

A Review of Machine Learning-Enhanced Tactile Sensing: Algorithms, Applications, and Future Directions

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Abstract. Tactile sensing has undergone significant advancements in miniaturization and flexibility, leading to a surge in data complexity that challenges conventional model-based processing methods. These methods often struggle with real-time responsiveness, heterogeneous signal analysis, and accurate judgment of sensation. This review explores the transformative integration of Machine Learning (ML) techniques with tactile sensing to overcome these limitations. We discuss the core principles of major tactile sensor types (resistive/capacitive, Fiber Bragg Grating (FBG), and event-driven) and their inherent compatibility with ML approaches. The review then critically examines key ML methodologies: Supervised Learning, Unsupervised Learning, and Spiking Neural Networks (SNNs). We highlight significant applications demonstrating ML's impact, including high-fidelity dynamic touch decoding for handwriting and Braille recognition, the F-TAC Hand achieving high surface coverage and multi-object grasping success, and neuromorphic tactile object classification. Despite progress, challenges remain in data acquisition, hardware-algorithm co-design, processing high-bandwidth spatio-temporal data, robustness, and scaling neuromorphic systems. The review concludes by outlining future directions, emphasizing cross-modal fusion, explainable ML, lightweight edge models, and bio-inspired adaptive co-evolution, paving the way for autonomous robots operating effectively in unstructured environments.

Keywords: component, Tactile Sensing, Machine Learning in Robotics, Spiking Neural Networks, Dexterous Manipulation

1. Introduction

For past decades, tactile sensors have evolved rapidly in material, mechanical structure, and fabrication, achieving flexible and miniaturized forms [1]. As a result, the total amount, density, and complexity of the data provided by tactile sensors have increased sharply, presenting new challenges for tactile information processing.

Meanwhile, model-based data analyzing methods fall behind in fulfilling the increasing demand for information analyzing and processing capability, thus limiting the potential of robotic tactile sensing. In a traditional situation, researchers apply a so-called "nested workflow", in which they first do precise calibration of sensor input-output response characteristics on tactile sensors, then

perform statistical analysis, employ transformation theories, rely on physical models or computer simulations, or utilize other mathematical tools to obtain further information from raw data [2].

