

Texture Discrimination Using a Neuromimetic Asynchronous Flexible Tactile Sensor Array with Spatial Frequency Encoding

Ariel Slepyan¹, Sriramana Sankar¹, and Nitish Thakor^{1,2}

Abstract—State-of-the-art tactile sensing arrays are not scalable to large numbers of sensing units due to their raster-scanned process. This interface process results in a high degree of wiring complexity and a tradeoff between spatial and temporal resolution. In this paper, we present a new neuromimetic tactile sensing scheme that allows for single-wire signal transduction and asynchronous signal transmission – without the incorporation of electronics into each sensing element. A prototype device with spatial frequency encoding was developed using flexible fabric-based e-textile materials, and the ability of this new sensing scheme was demonstrated through a texture discrimination task. Overall, the neuromimetic spatial frequency encoded sensor array had comparable performance to the state-of-the-art tactile sensor array and achieved a classification accuracy of 86.58%. Future tactile sensing systems and electronic skins can emulate the spatial frequency encoding architecture presented here to become dense and numerous while retaining excellent temporal resolution.

I. INTRODUCTION

Human fingertips have excellent spatiotemporal resolution due to their asynchronous transmission scheme and high density of mechanoreceptors in the skin [1]. Due to this spatiotemporal resolution, the fingertips have excellent texture discrimination capabilities. For example, the fingertips have been shown to differentiate textures that differ by only a single layer of atoms [2]. However, artificial tactile sensors are still unable to achieve human-like tactile perception, largely due to their poor spatiotemporal resolution.

Almost all tactile sensor arrays reported in literature are currently interfaced using time-divisional multiple access (TDMA) [3]. TDMA, or raster scanning, involves individually addressing each tactile sensing ‘pixel’, or taxel, in the sensing matrix independently before moving on to the next taxel [4].

Thus, TDMA presents a tradeoff between spatial and temporal resolution such that larger sensing arrays necessitate longer readout times to sample all the sensors in the array. This reduces the temporal resolution and poses a significant problem to the scalability of state-of-the-art sensing arrays. Moreover, as the number of sensing taxels increases, the number of wires necessary to interface with all the taxels increases as well, which leads to additional wiring complexity.

The tradeoff between spatial and temporal resolution is evident when considering attempts made to sensorize the entire hand [5], or other large areas like the entire body [6]. In the scalable tactile sensing glove (STAG) developed by Sundaram et al [5], 548 sensors are used to collect pressure data across the palmar side of the hand with a sampling rate of 7 Hz. While the STAG has a high spatial resolution due to its

high density of sensors, its low sampling rate leads to poor temporal resolution. Additionally, the STAG requires many wires to interface with all the sensing taxels.

To mitigate this problem some groups have explored asynchronous transmission schemes over a single conductor [7,8]. Unlike synchronous protocols that require a clock to synchronize sensor communication, asynchronous protocols allow for sensors to communicate independently at any time [9]. This allows sensors to communicate precisely at the time of their sensing events and leads to excellent temporal resolution. Moreover, asynchronous tactile sensing schemes are inherently biomimetic as the human body employs asynchronous transmission natively through its mechanoreceptors [1].

However, existing asynchronous tactile sensor arrays are limited by the integration of significant electronics into each taxel. For example, the asynchronously coded electronic skin presented by Lee *et al* requires a dedicated microcontroller for every taxel [7]. Moreover, the RFID Hand developed by Slepyan *et al* requires an RFID device to be integrated into each taxel [8]. There are additional practical limitations such as significant readout complexity in [7], and the use of complex reading antennas in [8].

In this work, we demonstrate a new approach to develop scalable asynchronous tactile sensor arrays using spatial frequency encoding. This encoding mechanism enables a simple readout and does not necessitate the integration of electronic components into each taxel. Furthermore, we demonstrate the ability of this new sensor design and encoding method by mounting a spatial frequency encoded tactile sensor array onto a soft biomimetic finger and performing a texture discrimination task (Fig. 1).

