Compressed Sensing for Scalable Robotic Tactile Skins

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A. Introduction

For robots to transfer from structured laboratories to our unstructured world, they need to be able to sense and respond to environmental situations. In addition to other sensing modalities, robots need full body tactile sensors (e.g. force sensors) to understand the physical interactions that arise. We refer to these full body tactile sensors as *tactile skins*.

While important, tactile skins are challenging to implement. It is believed that certain areas of the body should have $1mm$ spatial resolution [1], which implies 1,000s to 1,000,000s of individual sensing elements, often called *taxels*, to cover an adult-sized humanoid robot. Additionally, for real-time applications, such as force control, $1kHz$ response is desired [1]. An obstacle to achieving these characteristics is limited space for wiring, especially when the tactile skin is designed independently from the robot. Furthermore, the sensors are often noisy. There are also challenges in processing the massive amounts of data generated from the tactile skins for applications such as object classification.

We apply compressed sensing to tactile skins to help address these challenges. Compressed sensing has been applied with great success in image and video processing, among other applications [2]. Our inspiration in applying compressed sensing to tactile skins is that the signals from the taxels resemble images on the skin.

B. Background

Compressed sensing compresses a signal (e.g., force readings from a tactile array at particular time) during the acquisition process [2] by generating measurements consisting of linear combinations of the signal elements. Mathematically, let $\mathbf{x} \in \mathbb{R}^N$ be our signal of interest; each measurement y_i

$$y_i = a_{i1}x_1 + \cdots + a_{iN}x_N,$$

where a_{ij} are measurement coefficients. The vector $\mathbf{y} \in \mathbb{R}^M$ is the compressed signal, which can be generated in hardware. Provided the original signal is sparse in some basis and the measurements are taken appropriately, $\mathbf{x}$ can be efficiently recovered from $O(\log N)$ measurements. Furthermore, techniques exist that can reduce measurement and signal noise during recovery [2].

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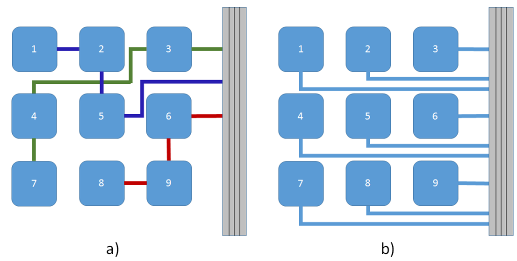

Fig. 1. Example wiring schematics for a) compressed sensing aggregated measurements on a 3×3 tactile grid and b) individual sensor measurements.

C. Data Acquisition Benefits

We have proposed an approach for data acquisition in tactile skins using compressed sensing techniques [3]. Our measurement coefficients are determined by the Scrambled Block Hadamard Ensemble (SBHE) [4], which has been successfully applied in image compression. We selected SBHE because it separates signal elements into distinct measurement groups. In tactile skins, this measurement approach can reduce wiring, as shown in Fig. 1. This figure shows a 3×3 tactile array with (a) measurements collected from three measurement groups compared with (b) individually wired taxels.

In addition to the reduced wiring, our approach requires fewer measurements than would be needed to sample each taxel individually. With appropriate hardware design, this can lead to a reduction in measurement acquisition time over full signal acquisition via single taxel measurements. Finally, our simulations have shown that it is possible to recover the full tactile signal from the compressed signal with high accuracy.

We have evaluated our approach on a simulated 64×64 taxel array using our tactile array simulator BubbleTouch (https://github.com/bdhollis/BubbleTouch). For reconstructing the full signal from the compressed signal, we use the Fast Iterative Soft-Thresholding Algorithm [5]. In preliminary work, we have achieved quality reconstructions at $50hz$ on a commodity computer [3]. Fig. 2 shows an example reconstructed signal from $N/3$ compressed measurements (right), the signal of noisy taxel readings that was sampled and compressed (center), and the ground truth signal with no sensor noise (left). Fig. 3 further shows the quality of the reconstruction by showing the peak signal to noise ratio (PSNR) for the reconstructed signals from various compression levels, as well as the PSNR for the noisy signal for comparison. Note that larger PSNR is better as it means less noise. In general, the reconstructed signals have similar or better PSNR than the noisy sampled signal.

