Training Tactile Sensors to Learn Force Sensing from Each Other

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***Abstract*— Humans achieve stable and dexterous object manipulation by coordinating grasp forces across multiple fingers and palms, facilitated by a unified tactile memory system in the somatosensory cortex. This system encodes and stores tactile experiences across skin regions, enabling the flexible reuse and transfer of touch information. Inspired by this biological capability, we present GenForce, the first framework that enables transferable force sensing across diverse tactile sensors in robotic hands. GenForce unifies tactile signals into shared marker representations, analogous to cortical sensory encoding, allowing force prediction models trained on one sensor to be transferred to others without the need for exhaustive force data collection. We demonstrate that GenForce generalizes across both homogeneous sensors with varying configurations and heterogeneous sensors with distinct sensing modalities and material properties. This transferable force sensing capability is also demonstrated in robot manipulation tasks including daily-object grasping, slip detection and compensation with multi-sensor force coordination. Our results highlight a scalable paradigm for cross-sensor robotic tactile sensing, offering new pathways toward adaptable and tactile memory-driven robot manipulation in unstructured environments. [Full Paper]**

I. INTRODUCTION

Human skin is equipped with diverse sensory receptors that detect mechanical stimuli and provide rich contact information. Inspired by this, tactile robotics aims to mirror the function of mechanoreceptors to enhance dexterity by developing tactile sensing systems. These tactile sensors are based on various sensing principles, such as capacitive [1], magnetic [2], and optical [3], [4] transductions, offering unique advantages in detecting contact information. However, diversity in sensing principles, structural designs, and material properties creates significant domain gaps among tactile sensors, hindering the transfer of learned tactile experience and necessitating repetitive data collection. Recent advances in transfer learning and representation learning [5] have made strides toward unifying latent tactile representations and enabling the transfer of tactile experience. However, existing approaches face significant limitations compared to the human capability of tactile memory.

We present GenForce (Fig. 1), the first general framework to enable transferable force sensing across diverse tactile sensors. GenForce unifies tactile signals from skin deformation into shared marker representations, analogous to sensory encoding, and enables deformation transfer across sensors regardless of sensing principles and physical configurations through marker-to-marker translation. Force prediction capability can therefore be learned with generated images and force labels from other sensors. GenForce further improves force accuracy by compensating for material differences. Extensively validated for generalizability, accuracy, and robustness, GenForce is applicable to diverse tactile sensors, including flat-surface vision-based tactile sensors (GelSight), flat-surface electronic sensor arrays (uSkin) with either three-axis sensing or z-axis-only sensing, and curved-surface vision-based tactile sensors (TacTip), spanning varying configurations. This approach significantly redefines the paradigm of training force prediction models: instead of relying on repetitive and time-consuming data collection for each sensor, models can be trained by learning across sensors, greatly facilitating large-scale tactile sensing deployment. Beyond transferable force sensing, GenForce demonstrates practical applicability in robot manipulation tasks with multi-sensor force coordination across heterogeneous tactile sensors, including daily-object grasping and slip compensation.

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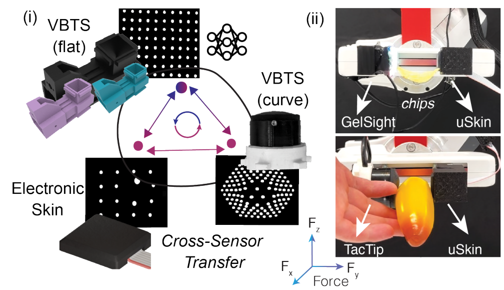

Fig. 1. (i) Transferable force sensing across diverse tactile sensors using GenForce. (ii) Coordinating heterogeneous sensors with transferred force.

II. METHODOLOGY

In a general case, we have one or more calibrated tactile sensors, referred to as source domains $\{S_i\}_{i=1}^n$, $n \in \mathbb{N}$ with paired tactile signal-force data $\{I^{S_i}, F^{S_i}\}$, while uncalibrated tactile sensors, referred to as target domains $\{T_j\}_{j=1}^m$, $m \in \mathbb{N}$, are without access to force labels $\{F^{T_j}\}$ for tactile signals $\{I^{T_j}\}$. The problem is how to leverage the collected force labels $\{F^{S_i}\}$ from $\{S_i\}_{i=1}^n$ to endow sensors $\{T_j\}_{j=1}^m$ with force prediction capability. Our proposed GenForce model can be divided into three steps (Fig. 2): (1) unified marker representation; (2) marker-to-marker translation; (3) spatiotemporal force prediction. The marker pattern is common in tactile sensors. In vision-based tactile sensors, it can be physically designed on the soft skin, such as GelSight, or transferred from markerless skin [6] by using deep learning methods. To align the image distributions of the source domains $p(I^{S_i})$ with target domains $p(I^{T_j})$, we train an image-conditioned diffusion model $G(I_t^{S_i}, I_0^{T_j})$ to map $I_t^{S_i}$ to $I_t^{T_j}$ at deformed time step t, $t \in \mathbb{N}$ such that

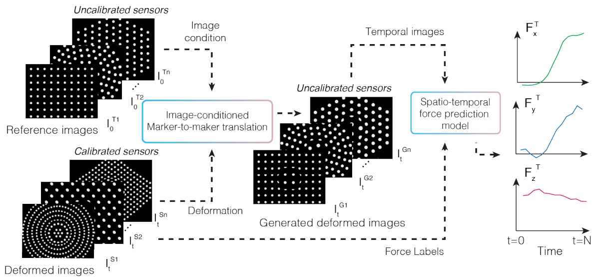

Fig. 2. The GenForce model comprised of marker-to-marker translation model and spatiotemporal force prediction model.