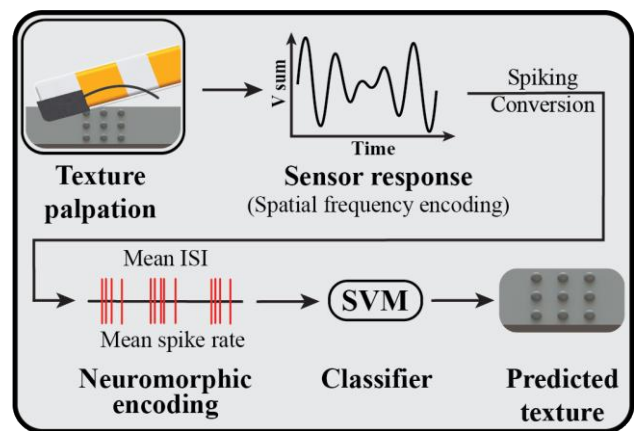


Figure 1. Diagram showing the overview of the texture discrimination.

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II. METHODS

A. Spatial Frequency Encoding

Spatial frequency encoding allows the elements of the tactile sensor array to communicate over a single conductor in an asynchronous and neuromimetic style (Fig. 2). For tactile sensing systems, spatial frequency encoding is achieved by assigning specific frequencies to different spatial positions based on the sensing taxel location. Due to the orthogonality of the different frequency signals, the signals can be combined and read on a single wire.

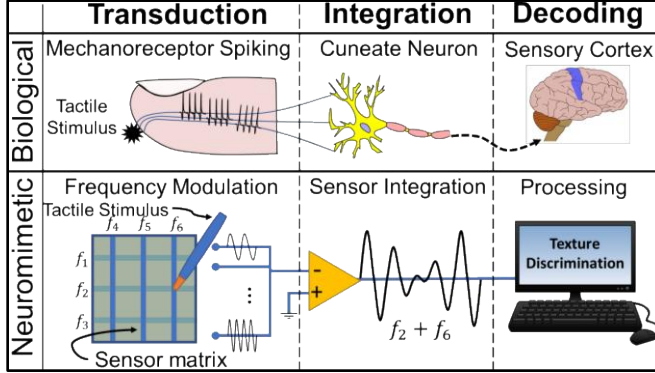


Figure 2. Schematic describing neuromimetic approach of spatial frequency encoding. The top row represents the biological pathway of tactile sensation and the bottom row describes the investigated neuromimetic approach.

To implement this encoding method, each element of the sensor array is designed to modulate a different frequency carrier wave (Fig. 3). Coordinate-based encoding is used to simplify fabrication and allow for a denser sensor array with fewer wires. Thus, each taxel modulates a tuple of frequencies to encode spatial location (frequency x , frequency y). Using a tuple of frequencies necessitates an $m+n$ number of oscillators rather than $m*n$ for non-coordinate-based encoding.

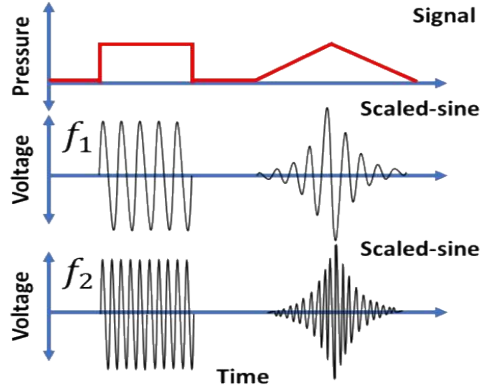


Figure 3. Diagram showing spatial frequency encoding of two sensors (with different frequencies f_1 and f_2). The applied pressure modulates the carrier wave of each sensor producing an amplitude modulated signal at a specific frequency.

