PAS: Probabilistic Adaptive Subsampling for Scalable Tactile Skins

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***Abstract*— High-resolution, full-body tactile sensing is essential for robots to interact safely and effectively in unstructured environments, enabling reflexive responses and closed-loop control. However, achieving both high spatial resolution and fast update rates remains a challenge, as large-area tactile arrays suffer from spatial-temporal resolution tradeoffs, often limiting readout rates to below 100 Hz, far from the 1 kHz needed for real-time force feedback. Compressive subsampling offers a potential solution by selectively sampling pixels and reconstructing the full tactile image, but existing methods degrade for medium and small objects. In this work, we introduce Probabilistic Adaptive Subsampling (PAS), a novel approach that dynamically adjusts its sampling distribution based on real-time measurements. PAS adapts and augments sampling probabilities, improving reconstruction accuracy across various object sizes. Our results show that PAS outperforms prior methods across object sizes, addressing a key limitation of existing approaches. Future implementations could extend PAS as a scalable, large-area high-speed tactile sensing strategy, advancing robotic perception and control.**

I. Introduction

High-speed, high-resolution tactile sensing is essential for robotic reflexes, precise manipulation, and closed-loop control [1], [2], [3]. Like human skin, robotic tactile arrays must capture fine-grained contact details at high frame rates for dynamic interactions [4]. However, achieving both high spatial resolution and high temporal resolution remains a key challenge, as conventional raster scanning and TDMA methods scale poorly with increasing sensor count [5]. Large-area tactile skins, which require reading hundreds or thousands of elements sequentially, suffer from high latency and rarely exceed 100 Hz frame rates [6], while real-time robotic force feedback desires at least 1 kHz [4]. This spatial-temporal resolution tradeoff remains a major bottleneck in scalable tactile sensing.

Recently, compressive subsampling was shown to offer a potential solution by sampling a subset of pixels and reconstructing the full tactile image, significantly reducing readout time while preserving force information [7]. However, the prior methods based on random subsampling improved frame rates but degrade in accuracy for medium and small sized objects, where measurements are wasted and distributions are not well captured by purely random selection. This size-dependent limitation restricts their broader applicability in robotic tactile sensing.

In this work, we introduce Probabilistic Adaptive Subsampling (PAS), a novel framework that dynamically refines its sampling distribution based on real-time measurements (Fig 1). Unlike random approaches, PAS prioritizes high-information regions while maintaining overall spatial coverage, adapting intelligently as new data is acquired. Our results show that PAS significantly improves tactile reconstruction accuracy across object sizes compared to existing random sampling approaches. By offering a scalable, high-speed subsampling strategy, PAS presents a generalizable solution for real-time, high-resolution tactile perception in robotic systems.

II. Method

To evaluate Probabilistic Adaptive Subsampling (PAS), we conducted experiments using seven medium-to-large objects pressed into our previously developed high-density tactile skin [7] with a UR5 robotic arm. The selected objects – foam brain, foam eraser, fidget spinner, pliers, ball, triangle, and an X-shaped object – were chosen to provide a diverse range of contact profiles. Since these objects were soft, their contact area expanded and contracted during pressing, allowing us to assess PAS performance across varying contact sizes.