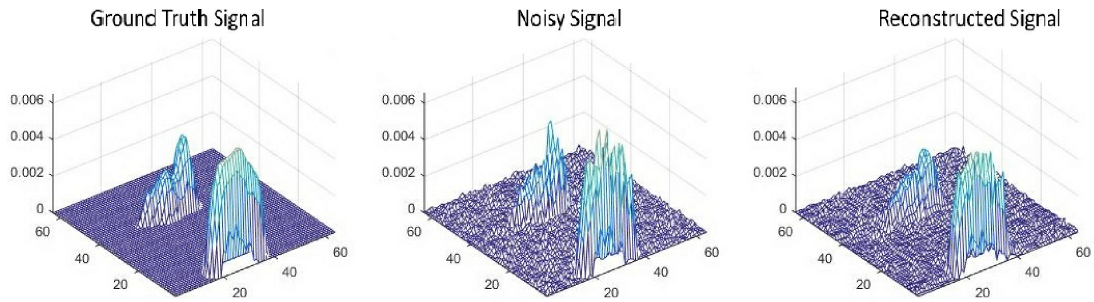

Fig. 2. Taxel values from a 64×64 tactile array (4096 taxels) for the ground truth signal (left), noisy signal (middle) and the reconstructed signal (right). The reconstruction was from 1365 measurements.

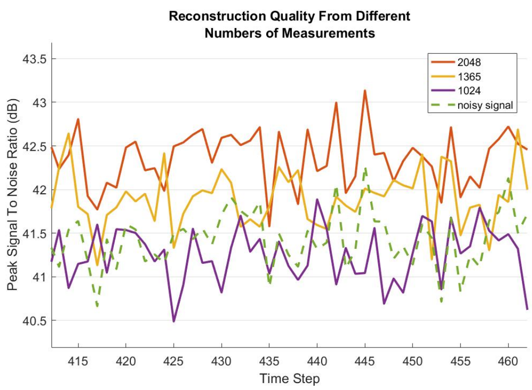

Fig. 3. Representative time sequences of PSNR of the reconstructed signal for the different numbers of measurements ($\frac{N}{4}$, $\frac{N}{3}$, $\frac{N}{2}$, where $N = 4096$) as well as the PSNR of the noisy signal.

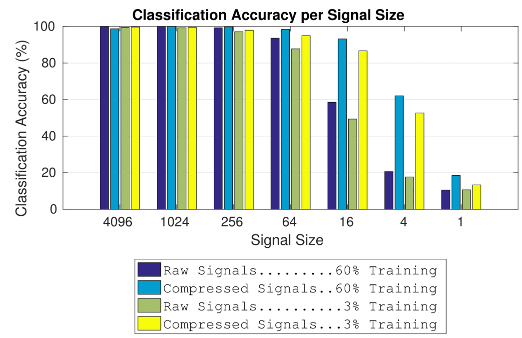

Fig. 4. The classification accuracy for various signal sizes using two training set sizes. For the raw signals, signal size refers to the number of taxels in the array, and for the compressed signals, signal size refers to the number of measurements.

D. Tactile Object Classification

Compressed sensing techniques have also been applied to classification tasks, an approach called *compressed learning*. It has been shown that it is possible to perform classification on the compressed signals with accuracy nearly that of classification using the original signals [6]. Utilizing the compressed signals directly reduces the dimension of each data point, thus reducing the processing time and resources needed for classification.

In recent work, we have explored the application of compressed learning to object classification in tactile skins [7]. As in our work with compressed sensing for data acquisition, compressed signals are generated by contact between the tactile array and various objects. We use compressed signals from single snapshots in time of individual objects to train a Directed Acyclic Graph Support Vector Machine (DAG-SVM). The DAG-SVM can then be used to classify an object based on a single time instance of contact with that object.

We have evaluated our method using BubbleTouch on 16 household objects. Fig. 4 shows the classification accuracy using various levels of compression. As a point of comparison, we also perform classification using the full *raw signals* from tactile arrays that have the same number of taxels as the number of measurements of the compressed signals. The results show our method achieves high classification accuracy, even with compression factors up to 64 and training data percentage as low as 3%. The figure also shows that a compressed learning approach performs better than lower resolution taxel arrays.

E. Future Work

We are investigating techniques to support higher compression and faster reconstruction, as well as other efficient in-hardware measurement approaches. We are also exploring additional applications that directly exploit the compressed signals. Finally, we are developing a hardware prototype of our compressed sensing-based tactile array.

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