In this paper, a 3x3 tactile sensor array was developed using spatial frequency encoding. Six different oscillator circuits were built to provide the carrier waves for each of the rows and columns in the array. These oscillators were constructed in the phase-shift style and had frequencies of 1.75 kHz, 2.72 kHz, 3.97 kHz, 4.50 kHz, 6.21 kHz, and 6.76 kHz. Frequencies above 1 kHz were chosen to maintain a high sampling rate to preserve the temporal information of the

textures during the texture discrimination task. Channel spacing was chosen as ~ 1 kHz to ensure facile separation in the Fourier transform.

B. Tactile Sensor Array Fabrication

The tactile sensor array was fabricated using e-textile materials to be flexible and conformable. This approach has been demonstrated before in our group's previous papers [10,11]. To achieve spatial frequency encoding the typical fabrication structure was slightly altered by introducing a large piece of conductive fabric to transmit the different frequency signals on a single common wire. An overview of the prototype fabrication is described in Figure 4.

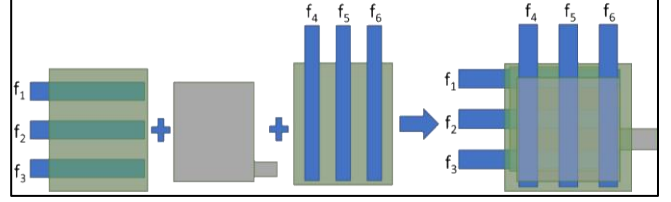


Figure 4. Fabrication schematic of the spatial frequency encoded prototype device. Green represents piezoresistive fabric (Stretchy Piezo LTT-SLPA-150k, Eeonyx), blue represents conductive fabric (Silver plated mesh, LessEMF), and gray also represents conductive fabric. Transparency in the colors represents overlapped elements with darker elements appearing on top of lighter ones.

C. Sensor Readout with Spectral Analysis

Spectral analysis is used to resolve which frequencies are present in the measured signal and with what amplitude they are present. A Fourier transform is used to convert the signal from the time domain into the frequency domain. The peaks present in the transformed signal are then analyzed to resolve the amplitudes of the different frequency signals.

The general encoding and decoding scheme is demonstrated below in Figure 5. As different spatial locations in the sensor matrix are activated, different frequency sinusoids are amplitude modulated and summed into a combined voltage. The spectrum of this combined voltage is then analyzed to resolve the frequencies, and their corresponding amplitudes, to determine the pressure signal applied on the sensor array.

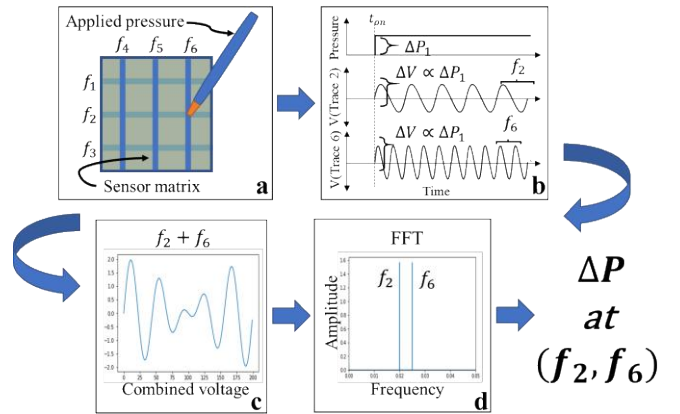


Figure 5. Flow chart showing spatial frequency encoding and decoding for a coordinate-based spatial frequency encoded tactile sensing matrix. (a) shows applied pressure to taxel (f_2 , f_6), (b) shows the different frequency voltage responses to be summed on the single conductor. (c) shows the combined voltage, and (d) shows the resolved frequencies in the FFT.

We demonstrate the use of the spatial frequency encoded sensor in a texture discrimination task. Thus, we calculate the short-time Fourier transform (STFT) in windows of length 1500 samples. This number was picked empirically by trying different window values and measuring the relative power of the spectrum.

