Tactile Image-to-Image Disentanglement of Contact Geometry from Motion-Induced Shear

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Abstract: Robotic touch, particularly when using soft optical tactile sensors, suffers from distortion caused by motion-dependent shear. The manner in which the sensor contacts a stimulus is entangled with the tactile information about the geometry of the stimulus. In this work, we propose a supervised convolutional deep neural network model that learns to disentangle, in the latent space, the components of sensor deformations caused by contact geometry from those due to sliding-induced shear. The approach is validated by reconstructing unsheared tactile images from sheared images and showing they match canonical tactile imaged collected with no sliding motion. In addition, the unsheared tactile images give a faithful reconstruction of the contact geometry that is not possible from the sheared data, and robust estimation of the contact pose that can be used for servo control sliding around various 2D shapes. The methods have broad applicability to deep learning models for robots with a shear-sensitive sense of touch.

Keywords: Robotic Touch, Disentanglement, Shear

1 Introduction

A fundamental aspect of tactile sensing is that it measures the environment via physical contact. Therefore, the manner in which the sensor contacts a stimulus is entangled with the tactile information about that stimulus. For example, when sliding or rubbing fingers across tactile stimuli, soft tactile sensors are inevitably distorted by motion-dependent shear, making the sensor response history-dependent and generalization hard in tactile tasks. This issue is prevalent in camera-based optical tactile sensors that use the lateral motion of markers to infer contact geometry, such as the TacTip [1], ChromaTouch [2], GelForce [3] and the optical tactile sensor described in [4], but may occur also in other shear-sensitive tactile sensors. Generally, this shear distortion of the sensor response when sliding along surfaces would make it difficult to perform tactile-dependent tasks such as shape modelling or reconstruction and continuously exploring or manipulating objects.

Therefore, an important capability is to separate the deformation due to the manner of contact from that due to the stimulus geometry. For example, when continuously exploring an object surface, the sliding-induced shear would need to be removed from tactile image to extract the local contact shape. Previous work on extracting pose information from contact to continuously slide a tactile sensor over complex objects used a deep convolutional neural network trained to map between shear-distorted inputs and the desired (pose) outputs, which was necessary for sliding exploration over a range of complex novel objects [5, 6]. However, this approach for training insensitivity to shear has the drawback that separate models would need learning for each new tactile dimension, such as predicting parameters of the local contact geometry in addition to pose when mapping the object shape.

In this work, we propose a supervised convolutional neural network model that learns to disentangle the components of sensor deformation caused by the contacted object geometry from those due to motion-induced shear. The models were trained using paired data from discrete (tapping) and continuous (sliding) touch, which was collected by vertically tapping and horizontally sliding over an edge stimulus with matched poses (Fig. 1). The validation: (1) quantified that disentangled tactile images from continuous motion match their paired tactile images from discrete taps; (2) demonstrated that disentangled tactile images match the local object geometry over several stimuli shapes, using a

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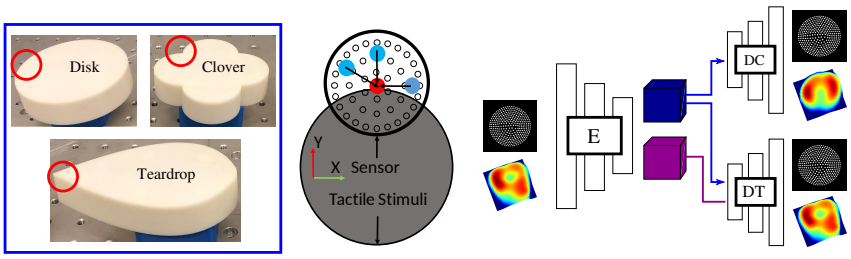

Figure 1: **Experiment setup and schematic of model architecture.** Left: 3D-printed tactile stimuli with approximate locations of data collection (red circles). Middle: Schematic of data collection, showing target location (red dot) and initial contact location (blue dots). Canonical (tapping) data was collected by vertically contacting the target location; sheared (sliding) data was collected by first contacting at a random initial location and sliding to the target. Right: Schematic of the *Disentangled UnshearNet* model architecture with some input/output images and contact shape reconstructions.

