, for use as a loss function, the LPIPS is subtracted from one. Here, an implementation of the LPIPS loss provided by the open-source `torchmetrics` package [45] was used.

(4) To compute the rewarp loss, the deformed frame (Def.) is warped to approximate the reference frame (Ref.) using the inverse of network's displacement estimates ($-\mathbf{u}_{\text{pred.}}$). This is achieved using the same method as that used for simulating the deformed image (Section 5.2). To mimic the correlation coefficient used in DIC as a loss function, we calculate the negative of the Pearson Correlation Coefficient (NPCC):

$$\mathcal{L}_{\text{NPCC}} = -\frac{\sigma_{ab}}{\sigma_a \sigma_b} , \tag{4}$$

using the symbols defined in Eq. 2, where a is the real reference and b is the 'rewarped' deformed image.

5.4 DEFORM-Net software

We include the complete source code, implemented in PyTorch, as well as compiled versions of the network inference for open and rapid dissemination. The source code can be found at `https://github.com/philipwijesinghe/displacement-estimation-for-microscopy`. The compiled software, models and datasets can be found at `https://doi.org/10.17630/feab7fa3-d77b-46e8-a487-7b47c760996a` [46]. The original *Drosophila* data can be accessed in [28]. Details about the data and software are included in the Supplementary Information.

A major challenge in sharing deep learning methods is the requirement for particular development environments, hardware (specifically graphics processing unit (GPU)) and associated CUDA platforms. Training a new model without a GPU is unadvised due to exceptionally long training times. We provide open source displacement data simulation, PyTorch code and relevant environment specifications for those with the relevant hardware and those familiar with such methods.

However, inference using pre-trained models can be quick and accessible. Thus, we simplify the step of network inference in two ways. First, we provide a compiled version of the inference software and pre-trained models which can be executed on most consumer hardware using a command-line interface. Second, we provide an ImageJ/FIJI distribution which can perform this inference within its interface. Further documentation on the use of the software is provided in the Supplementary Information.

5.5 Optical flow

When considering a sequence of images, optical flow may be defined as the apparent motion of objects within a scene relative to the viewer. Optical flow results from the combination of objects' actual motion and the motion of the camera. In many situations, accurately determining the optical flow allows objects' true displacement between frames to be calculated. In the case of microscopy images, the camera is stationary, so determining the in-plane displacement of subjects only requires scaling the optical flow.

The brightness of pixels within an image may be represented by an intensity function $I(\mathbf{x}, t)$. The foundation of classical methods of determining optical flow (optical flow methods) is the brightness constancy assumption

$$I(\mathbf{x}, t) = I(\mathbf{x} + \mathbf{u}(\mathbf{x}), t + \Delta t)\,, \tag{5}$$

stating that the brightness of pixels representing features remains constant as those features move. $\mathbf{u}(\mathbf{x})$ is the displacement field determined by the projection of the three-dimensional motion of the scene into the image plane, and Δt is the time-step between images. Applying a 1st order Taylor expansion leads to

$$I(\mathbf{x}, t) \simeq I(\mathbf{x}, t) + \mathbf{u}(\mathbf{x}) \cdot \boldsymbol{\nabla} I + \Delta t \frac{\partial I}{\partial t} \tag{6}$$

$$\Rightarrow \qquad 0 \simeq \mathbf{u}(\mathbf{x}) \cdot \boldsymbol{\nabla} I + \Delta t \frac{\partial I}{\partial t} = E_{\mathrm{B}}^2, \tag{7}$$

where E_{B}^2 is commonly known as the brightness constraint. However, this equation is under-determined. Thus, to find the $\mathbf{u}(\mathbf{x})$ which minimises the brightness constraint additional assumptions must be introduced. Different optical flow methods are primarily distinguished by the additional assumptions they make.

The Lucas-Kanade algorithm [47, 48] splits the field into small subsets and requires that $\mathbf{u}(\mathbf{x})$ is homogeneous within them. The Horn-Schunck algorithm [49] is similar, but only stipulates that neighbouring pixels must have similar displacements. It adds a smoothness constraint, $E_{\mathrm{S}}^2 = |\boldsymbol{\nabla}\mathbf{u}(\mathbf{x})|^2$, to Equation 7, and uses a variational approach to minimise $E_B^2 + E_S^2$ over the entire image. For our experiments, the LV-L1 method [35] was used. This is a improvement of the Horn-Schunck algorithm, modified to allow discontinuities in $\mathbf{u}(\mathbf{x})$ while maintaining the same principles.

These gradient-based classical optical flow methods are fast to compute, but the accuracy of the displacement estimates they produce is inherently limited. Their reliance on a truncated Taylor expansion means that the actual displacements must be sufficiently small for this approximation to be valid. Although image pyramids or alternative brightness constraint formulations [50] may be used to attempt to circumvent this limitation, this comes at the cost of computation time, and is not always wholly effective [18]. Moreover, the additional constraints introduced often relate the displacements of neighbouring pixels to one another, limiting the effective resolution of the results.