An example STFT plot for the sensor fabricated in Figure 3 is shown below (Fig. 6). This plot represents an STFT calculated after sequentially indenting the nine different taxels of the tactile sensor array. Notably, the plot shows how an indentation of each taxel results in two dominant frequencies in the STFT. This combination of frequencies is used to resolve the location of the applied pressure.

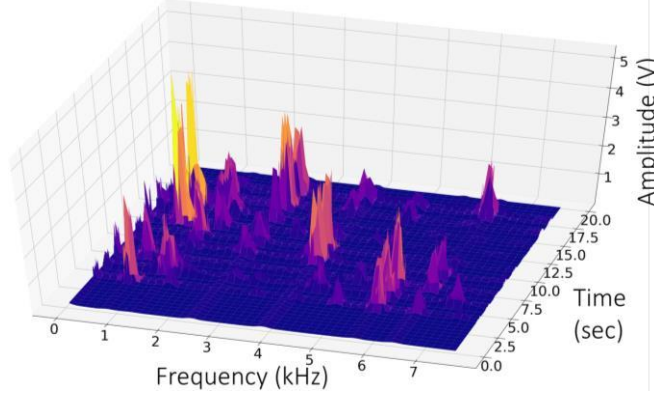


Figure 6. Generated STFT plot of frequency vs time vs amplitude in response to sequentially indenting the nine different taxels of the tactile sensor array presented in Fig. 3a. As time increases, pressure is applied to different taxels and is represented in the STFT as a peak at two different frequencies.

To convert the spectral data into different taxel values, the following algorithm was used. In the algorithm, ‘amp’ refers to the amplitude of the frequencies ($f_1, \dots, f_6$) measured by the STFT.

$$\begin{aligned} \text{Taxel 1} &= \text{amp}(f_1) \times \text{amp}(f_4) \\ \text{Taxel 2} &= \text{amp}(f_1) \times \text{amp}(f_5) \\ &\dots \\ \text{Taxel 9} &= \text{amp}(f_3) \times \text{amp}(f_6) \end{aligned}$$

Following this algorithm, nine taxel values were calculated for each window in the STFT based on the amplitudes of the six carrier frequencies present in that time window. These taxel values were the metrics used to perform the texture discrimination task.

D. Experimental Procedure

To test the spatial frequency encoded sensor, a texture discrimination task was performed using an experimental procedure from a previous study [12]. The sensor was attached to a soft biomimetic fingertip, which was mounted on a UR5 Robot arm (Universal Robotics). The pneumatically actuated soft biomimetic finger had an input pressure of 15 psi, which resulted in a 30° angle of flexion. The finger then palpated across a library of 10 3D printed textured plates (Fig. 7), for a total of 38 trials per texture. The signal was measured on the single common conductor and saved for offline analysis (Fig. 1). After obtaining the data, the spectral content was examined as described in section C, and the taxel values were resolved. To further emulate the firing pattern of

biological mechanoreceptors, taxel values from each taxel were converted into neuromorphic spike trains using the Izhikevich neuron model [13]. The taxel information was compressed into two spike-based features, mean spike rate and mean inter-spike interval, and then classified using support vector machine (SVM) to differentiate the textures.

As a comparison, the texture discrimination task was also performed on a 3x3 TDMA sensor constructed from the same materials as the spatial frequency encoded sensor. In the TDMA sensor, there are 3 input wires and 3 output wires.

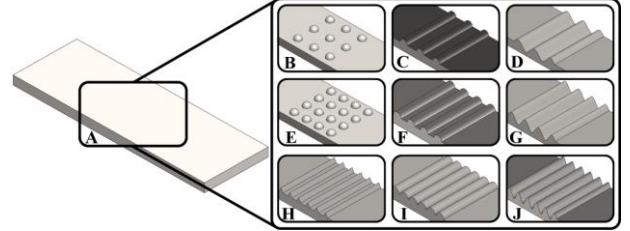


Figure 7. 3D printed textured plates used in texture discrimination task.