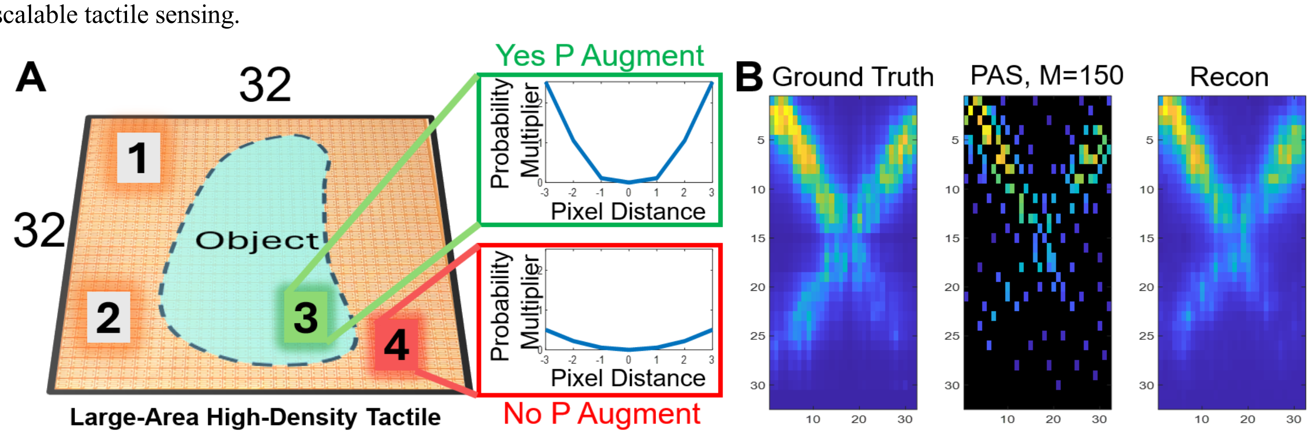

Fig 1. Probabilistic Adaptive Subsampling (PAS) Method. **(A)** PAS adaptively refines its sampling strategy based on measurements. When pressure is detected, sampling probability increases at a set radius while avoiding direct neighbors; when no pressure is detected, nearby sampling probability decreases. **(B)** PAS applied to an X-shaped object on a 32×32 tactile skin. With only 150 measurements (~15%), PAS reconstructs the X with high fidelity. Black pixels in the middle column were never sampled, and colored pixels show measurements.

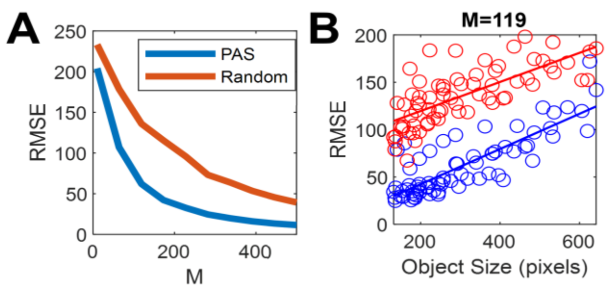

Fig 2. (A) Root-mean-square error (RMSE) of tactile image reconstruction as a function of measurement level (M) for Probabilistic Adaptive Subsampling (PAS) and random subsampling. **(B)** RMSE as a function of object contact size for PAS (blue) and random subsampling (red) at M = 119, with best-fit lines shown for each method.

Ground-truth tactile images were obtained by densely raster scanning the entire sensor array. PAS measurements were then collected by selectively sampling pixels based on an adaptive probability distribution. To implement PAS, we designed a probability distribution function (PDF) using two Gaussian components: one with a large standard deviation to encourage wide-area sampling and another with a smaller standard deviation, subtracted from the former, to reduce the likelihood of sampling immediately adjacent pixels. This subtraction created a sampling pattern that avoided clustering around previously sampled points while maintaining sufficient spatial coverage. For "Yes Pressure" probability augmentation, this differential Gaussian approach increased the likelihood of sampling at a radius from previously selected points. For "No Pressure" probability augmentation, a negative Gaussian distribution was applied, discouraging sampling nearby pixels. Fig 1 illustrates both probability distributions.

Reconstruction of the tactile images was performed using sparse recovery techniques, following our prior work on compressive tactile sensing [7]. PAS performance was evaluated by computing the root-mean-square error (RMSE) between the reconstructed images and the ground-truth tactile images obtained via raster scanning. We further compared PAS against random subsampling at different measurement levels (M) and analyzed how contact size influenced RMSE.