$G : I_t^{S_i} \rightarrow I_t^{T_j}$. The conditional inputs used here are the reference images $I_0^{T_j}$, captured when target sensors are in a non-contact state. Once the model G is trained, $I_t^{S_i}$ can be translated into $I_t^{G_i}$, which matches the image styles of $I_t^{T_j}$ while preserving the deformation information of $I_t^{S_i}$. Upon marker-to-marker translation, we can construct new datasets $\{I^{G_i}, F^{S_i}\}$ from existing datasets $\{I^{S_i}, F^{S_i}\}$ to train force prediction models $\hat{h}_{i \rightarrow j}$ for new sensors T_j, where we focus on three-axis force prediction $F = (F_x, F_y, F_z)$ in this paper.

III. EXPERIMENT RESULTS & ANALYSIS

A. Arbitrary marker-to-marker translation

We test the generalizability of the marker-to-marker (M2M) translation model with deformed marker images from 132 sensor pairs based on a simulation pipeline. Before using M2M, as each type of marker pattern is visually distinctive, the difference is prominent with an average FID larger than 400 and an average KID larger than 0.75. The source images and target images are separated distinctly in the feature space. After using M2M, the average FID drops to 4 and the average KID drops to 0.01. The generated images and target images are aligned closely in feature space and visually indistinguishable. This suggests the effectiveness of the M2M translation across various marker patterns.

B. Learning across homogeneous tactile sensors

Similar to the simulation results, image similarity improves significantly and the generated images and the target images across 20 sensor pairs are well-aligned. The FID and KID values both drop by more than 98%. Regarding force prediction performance, after using GenForce model, all force errors are significantly reduced, and R^2 values improve across all combinations. For normal force, the maximum error is below 1 N, while the minimum error decreases to less than 0.7 N. Notably, the maximum force error in C-II_D-I improves from 4.8 N to 0.96 N (80% reduction). For shear forces, the minimum errors decrease to less than 0.06 N. The R^2 values show consistent improvement in both normal and shear direction, averaging above 0.8. Real-time force predictions demonstrate well-aligned predicted forces and ground truths with high-accuracy force prediction in both normal (-8 N to 0 N) and shear (–3 N to 3 N) directions.

C. Learning across heterogeneous tactile sensors

The improved FID and KID scores, along with the aligned feature space in tSNE, suggest the M2M model's generalization capability across three heterogeneous sensors. For force prediction, the R^2 values are negative across all three axes when transferring from lower marker density to higher density using source-only method. The maximum MAE reaches 7.76 N for F_z, 0.59 N for F_y, and 0.37 N for F_x. Upon using GenForce, all R^2 values improve to positive values. The average of MAE over all six combinations decreases below 0.92 N for normal force, while F_x and F_y reduce below 0.22 N and 0.3 N. All groups exhibit strong generalizability to new objects and achieve low force prediction errors in real-time when compared against a commercial high-accuracy F/T sensor. The force errors for all combinations are centered around zero within ranges of -4N to 0N in the normal direction and -3N to 3N in the shear direction, demonstrating both the accuracy and reliability of our model in the most challenging task of heterogeneous translation.

D. Transferable force sensing in robot manipulation

To demonstrate the applicability of our model in robot manipulation, we install heterogeneous tactile sensors on a robot hand to show the transferable force sensing and control during daily-object grasping, slip detection and compensation tasks (Fig. 3). The robot equipped with transferable force sensing successfully grasps all objects without causing damage. Even with fragile objects such as chips and fresh fruits, the robot achieves delicate grasping. For the second task, we extend the robot grasping scenario to include slip detection and compensation via multi-sensor force coordination. We use three objects with different sizes and surface conditions from the YCB dataset: a strawberry (rough), a banana (moderately smooth) and an egg (smooth). External forces are applied by a human operator at the top position to induce slip. The robot completes all stages successfully by coordinating the transferred forces from multiple sensors.

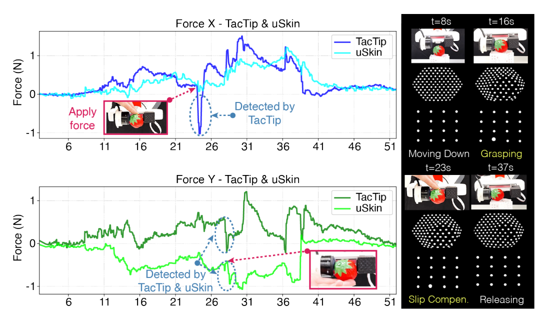

Fig. 3. Multi-sensor coordination with transferred force models.

IV. CONCLUSION

By employing a unified marker representation, analogous to human sensory encoding, our method explicitly transfers skin deformation information between sensors through marker-to-marker translation and validates the transferable force sensing in robot manipulation tasks with multi-sensor coordination. By establishing a unified framework for transferable sensing across diverse tactile sensors, our work paves the way for cost-effective and scalable tactile sensing systems in next-generation tactile robots.

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