III. RESULTS

The sensor had a spatial resolution of 4 mm², based on the width of the conductive fabric, and a temporal resolution of 1.75 kHz, which was limited by the minimum carrier wave frequency and the ADC sampling rate. For reliable FFT detection, at least one period is required to be present in a sampling window; thus, the minimum frequency carrier wave determines the sampling window size and limits the temporal resolution.

In the texture discrimination task, the spatial frequency encoded sensor achieved an accuracy of 86.58%. The TDMA tactile sensor achieved an accuracy of 98.95% over the same texture library. The classifier metrics of the texture discrimination task with a comparison between the spatial frequency sensor and the TDMA sensor are presented in the table below.

TABLE I. TEXTURE DISCRIMINATION CLASSIFIER METRICS

	Spatial Freq. Sensor	TDMA Sensor
Accuracy	0.8658	0.9895
Error rate	0.1342	0.0105
Sensitivity	0.9737	1
Specificity	0.9912	1
Precision	0.925	1
Negative Predictive Value	0.9971	1

IV. DISCUSSION

In the texture palpation experiment, the spatial frequency encoded sensor array had comparable performance to the TDMA sensor array, but with slightly lower accuracy. However, because we are the first to present spatial frequency encoding in the application of tactile sensor arrays, it is possible that the decoding algorithms (i.e. STFT) can be further optimized to increase classification accuracy.

Overall, the neuromimetic spatial frequency encoded tactile sensor system presented here had many advantages over the current raster-scanned state-of-the-art. Notably, these advantages include single-wire signal transduction and

asynchronous sensor responses. Thus, the only potential latency in the sensing system is introduced by the sampling rate of the ADC. The prototype sensor developed here had 6 wires coming into the device because the phase shift oscillator circuits were built on an off-the-sensor circuit board. In future works, these circuits can be miniaturized to fit on the perimeter of the tactile sensor array through fPCB development. By placing the oscillators on the perimeter of the sensor, only three total wires will be necessary: one for power/Vcc, one for ground, and one for signal transmission. This is a significant reduction since TDMA sensor arrays require $m+n$ number of wires.

The matrix design and coordinate-based encoding strategy minimized the necessary oscillators to $(m + n)$ rather than $(m \times n)$ but has some inherent limitations as well. For example, because there are only six frequencies present, and nine possible taxels to be activated, if multiple taxels are activated along the same row or column simultaneously, there is some averaging in the response. This can be understood because of the additive model where the amplitude of a frequency depends on the total pressure applied to a certain row or column. To mitigate this issue, $(m \times n)$ carrier frequencies can be used. This would ensure that each taxel has an independent frequency and eliminate the averaging issue. However, this approach requires integrating an oscillator into each taxel of the sensor array and can pose limitations for creating sensor arrays with a very high density.

Ultimately, the bandwidth of a spatial frequency encoded system is limited by the ADC and the desired resolution of the application. For reliable FFT detection, it is generally required that at least one period of a signal is present in the time window investigated. This implies that depending on the desired resolution of the system, the lowest possible frequency used for encoding must equal the desired resolution. The maximum frequency that can be used for encoding is limited by the ADC frequency and Nyquist sampling. Furthermore, the minimum channel spacing is equal to the desired resolution. Thus, the spatial frequency encoding scheme can support a multitude of sensors as described by the equation below:

$$\text{Max Sensor Number} = \frac{\frac{1}{2} \times \text{ADC}_f - \text{Min Resolution}}{\text{Min Resolution}} \quad (1)$$

V. CONCLUSION

In conclusion, the developed neuromimetic spatial frequency encoded tactile sensor array achieved a texture classification accuracy of 86.58% and had comparable performance to the state-of-the-art TDMA-based tactile sensor array. Moreover, the developed prototype had a higher sampling rate than the TDMA-based tactile sensor array and transduced sensor data over a single wire rather than a multitude of wires. The method of spatial frequency encoding enabled no latency between sensor responses and is promising for discriminating textures with a high degree of spatiotemporal complexity. Overall, the developed neuromimetic spatial frequency encoded system demonstrates how future tactile sensing systems and e-skins can be fabricated to be numerous and dense, while retaining excellent temporal resolution and signal transduction over a single wire.