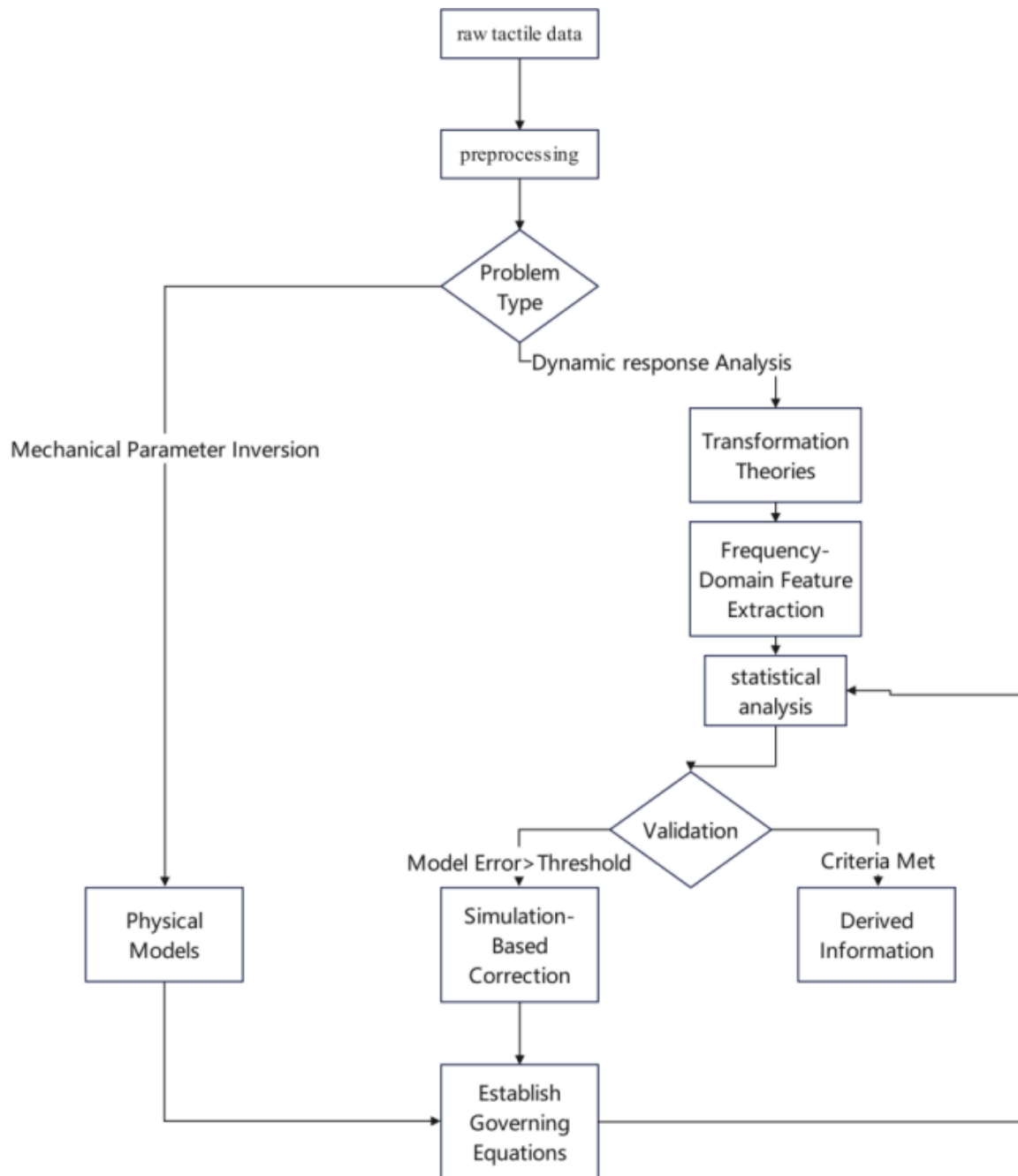


Figure 1. A typical nested workflow process of model-based data analyzing method

Conventional approaches prove inadequate for complex tactile challenges: poor millisecond response, laborious manual feature extraction, and unreliable judgment accuracy hinder robotic interaction in intricate environments [2]. This drives the adoption of ML methods to enhance processing speed/accuracy for advanced applications. Researchers in tactile sensing have attempted to utilize machine learning algorithms that are designed for handling complex and dynamic data to enhance the speed and accuracy of tactile information processing as well as create future practical applications.

In this article, several machine learning (ML) approaches for tactile sensing will be discussed and some latest progress in integrating ML into tactile sensing will be covered and reviewed. Section 2 demonstrates the core principles of several types of tactile sensors and how they can cooperate with ML methods. Section 3 dives into the actual process and advantages of ML techniques integrated with tactile sensing. Section 4 covers applications of ML-based tactile sensors in some industries. The final section presents the challenges and future expectations.

2. Core principles of tactile sensors

Several types of sensors were developed to meet various requirements and applications. In this section, the core physical principles of these sensors will be addressed to have a better vision of how ML approaches can be integrated with them.

2.1. Resistive/capacitive tactile sensor

Resistive tactile sensors utilize the change of the resistivity of the interface between two surfaces affected by the applied load. Today resistive tactile sensors use conductive polymers and the change of resistivity is acquired through an electrode matrix and simple conditioning electronics, showing a hyperbolic style characteristic between applied load and resistivity [3].

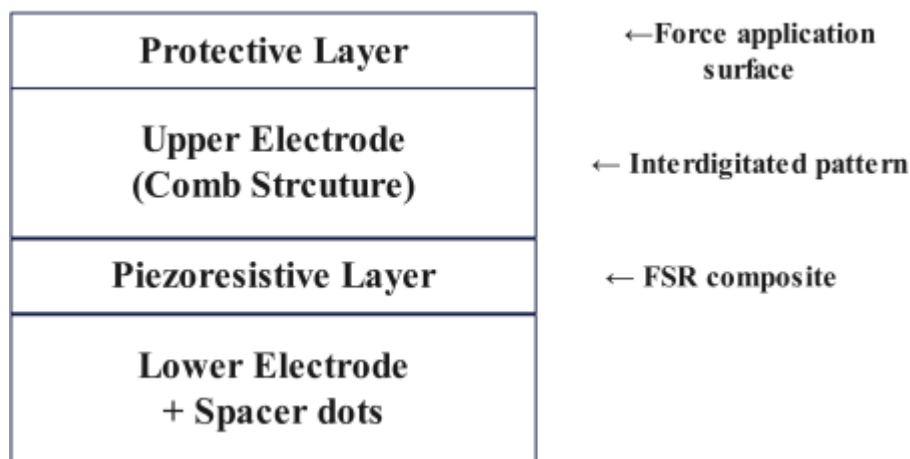


Figure 2. Resistive tactile sensor architecture

On the other hand, capacitive tactile sensors rely on detecting changes in electrical capacitance between conductive elements. The fundamental capacitance (C) is governed by the equation (1):