Voronoi reconstruction of the deformation geometry; and (3) inferred pose from the sheared tactile images by re-using a convolutional neural network model trained on discrete (tapping) data, which was then applied to controlling robust sliding exploration around several planar objects.

2 Background

Measuring strain is a fundamental component of tactile sensing, as emphasised by Platkiewicz, *et al* [8]: 'the pressure distribution at the surface of a tactile sensor cannot be acquired directly and must be inferred from the [strain] field induced by the touched object in the sensor medium.'

There are many mechanisms whereby normal strain and shear strain are measured by tactile sensors. Taxel-based tactile sensors such as the iCub fingertip [9] and BioTac [10] directly measure normal strain. Nevertheless, this measurement of normal strain will be affected by shearing of the soft sensor medium, although the effects on sensor output will be much smaller than those from normal pressure.

Camera-based optical tactile sensors can be very sensitive to shear because they transduce deformation of the soft sensor surface into a lateral image. For optical tactile sensors such as the TacTip biomimetic optical sensor used here [12, 1] and other marker-based sensors [2, 4], the surface shear will also distort the apparent geometry of the contact. This distortion is because the normal indentation is represented in the local shear strain of the markers, upon which the global shear strain is superimposed. This contrasts with optical tactile sensors that reconstruct the indentation field from reflection, such as the GelSight [13], where shear will shift the imprint on the tactile image but otherwise the imprint shape should be relatively unaffected.

This effect of shear complicates tactile perception under general motions against an object, and restricts the application of touch on challenging tasks such as tactile exploration and surface shape reconstruction. Studies have been limited to discrete contacts where the sensor taps discretely over the object to minimize shear [15, 16, 18], or to rigid planar tactile sensors [19, 20] that do not shear.

A recent body of work on the TacTip sensor used here focused on removing the effects of motion-dependent shear during tactile servo control to slide around planar shapes [5, 17] and complex 3D objects [6, 7]. The shear-dependence problem was addressed in three studies that used a deep convolutional neural network to predict pose by training insensitivity to shear into the prediction network [5, 6, 7]. While effective, this has a drawback that procedures for learning shear-invariance needs to be introduced into the training for each individual task, and thus would not generalize easily to new tasks. Another study did not use deep learning, but instead dimensionally reduced the tactile data [17], where the the pose components naturally separated from the shear components.

This work pursues an alternate approach using deep learning to remove the effect of motion-dependent shear from the original tactile image, obviating the need to relearn the mappings for each new tactile task. Our approach first disentangles the sliding-induced shear deformation component from the contact geometry-dependent component in the model latent space, followed by reconstructing the contact-only unsheared response alongside the purely sheared response (Fig. 1).

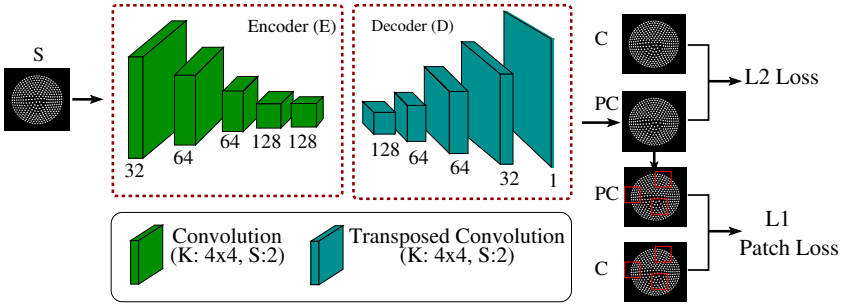

Figure 2: **Entangled UnshearNet architecture:** A shear-distorted tactile image S was processed by the encoder E and decoder D with output PC: the unsheared counterpart of input S post removal of sliding-induced distortion. The match between predicted unsheared data PC and canonical data C was enforced by training with a direct comparison between PC and C along with a comparison between corresponding patches (20×20 pix.) taken randomly from PC and C to enforce local compliance. K & S refer to convolutional kernel and stride respectively.