For this work, we used an implementation of the LV-L1 method [51] in an image pyramid form provided by `scikit-image` [52]. We found this resulted in the best performance metrics in supervised test data compared to other conventional methods, including the Lucas-Kanade and Horn-Schunck algorithms implemented natively in MATLAB (MathWorks, USA) and Farneback algorithm implemented using `opencv-python` [53].

5.6 Digital image correlation

Digital Image Correlation (DIC) is a related but distinct method of determining the displacement of objects within images between frames. The deformed image is split into patches, known as subsets. Each subset is then transformed in such a way as to maximise its correlation to the corresponding location on the reference image. This search process is iterative and slow. Typically, the process is sped up by determining an estimate for the translation of a chosen seed patch by computing its cross-correlation across the entirety of the reference image. This estimate is then iteratively refined, while allowing for affine deformation within the patch. Subsequent patches are then matched by progressively moving outwards from the seed. This significantly reduces the computational demand by computing the cross-correlation locally.

The accuracy of patch matching is dependent on the strength and distinctiveness of the texture within each patch; if repetitive patterns are present, false maxima in the cross-correlation can lead to incorrect displacement estimates. To counter this, speckle patterns are often applied to the objects, which can enable greater sub-pixel accuracy.

DIC offers several advantages over optical flow methods; for example, it is not inherently limited to small displacements, and the resolution of its estimates is flexible through the choice of the subset size and spacing (stride). Overlapping subsets can yield accurate, full-resolution estimates. However, in practice, it is more common to sacrifice resolution in order to speed up the process. Modern implementations, such as the open-source `ncorr2` [34], employ various optimisation strategies; nonetheless, processing is still substantially slower than gradient-based optical flow methods due to the iterative refinement performed for each patch in series.

We used `ncorr2` in this work. Specifically, we have adapted the MATLAB implementation [34] to automatically evaluate the `ncorr2` algorithm on image pairs. we used a spacing of 3 and subset size of 30, which we have experimentally found to produce, both, a reliable estimate in biological data and a high spatial resolution. DIC on a pair of images took approximately 120 s. Larger subsets resulted in lower spatial resolution, while smaller subets generated substantial artefacts. Several frame pairs from the 1,000+ frames generated artefacts and were automatically excluded from the evaluation of performance metrics.

5.7 Biological data

All biological videos were shared as part of previous studies or previously published work by others. No new biological experiments were carried out for this work.

Neonatal cardiomyocytes were obtained from postnatal day three wildtype mice as part of ongoing and previously published work in cell contractile sensing [54, 26, 27]. Briefly, the hearts were extracted from the pups and transferred to a dish containing ice-cold, calcium- and magnesium-free Dulbecco's phosphate-buffered saline (DPBS) to preserve tissue integrity. The tissue was cut into pieces and placed in a falcon tube with papain (ten units per mL) and incubated for 30 minutes at 37 °C with continuous rotation. Gentle reverse pipetting was utilised to disperse the tissue. A pre-wet cell strainer (70 μm nylon mesh) was used to filter the cell suspension and remove large tissue debris. The cell suspension was centrifuged at 200× g for 5 minutes and resuspended into cell culture media (Dulbecco's Modified Eagle's Medium (DMEM) with 25 mM glucose and 2 mM Glutamax, 10% (v/v) FBS, 1% (v/v) non-essential amino acids, 1% (v/v) penicillin/streptomycin). Cells were pre-plated on uncoated petri dishes for 1–3h, this step removes fibroblasts and epithelial steps which will adhere to the uncoated dish. Cells were counted and plated in a gelatin and fibronectin coated ibidi dish at a density of 6×10^4 cells per cm^2. Cell cultures were allowed to settle for 24h and kept in a humidified incubator at 37°C, with a 5% CO_2 concentration. Cells were labelled with 1000 nM SIR-actin in DMEM with 10% FBS for 1h at 37°C. Cells were imaged 2 days post extraction. In the videos used in this work, 6-8 neonatal cardiomyocytes are visible in the field of view. The same cells were imaged sequentially in different imaging modalities at an acquisition rate of 50 Hz.

The *Drosophila* LECs data were previously published in Pulido Companys et al. (2020) [28]. Briefly, LECs of the posterior compartment overexpress GMA-GFP, a fluorescent marker for F-actin [55], which enables visualisation of their pulsed contractions (hh.Gal4>UAS.gma-GFP). In the video used for this work, two cells are visible in the field of view. The time interval between frames is 10 s.

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Author contributions

PW conceived the project. SW, PW developed the methodology. SW, PW carried out the work and generated the results. SC provided the cardiomyocyte data and the related biological input. MB provided the *Drosophila* data and the related biological input. JK provided expertise in optical flow methods. All authors analysed the data. SW, PW drafted the manuscript with input from all authors. All authors edited and reviewed the manuscript. GB, PW supervised the work.

Competing interests

The authors declare that they have no competing interests.

Data Availability

The source code can be found at `https://github.com/philipwijesinghe/displacement-estimation-for-microscopy`. The compiled software, models and datasets can be found at `https://doi.org/10.17630/feab7fa3-d77b-46e8-a487-7b47c760996a` [46]. The original *Drosophila* data can be accessed in [28]. See Methods and Supplementary Information for additional details. Any additional training data not included here can be provided upon request.

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