$$C = \varepsilon \frac{A}{d} \quad (1)$$

Where ε equals the dielectric material, A equals overlapping electrode surface area, and d equals the distance between electrodes. External force affects the capacitance by reducing electrode separation before capacitance changes are detected and converted into measurable electrical signals.

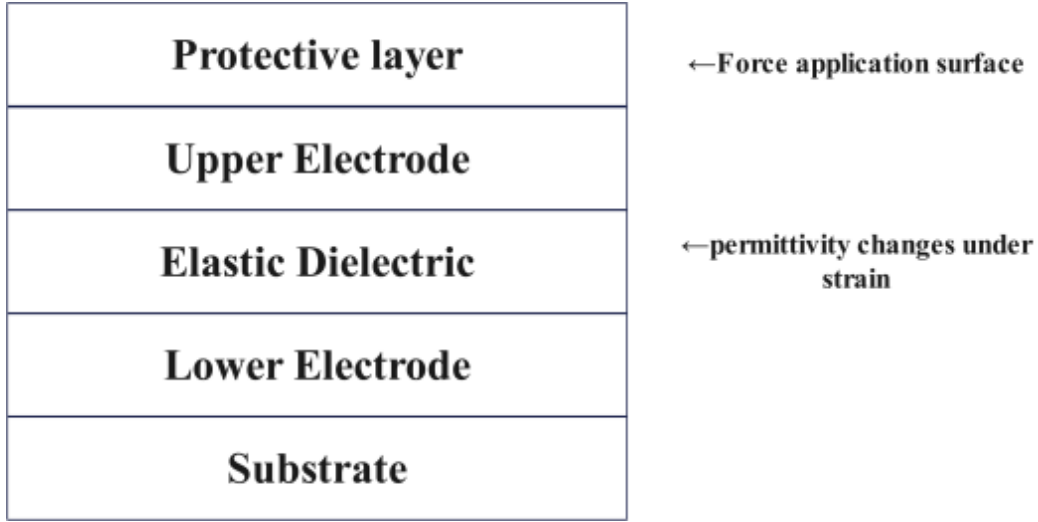


Figure 3. Key structural elements of capacitive tactile sensors

It is noted that both of the sensor types feature structured, low-dimensional outputs with highly interpretable physical correlations, which is of special interest in supervised learning since it requires structured regression datasets.

2.2. Fiber Bragg grating tactile sensor

FBGs are periodic structures inscribed in optical fibers and have a periodically modulated core index along the fiber axis [4]. When a broadband light passes through, FBG will reflect a specific incident light wavelength satisfying the Bragg reflection condition. The Central wavelength of the reflected light λ_B is determined by (2) :

$$\lambda_B = 2n_{eff}\Lambda \quad (2)$$

Where n_{eff} equals effective refractive index and Λ equals grating period. Applying external force alters n_{eff} and Λ , shifting λ_B . The shift $\Delta\lambda_B$ is linearly proportional to applied strain ε and temperature change T as expressed in (3):

$$\Delta\lambda_B = \lambda_B[(1 - P_e)\varepsilon + (\alpha f + \xi) \Delta T] \quad (3)$$

Where P_e equals photoelastic coefficient, αf equals thermal expansion coefficient, and ξ equals thermo-optic coefficient.

FBG arrays generate coupled spectral shifts where wavelength changes reflect both spatial distribution and temporal evolution. Conventional methods fail to decouple spatial and temporal features simultaneously. Besides, high-density FBG arrays can produce up to 1.2 GB/s of data streams. On the other hand, Spatio-Temporal Graph Neural Networks (ST-GNN) offer strong spatio-temporal modeling and cross-sensitivity handling capability, making it essential for the dynamic deformation of FBG tactile sensors.