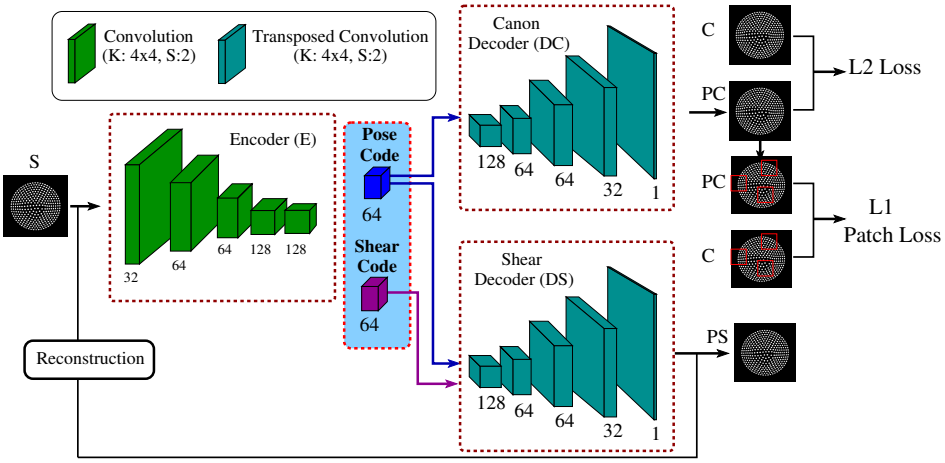

Figure 3: **Disentangled UnshearNet architecture:** Labelling as in Fig. 2, with two decoders DC and DS. The first decoder has output PC: the unsheared counterpart of input S post removal of sliding-induced distortion; the second DS reconstructed the input S, denoted PS.

3 Methods

3.1 Experimental Setup

The setup in this study followed recent experiments with the TacTip biomimetic optical tactile sensor [5, 17, 6, 7] where it is mounted as an end effector on a robot arm (Fig. 1). The TacTip is biomimetic in that its skin morphology is based on the layered dermal and epidermal structure of the human fingertip [12, 1]; the tactile sensor measures the shear displacement of an array of papillae pins on the inner side of the sensing surface caused by the skin deformation.

The TacTip can be designed with varied morphologies dictated by the application [1]. The TacTip sensor used in this work had a soft rubber-like hemispherical dome (40 mm radius, TangoBlack+) manufactured using multi-material 3D printing. Its inner side was covered with an array of 331 pins with hard white tips arranged in a concentric circular grid. The dome was filled with an optically-clear silicone gel to give it a compliance similar to a human fingertip. A camera was used to collect tactile images of the internal surface of the dome. For more details, we refer to the references above.

The tactile stimuli used here were three 3D-printed (ABS plastic) planar shapes: a circular disk, clover and teardrop (Figure 1). These objects were chosen to give different edge shapes for application of our methods, and were fastened securely to the workspace to prevent accidental motion.

3.2 Data Collection

3.2.1 Paired Canonical and Sheared Data

This work proposes a supervised deep learning model *Disentangled UnshearNet* to remove the effect of motion-induced global shear in the tactile images, caused by the friction between the sensor skin and its contacted surface during contact. We emphasise this motion-induced shear is different from the skin deformation due to local shear from the geometry of the stimulus imprint.

Our method requires paired tactile data with minimal global shear taken from vertically tapping onto the stimulus (referred to as canonical data) and sliding data with random global shear (referred to as sheared data). The sheared data is collected after sliding randomly along the x- and y-axes or simultaneously in both lateral directions, and is paired with a tactile image from the canonical data by considering the same set of relative poses between the sensor and the stimuli (Fig. 1). The raw tactile data was cropped, subsampled to 256×256-pixel region and finally converted to binary images using an adaptive threshold to minimise sensitivity to lighting changes inside the sensor.

In total, data for 200 distinct poses were collected. To generate poses, the sensor location relative to the initial contact location was sampled randomly from a uniform distribution spanning the range [-5, 5] mm in the two lateral directions (along the x- and y-axes), [-45, -45] deg in yaw (θn_Z) and [-6, -1] mm in depth (z-axis). Ranges of the target poses and perturbations to generate canonical and sheared data were chosen to ensure safe contact of the sensor with the stimulus.

Canonical Data: The canonical data was taken by vertically tapping onto the stimulus, to give a representative sample of tactile data with minimal global shear just due to the stimulus geometry. This gives target (reference) data that the sheared data from sliding contacts should be restored to.

The dataset, in total, had 30,000 samples: 50 instances of each of the 200 poses recorded previously for each of the three stimuli shapes (Fig. 1). To generate instances, the indentation depth (z-axes) was varied randomly between [-1, 1] mm from the original indentation depth.