III. Results

Our results demonstrate that Probabilistic Adaptive Subsampling (PAS) outperforms random sampling for medium and small objects (all tested), representing a notable improvement over the state of the art. Specifically, PAS reduces root-mean-square error (RMSE) by a factor of 2 to

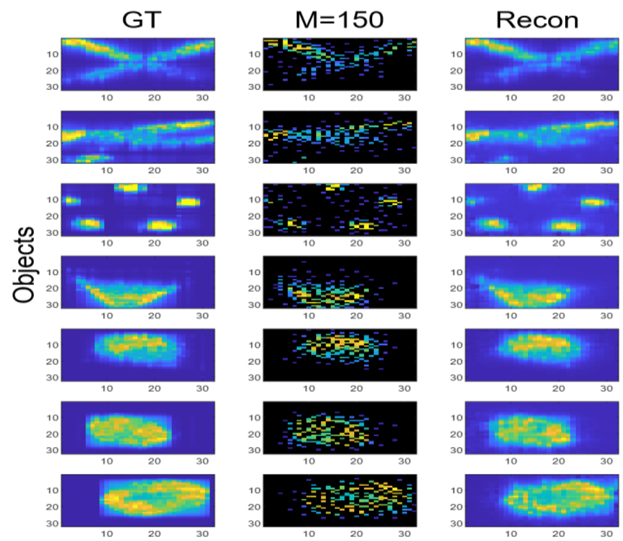

Fig 3. Examples of tactile reconstructions at M = 150 for the objects tested in this study. The left column displays the ground truth (GT) tactile images of the seven objects. The middle column shows the sampled pixels at M=150, where black pixels indicate unsampled regions, and colored pixels represent measured values, with color intensity corresponding to the magnitude of measured pressure. The right column presents the reconstructed tactile images, which closely approximate the ground truth, demonstrating the effectiveness of the reconstruction method.

3.5 as the number of measurements increases from M = 100 to M = 500 (Fig 2). Furthermore, across all tested contact sizes, PAS consistently achieves lower average error compared to random sampling, indicating its robustness and scalability in high-resolution tactile sensing of various contact sizes. Visual reconstructions (Fig 3) further confirm that PAS provides higher-fidelity tactile reconstructions, closely approximating the ground truth tactile images, even at low measurement levels (M = 150). Example of evolution of pressure samples and sampling probability is in Fig. 4.

IV. Discussion and Conclusion

This work introduces Probabilistic Adaptive Subsampling (PAS) as a novel approach to improving high-speed, large-area tactile sensing. By dynamically adjusting its sampling distribution based on real-time measurements, PAS overcomes the limitations of prior random subsampling methods for smaller objects. Our results demonstrate that PAS significantly reduces RMSE, achieving more accurate tactile reconstructions while maintaining efficiency across different contact sizes.

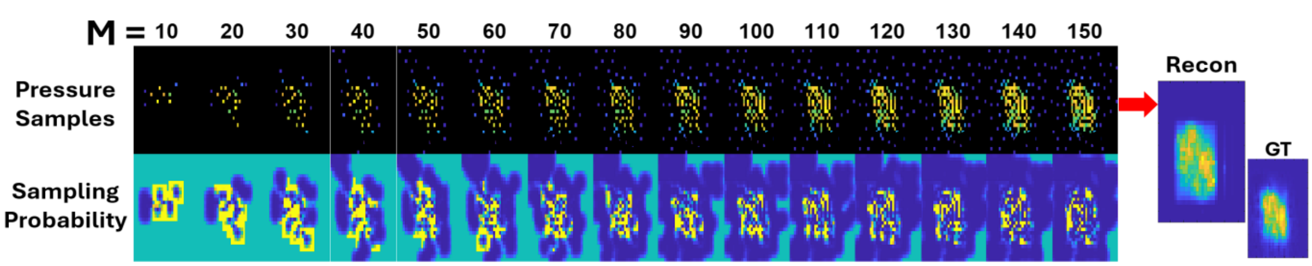

Fig 4. Evolution of pressure measurements and sampling probability over time as 150 measurements are taken.

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