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REFERENCES

- [1] Johansson, R. S., & Flanagan, J. R. (2009). Coding and use of tactile signals from the fingertips in object manipulation tasks. *Nature Reviews Neuroscience*, 10(5), 345-359.
- [2] Carpenter, C. W., Dhong, C., Root, N. B., Rodriguez, D., Abdo, E. E., Skelil, K., ... & Lipomi, D. J. (2018). Human ability to discriminate surface chemistry by touch. *Materials Horizons*, 5(1), 70-77.
- [3] Taunyazov, T., Sng, W., See, H. H., Lim, B., Kuan, J., Ansari, A. F., ... & Soh, H. (2020). Event-driven visual-tactile sensing and learning for robots. *arXiv preprint arXiv:2009.07083*.
- [4] Lee, W. W., Cabibihan, J., & Thakor, N. V. (2013, November). Bio-mimetic strategies for tactile sensing. In *SENSORS*, 2013 IEEE (pp. 1-4). IEEE.
- [5] Sundaram, S., Kellnhofer, P., Li, Y., Zhu, J. Y., Torralba, A., & Matusik, W. (2019). Learning the signatures of the human grasp using a scalable tactile glove. *Nature*, 569(7758), 698-702.
- [6] Inaba, M., Hoshino, Y., Nagasaka, K., Ninomiya, T., Kagami, S., & Inoue, H. (1996, November). A full-body tactile sensor suit using electrically conductive fabric and strings. In *Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems. IROS'96* (Vol. 2, pp. 450-457). IEEE.
- [7] Lee, W. W., Tan, Y. J., Yao, H., Li, S., See, H. H., Hon, M., ... & Tee, B. C. (2019). A neuro-inspired artificial peripheral nervous system for scalable electronic skins. *Science Robotics*, 4(32), eaax2198.
- [8] Slepian, A., & Thakor, N. (2020, November). Towards scalable soft e-skin: Flexible event-based tactile-sensors using wireless sensor elements embedded in soft elastomer. In *2020 8th IEEE RAS/EMBS International Conference for Biomedical Robotics and Biomechatronics (BioRob)* (pp. 334-339). IEEE.
- [9] Cassidy, A., & Ekanayake, V. (2006, November). A biologically inspired tactile sensor array utilizing phase-based computation. In *2006 IEEE Biomedical Circuits and Systems Conference* (pp. 45-48). IEEE.
- [10] Osborn, L., Lee, W. W., Kaliki, R., & Thakor, N. (2014, August). Tactile feedback in upper limb prosthetic devices using flexible textile force sensors. In *5th IEEE RAS/EMBS International Conference on Biomedical Robotics and Biomechatronics* (pp. 114-119). IEEE.
- [11] Osborn, L. E., Dragomir, A., Bethausen, J. L., Hunt, C. L., Nguyen, H. H., Kaliki, R. R., & Thakor, N. V. (2018). Prosthesis with neuromorphic multilayered e-dermis perceives touch and pain. *Science robotics*, 3(19).
- [12] Sankar, S., Brown, A., Balamurugan, D., Nguyen, H., Iskrou, M., Simcox, T., ... & Thakor, N. (2019, October). Texture Discrimination using a Flexible Tactile Sensor Array on a Soft Biomimetic Finger. In *18th IEEE Sensors, SENSORS 2019* (p. 8956704). Institute of Electrical and Electronics Engineers Inc.
- [13] Izhikevich, E. M. (2003). Simple model of spiking neurons. *IEEE Transactions on neural networks*, 14(6), 1569-1572.