Sheared Data: The sheared data accords to a canonical tactile image distorted by global shear from lateral sliding motion of the sensor on the stimulus. Thus, the sheared data does not give contact-only information akin to canonical data that represented the geometry of the contacted stimulus, but has a significant component due to the contact motion.

The dataset, in total, had 90,000 samples: 150 instances of each of the 200 random poses recorded previously for each of the three stimulus shapes (Figure 1). To generate instances for each pose, the lateral position offset for sliding to the target pose was varied randomly between [-2.5, 2.5] mm in lateral direction(s) (along the x- or y-axes or both), using the procedure shown in Figure 1.

Training and Test Data: The canonical and sheared datasets were partitioned randomly into training, validation and test sets (ratio 60:20:20); i.e. from the 200 unique poses for each stimulus shape (Fig. 1), 120 poses were assigned to a training set and 40 poses each to validation and testing sets. Overall the canonical and sheared training set contained 18,000 and 54,000 samples respectively, while the validation and testing sets contained 6,000 and 18,000 samples respectively.

To generate paired canonical and transformed data for training, each transformed tactile image was paired randomly with one of the canonical instances having the same pose.

3.2.2 Pose-labelled Data

To train pose prediction network *PoseNet*, a separate set of pose data was collected. This dataset had, in total, 30,000 samples: 10,000 samples from each of the three object shapes (Fig. 1). To generate contact poses, the sensor location relative to the initial contact location was sampled randomly from a uniform distribution spanning the range [-5, 5] mm laterally (x- and y-axis directions), [-45, -45] deg in yaw (θn_Z) and [-6, -1] mm in depth (z-axis). Ranges of the target poses, as before, were chosen to ensure safe contact of the sensor without causing damage. As discussed above, all tactile images were cropped, sub-sampled and thresholded to 256×256-pixel to binary (black/white) tactile images.

The dataset was partitioned randomly into training , validation and test sets in the ratio 60:20:20 as above, containing 18,000, 6,000 and 6,000 samples respectively.

3.3 Image-to-Image Models for Shear Removal

3.3.1 Problem Formulation

To achieve our goal of removing the effects of shear induced by the sliding motion, we trained two models based on the encoder-decoder framework – *Entangled UnshearNet* (Fig. 2) and *Disentangled UnshearNet* (Fig. 3). The former model (baseline) learns the mapping between the input sheared data and its corresponding canonical (tap) data directly. The later model instead, first disentangles the contact-only (pose) sensor response component from the sliding-induced global shear component in the latent space of the encoder E; followed by accurate reconstruction of the input sheared image and its corresponding canonical (tap) image using decoders DS (sheared or sliding) and DC (canonical or tapping). We hypothesized that a more robust mapping between sheared and canonical (tap) data can be learned by disentangling the contact-only and sliding-induced components of sensor response. The mathematical formulation of the *Disentangled UnshearNet* is listed below:

The encoder E splits the latent space into two components $\mathbf{z} = (\mathbf{z_p}, \mathbf{z_s}) \in Z_p \times Z_s$, given paired canonical $\{x_c\}_{i=1}^{N}$ and shear-transformed training samples $\{x_s\}_{i=1}^{N}$, where $x_c \in X_c$ and $x_s \in X_s$ are in the sets of canonical and sheared data, respectively.

The decoder DC takes as input only the pose part of the latent code $\mathbf{z}_p$ and reconstructs the canonical sample corresponding to the input sheared sample. In combination with the encoder E, it thus learns a mapping $M : X_t \rightarrow X_c$ from the sheared to canonical data.

The other decoder DS, takes as input the full latent code $\mathbf{z}$ and reconstructs the input sheared sample. In combination with the encoder E, it thus acts as an auto-encoder and learns a mapping $N : X_s \rightarrow X_s$ from the sheared data to itself.

Our objective function has three components:
(1) *L2 loss* for matching the generated canonical samples $M(x_t)$ to their targets x_c;
(2) *L1 patch loss* for matching random patches extracted from generated canonical images $M(x_t)$ and corresponding targets x_c for enforcing image similarity locally as changes in sensor response due to change in contact conditions are predominately local in nature;
(3) *Reconstruction loss* for matching the generated sheared samples $N(x_t)$ to their target input sheared samples x_s.