2.3. Event-driven tactile sensing

Event-driven tactile sensors represent a paradigm shift from synchronous, frame-based sensing to asynchronous, activity-dependent data acquisition. These sensors operate on a fundamental principle

that discrete spikes ("events") are generated only when local mechanical stimuli exceed threshold-based dynamics at individual taxes.

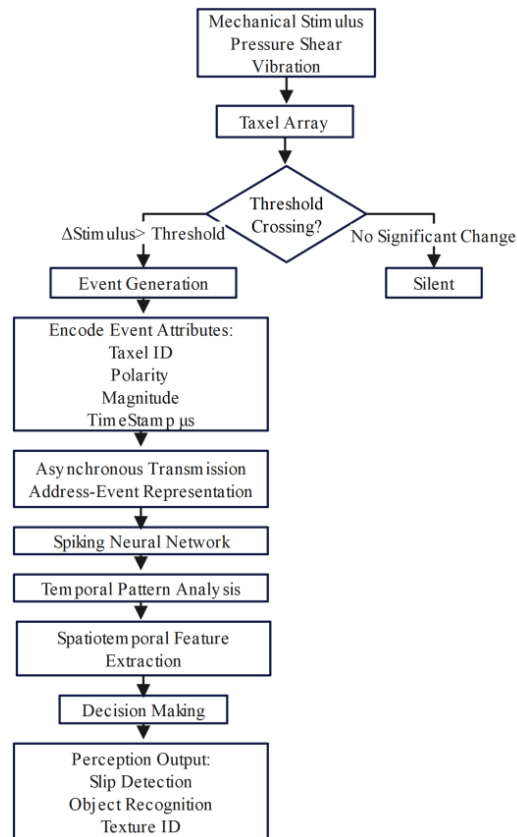


Figure 4. Process of event-driven tactile sensing

The output is restricted to changes in contact features (onset, release, or intensity shifts), which eliminates redundant static-state transmissions. Events are time-stamped with microsecond resolution, preserving precise stimulus dynamics critical for real-time interaction. Also, by avoiding global sampling, readout latency remains low regardless of texel count—enabling high-resolution tactile skins without wiring bottlenecks. Thus, the sensor's native spike output aligns intrinsically with Spiking Neural Networks (SNN) computation.

3. ML for tactile sensing

In this section, we present several machine-learning methods for tactile sensing and highlight their advantages over conventional approaches. Representative studies and recent progress will also be discussed to elucidate their underlying mechanisms.

3.1. Supervised learning

Supervised learning involves training an algorithm on a labeled dataset where each input data point is paired with a corresponding target output. The core principle is to learn a mapping function from input features to the desired outputs (labels) by minimizing a defined error or loss function between the predicted and actual labels. The trained model can then be generalized to make predictions on unseen data.