The objective functions are:

$$\mathbb{L}_{\text{rec}}(E, DS) = \mathbb{E}_{x_s \sim X_s}[\|x_t - DS(z_p, z_s)\|_2], \tag{1}$$

$$\mathbb{L}_{\text{sup}}(E, DC) = \mathbb{E}_{x_s \sim X_s, x_c \sim X_c}[\|x_c - DC(z_p))\|_2], \tag{2}$$

$$\mathbb{L}_{\text{patch}}(E, DC) = \mathbb{E}_{x_s \sim X_s, x_c \sim X_c}[\|\text{crops}(x_c) - \text{crops}(DC(z_p)))\|_1], \tag{3}$$

where $(z_p, z_s) = E(x_s)$ for all $x_s \in X_s$. The function crops() selects a patch of size 20×20 pix from $M(x_t)$ and x_c. The objective functions L_{rec}, L_{sup} and L_{patch} represent sheared reconstruction loss, canonical supervised loss and canonical supervised patch loss respectively.

The final objectives for Encoder E and Decoders DC, DS are:

$$\mathbb{L}_E = \mathbb{L}_{\text{rec}}(E, DS) + \mathbb{L}_{\text{sup}}(E, DC) + \lambda \cdot \mathbb{L}_{\text{patch}}(E, DC), \tag{4}$$

$$\mathbb{L}_{DC} = \mathbb{L}_{\text{sup}}(E, DC) + \lambda \cdot \mathbb{L}_{\text{patch}}(E, DC), \tag{5}$$

$$\mathbb{L}_{DS} = \mathbb{L}_{\text{rec}}(E, DS), \tag{6}$$

where λ is the relative loss scale factor.

3.3.2 Network Architectures

Entangled UnshearNet: The encoder E compresses the input 256×256-pixel tactile image using five convolutional (Conv) layers, each followed by batch normalization (BN) and rectified linear unit (ReLU) activation layers respectively (architecture in Fig. 2). The output of the last Conv layer ($8 \times 8 \times 64$) is passed to the decoder D which upsamples it to an output 256×256-pixel canonical image PC. Similarly to the Conv layers, all transposed convolutional layers (T-Conv) were followed by BN and ReLU activation layers except the output layer which used sigmoid activation function instead (see also Fig. 2).

This model was used as a baseline to evaluate the performance of proposed *Disentangled UnshearNet* model on its effectiveness in removing distortion in sensor response caused by sliding-induced global shear. For details of the training, please see Appendix B.

Disentangled UnshearNet: The encoder has the same inputs and architecture as the *Entangled UnshearNet*, except the the output of the 5th Conv layer is followed by two additional Conv layers, one each for the two latent codes: Pose ($8 \times 8 \times 64$) and Shear ($8 \times 8 \times 64$).

One decoder *DC* takes as input pose latent code and upsamples it to 256×256-pixel canonical output tactile image *PC*. All T-Conv layers were followed by BN and ReLU activation layers except the output layer which used sigmoid activation layer instead (architecture shown in Fig. 3).

The other decoder *DS* takes as input both pose and shear codes, merges them and upsamples to an output 256×256-pixel sheared image *PS* (intended to match the encoder input). Apart from the above differences, *DS* uses exactly the same architectures as *DC*. For details of the training, please see Appendix B.

PoseNet: This model takes as input 256×256 image, compresses it to extract features using the Conv part which are then combined using fully connected (FC) part to predict continuous-value pose components at the output. In total, the network consists of five convolution layers, two max pooling (MP) layers following 2nd and 4th Conv layers; the CONV layers were followed by BN and ReLU activation layers respectively. The 1st FC layer used ReLU activation while the output FC layer used sigmoid activation. For details of the architecture and training see Appendices A and B respectively.

4 Experimental Results

4.1 Shear Removal from Tactile Images

The first test of the performance of our approach for removing motion-induced global shear from tactile images used the multi-scale structural similarity index (SSIM) [24] to compare the tactile images taken from the shear-transformed test data set with the paired canonical and the *Disentangled (Entangled) UnshearNet*-generated unsheared tactile images. All three images represent the same pose.

To compare, we computed the average SSIM between the canonical (tap)-sheared and canonical (tap)-unsheared images in several distinct scenarios (stimuli: disk edge, clover corner, teardrop corner). The unsheared images were structurally closer to the target canonical (tap) samples than their sheared counterparts. The overall SSIM value for unsheared samples was 0.93 (0.90) in comparison to 0.32 for sheared samples, with closeness to unity indicating a good match (Table 1). Performance was similar for all stimuli considered with *Disentangled UnshearNet* achieving closer match to canonical samples than its *Entangled* counterpart.

Table 1: **Multi-Scale Structural Similarity Index (MS-SSIM)**

Image Similarity Index				
	Disk Edge	**Clover Corner**	**Teardrop Corner**	**Overall**
Tap Data & Tap Data	1	1	1	1
Tap Data & Shear Data	0.33	0.31	0.33	0.32
Tap Data & Unsheared (Entangled)	0.91	0.90	0.90	0.90
Tap Data & Unsheared (Disentangled)	0.94	0.92	0.92	0.93

4.2 Reconstructed Contact Geometry

As stated in the introduction, an application of shear removal is to aid reconstruction of the stimulus geometry from the tactile images. This is validated by using a Voronoi-based method to infer an approximate indentation field, using the method introduced in Cramphorn *et al* [11] on tactile data from the TacTip. The Voronoi method transforms the displacements of the tactile markers into areas of hexagonal cells tesselating the grid of the markers [11, Fig. 4]. The change in Voronoi areas of the cells represents the skin distortion, which correlates with the indentation due to contact geometry.

For display purposes, we fit a 3D surface to the (x, y) centroid coordinates using the Voronoi cell areas as the corresponding height values (Fig. 4). The fitted surface from the original canonical tactile

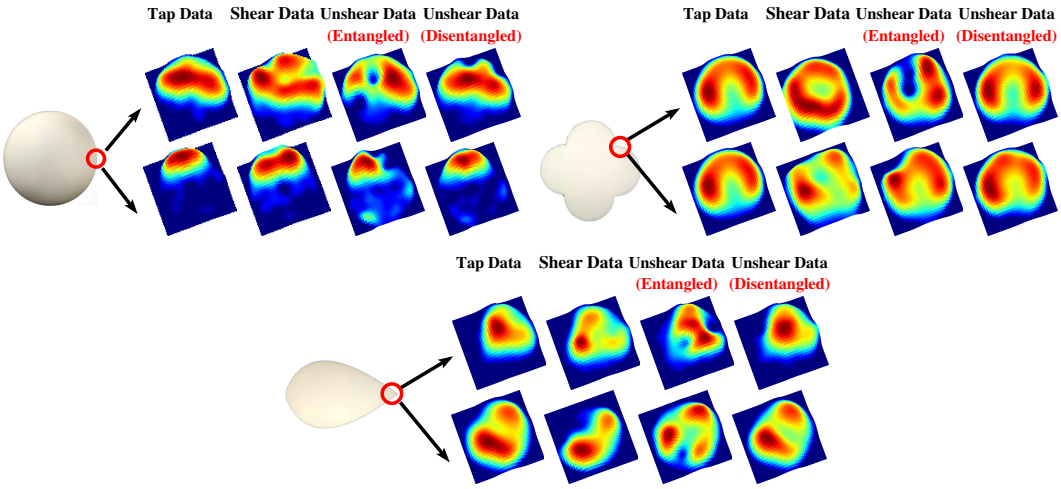

Figure 4: **Contact geometry reconstruction:** We used (x, y)-centroid values along with the Voronoi cell areas as z values to fit a 3D surface using cubic interpolation. The approximate contact geometry can be recovered from sheared data using the unsheared images generated by the two types of *UnshearNet* (entanged and disentangled), but not from the original sheared data. Note also the more faithful reconstruction with use of the disentanged network.

images taken under tapping visibly represents the shape of the indentation on the tactile sensor, as expected (Fig. 4, first column). The same stimulus under sliding motion is visibly distorted by shear, resulting in an indentation field that does not resemble the stimulus shape (Fig. 4, second column).

Evidently, the indentation field reconstructed from the model-generated unsheared tactile images under sliding motion more closely resemble that from the original canonical data for all stimuli (Fig. 4, last column). This again confirms the successful removal of sliding-induced distortion from the tactile image.