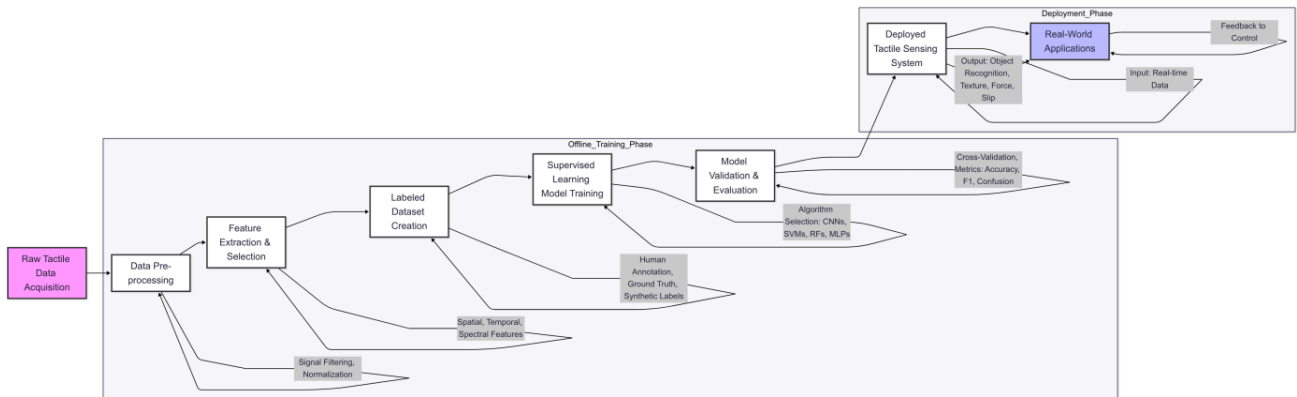


Figure 5. An overview of supervised learning method

Supervised learning enables complex touch pattern recognition, exemplified by Y. Lu et al.'s SVM-optimized design of LIG-based tactile sensors. By leveraging classification accuracy and cluster separability metrics, SVM inversely optimized fabrication parameters (signal type/electrode density/microstructure), achieving high-fidelity dynamic touch decoding [5].

In regression tasks that predict continuous numerical values rather than discrete labels, the paradigm trains models on labeled datasets to learn complex mappings from input features to real-valued outputs by minimizing prediction errors (e.g., mean squared error). Regression is indispensable for quantifying physical interactions, such as contact force estimation.

3.2. Unsupervised learning

Unsupervised learning discovers inherent structures in unlabeled data by optimizing objectives like reconstruction fidelity or sparsity, avoiding costly manual labeling. This provides a critical framework for extracting informative representations directly from raw tactile streams.

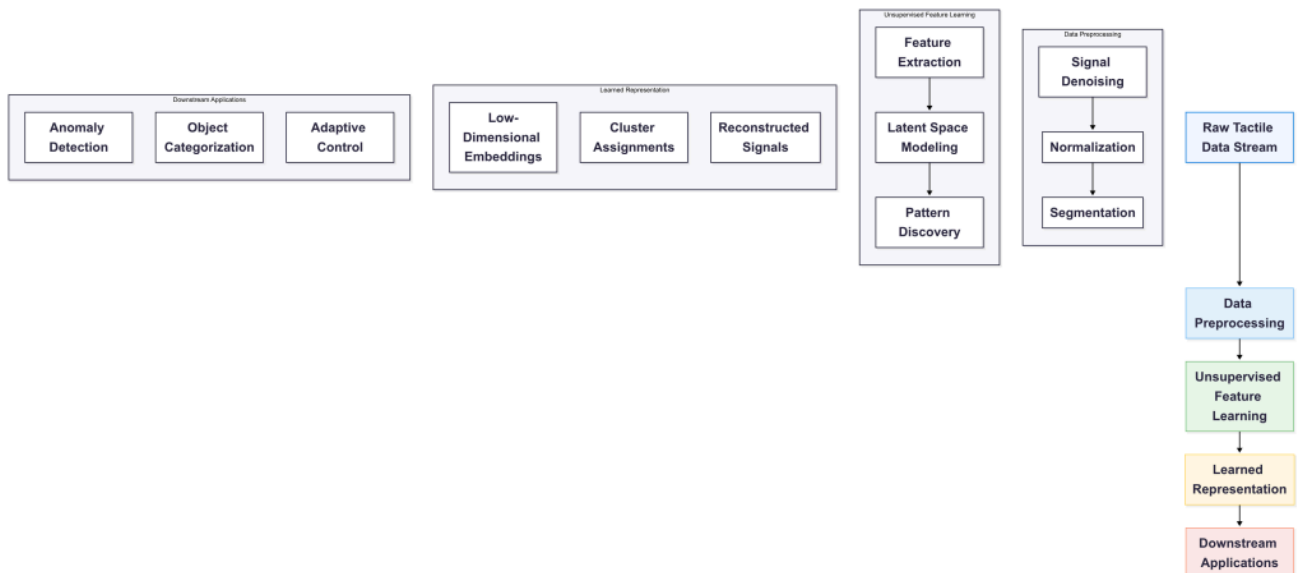


Figure 6. The application of unsupervised learning in tactile sensing

A key example is ST-HMP (Madry et al.), which applies K-SVD dictionary learning to derive spatiotemporal codewords from tactile sequences. It then computes sparse codes via OMP and

aggregates multi-scale features through spatiotemporal pyramid pooling. Validated on robotic grasp stability and object recognition, ST-HMP outperformed hand-crafted methods by 5.1–12.9%, proving autonomous spatio-temporal feature learning from unlabeled data [6].