4.3 Validation on Shape Exploration

To further confirm that our model can remove shear from transformed images, we trained a prediction network (PoseNet) on stimulus pose parameters: lateral position (x-horizontal, τ_X) and in-plane orientation (yaw, θn_Z), using canonical tactile images from vertical tapping contacts. PoseNet performance was quantified with the mean-absolute error (MAE) between predicted pose and target when input data were canonical, sheared and model-generated unsheared tactile images respectively using both the entangled and disentangled networks (results in Table 2). On the sheared data, the lowest prediction error was obtained on unsheared samples with the disentangled network, with the entangled network about 50% higher, and on the original sheared samples about 5× poorer. Again, the *UnshearNet* managed to successfully correct the distortion in sensor response cause by slide-induced global shear, with the disentanged representation giving the best performance.

Another application of shear removal that also tests the real-time performance of UnshearNet is to use the above pose prediction network to servo control smoothly over varied object shapes during sliding motion. The robot successfully traced contours across all three shapes by a combination of the use of

Table 2: **Mean Absolute Error (MAE) in Pose Predictions**

Pose Prediction Error				
	Tap Data	**Sheared Data**	**Unsheared Data (Entangled)**	**Unsheared Data (Disentangled)**
horizontal, τ_x (mm)	0.43	2.72	0.95	0.64
yaw, θn_Z (degrees)	2.13	22.20	6.73	4.38

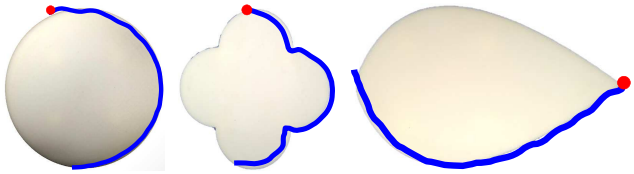

Figure 5: **Contour following:** Robust sliding post removal of sliding-induced shear using *Disentangled UnshearNet* across stimuli shapes: 1) Disk, 2) Clover and 3) Teardrop. Only one-half of each object was traversed because of a limit on the joint angles of the robot in the particular setup for this experiment. Red dot shows the starting point.

UnshearNet for global shear removal, *PoseNet* for prediction of object pose from unsheared images (Figure 5) and a simple control policy (see Appendix C). This clearly indicates that the proposed *Disentangled UnshearNet* is well suited for correcting the sliding-induced shear-distorted sensor response for real-time servo control applications.

5 Conclusion

In this work, we proposed a tactile image-to-image supervised convolutional neural network model to remove the effects of motion-induced global shear from the tactile sensor response while preserving the sensor deformations due to the spatial geometry of the contacted stimuli. Two *UnshearNet* models were considered: one based on a basic encoder-decoder structure with an entangled pose and shear latent space, and a second that disentangled these components in the model latent space (Figs. 2, 3).

This approach was validated in three ways: (1) Comparing similarity of tactile images collected by vertically tapping without a shearing motion to those collected with an unknown shearing perturbation, for which the unsheared data passed through the *Disentangled UnshearNet* gave a good match according to the structural similarity index (Table 1). (2) Reconstructing the indentation field from the contact geometry using sheared tactile images passed through the *Disentangled UnshearNet* (Figure 4), via a (Voronoi) method used previously to reconstruct the sensor deformation [11]. The removal of motion-induced shear was apparent in the model-generated unsheared tactile images, with the contact geometry only visible after use of the UnshearNet with the original sheared image obscuring the contact shape. (3) Predicting the local pose of part of an object in a shear-insensitive manner with a prediction network trained only on canonical (tapping) data (Table 2). This approach was then applied to smooth servo control around several planar objects (Fig. 5).

The combination of smooth servo control and local shape reconstruction can be used for shape reconstruction, which remains an problem under active investigation in the field [22, 23]. Our approach improves upon related work [5, 6] that instead trained insensitivity to shear into the prediction network itself. An obvious drawback of this approach, even though it works well for smooth servo control, is that it does not extend readily to predict other tactile dimensions such as parameters of the local contact geometry. In that case, new labelled data would need collecting to train a new model for each intended task. Our approach, of shear removal from tactile images, instead means that a single model based on the canonical (tapping) data can be re-used.