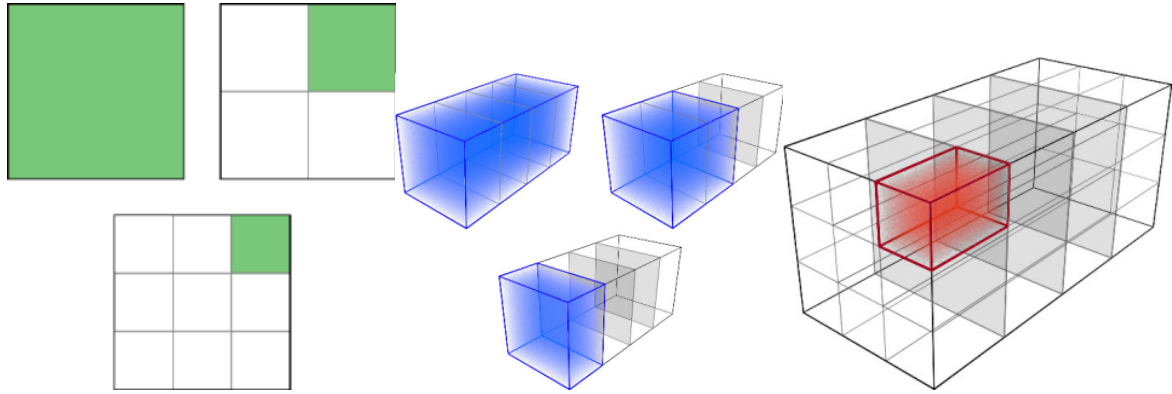


Figure 7. Schematic illustration of a partition of data in the spatial, temporal, and spatio-temporal pyramid

3.3. Spiking Neural Network (SNN)

Spiking Neural Networks (SNNs) offer significant advantages for tactile sensing through event-driven spike-based communication. Unlike traditional ANNs requiring constant high-power computations, SNNs activate neurons only upon sufficient input, enabling ultra-low-power operation ideal for resource-constrained devices. They inherently excel at processing spatio-temporal spike patterns from tactile sensors: spike timing encodes contact dynamics, while spatial patterns reflect pressure distribution. Crucially, mechanisms like STDP enable automatic spatio-temporal feature extraction without manual algorithm design.

Wang et al.'s RandHet-SNN enhances robustness by randomizing LIF neuron time constants (τ). Each neuron samples τ during propagation, mimicking biological heterogeneity to improve defense capabilities. This achieved 48.59% adversarial accuracy (vs. 29.29% baseline) at milliwatt power [7].

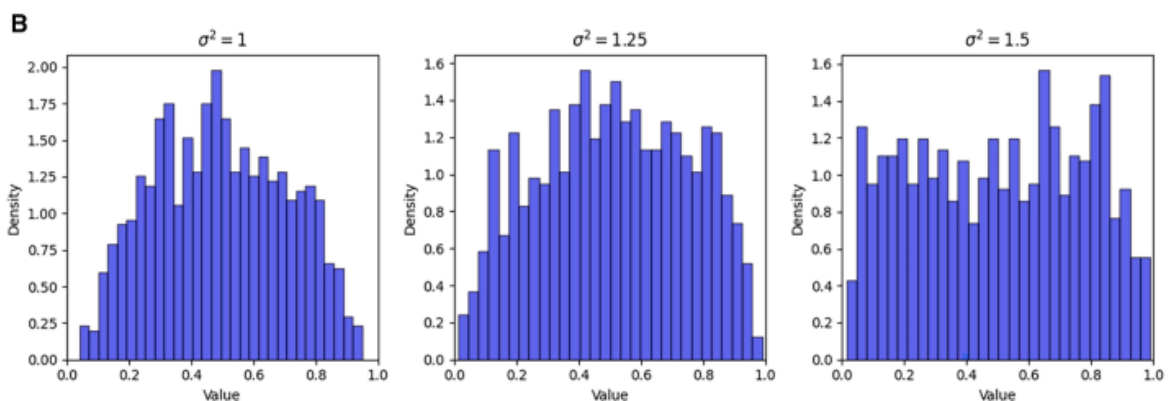


Figure 8. Making the time constant τ random mimics the natural differences found in biological neurons

By introducing randomness to τ , RandHet-SNN creates dynamic defense barriers: adversarial samples generated from one sampling become significantly less effective after model parameters are

resampled [7].