The present study considered only planar objects in 2D and two components of pose. As recent results have shown how to extend the *PoseNet* to 3D surfaces (3 pose components) or 3D edges (5 pose components) for tactile servo control [5, 6], we expect the present results will extend over also, although questions remain on the best way to do this with the large number of degrees of freedom. Another limitation of the supervised approach investigated here is the requirement of paired canonical and sheared data which complicates the data collection. Thus a semi-supervised approach would be a worthwhile extension to this work which by obviating the need for collection of paired data, will significantly simplify the data collection.

Overall, we expect the methods developed here can can be applied more widely to various other exploration and manipulation tasks involving soft tactile sensors that are adversely affected by motion-induced shear.

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APPENDIX

A: PoseNet Model Architecture

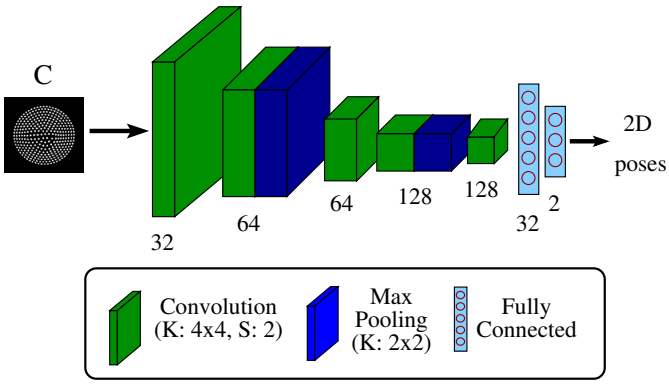

Figure 6: **PoseNet schematic:** This network takes as input, a tapping binary sensor image, C. The convolution part compresses input to extract relevant features which are then combined by fully connected part to predict continuous-valued object pose parameters at output.

B: Training Details

All the inputs (binary 256×256-pixel images) and outputs (binary 256×256-pixel images for image-to-image models, pose parameters for image-to-pose model) were scaled to the range $[0, 1]$. All networks weights were initialized from a zero-centered normal distribution with 0.02 standard deviation.

For image-to-image models, we used a batch size of 32. All convolutional/transposed convolutional layers used L1/L2 regularization (10e-4) along with random image shifts, 1-2% of image size to prevent overfitting. The *L2 loss* computed across the entire image and *L1 patch loss* – computed between 100 random crops of size 20×20 of generated unsheared images and corresponding canonical images – were used to train the networks in the ratio 10:1. In case of *Disentangled UnshearNet*, the encoder (E) and shear decoder (DS) were trained using reconstruction loss.

For image-to-pose model, we used a batch size of 256. Like image-to-image models, all layers used L1/L2 regularization (10e-4) along with random image shifts, 1-2% of image size to prevent overfitting. The network was trained via the *L2 loss* computed between predicted and target pose parameters.

We used ADAM optimizer [21] with learning rate of 0.0001, $\beta 1 = 0.5$ and $\beta 2 = 0.999$. We used learning rate scheduling for training. For image-to-image models, the learning rate was reduced to one-fifth and one-tenth after 40 and 80 epochs. The models were trained, in total, for 100 epochs. For image-to-pose model, the learning rate was reduced to half and one-tenth after 100 and 200 epochs respectively. The model was trained for 250 epochs. For all models, the model with best validation accuracy was used for testing.

Finally, training and optimization of the networks was implemented in the Tensorflow 2.0 library on a NVIDIA GTX 1660 (6 GB memory) hosted on a Ubuntu machine.

C: Control Policy for Continuous Contour Following

Local pose estimation allows a robot to maintain contact while safely moving over the object, thus enabling complex robot-object interactions. To demonstrate continuous 2D contour following, we used a simple control policy with following two aims: 1) keep the sensor normal to object surface while in motion and 2) at every time step t, move the sensor tangentially along the surface by a predefined step (0.5 mm in this case). To achieve these aims, a discreet time proportional-integral (PI) controller was implemented to output a change in the pose of the sensor ($\Delta p(t)$) in its reference

frame

$$\Delta p(t) = K_p e(t) + K_i \sum_{t'=0}^{t} e(t') \tag{7}$$

where K_p and K_i are diagonal gain matrices with proportional gain of 0.5 and integral gains of 0.3 and 0.1 for translations and rotations respectively. e was error between the predicted pose and a reference normal to the edge.