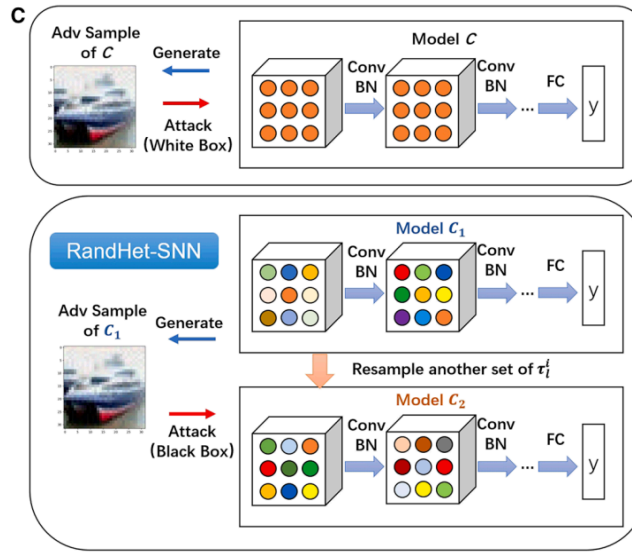


Figure 9. Diagram of the RandHet-SNN

Experimental results show this mechanism improves defense accuracy against AutoAttack on CIFAR-10 from 29.29% (baseline) to 48.59% [7] while maintaining milliwatt-level power consumption.

4. Applications

The integration of machine learning and tactile sensing has opened up new frontiers in various fields. In the following, we present some of the latest breakthroughs in the field of ML-based tactile sensing and applications in different industries.

4.1. Machine learning significantly improves the decoding ability of dynamic touch

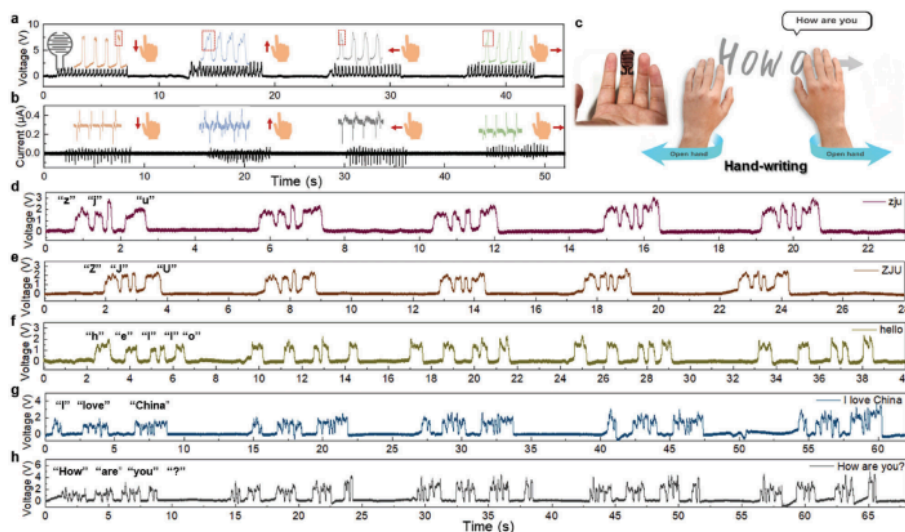


Figure 10. Optimized tactile sensing performance in handwriting applications

In the work by Lu et al. on ML-enabled tactile sensor design for dynamic touch decoding, researchers have applied the optimized tactile sensor to the field of handwriting recognition. The system uses the Support Vector Machine (SVM) algorithm to optimize the hardware parameters of the sensor and finally achieves an amazing classification accuracy of 99.58% [5]. This achievement significantly exceeds the traditional intuition-driven sensor design methods.

4.2. The F-TAC hand improves the precision of machine operation through tactile feedback

The F-TAC Hand (Peking University et al.) pioneers full-hand tactile-motor integration, using 17 dual-function sensors to achieve >95% surface coverage with 24-DoF dexterity. Its probabilistic control enables 19 human-like grasping strategies and real-time adaptation. Experiments demonstrated 0.1s obstacle detection and 100% multi-object grasping success—46.5% higher than non-tactile systems [8]. This breakthrough resolves sensorimotor integration challenges for embodied intelligence.

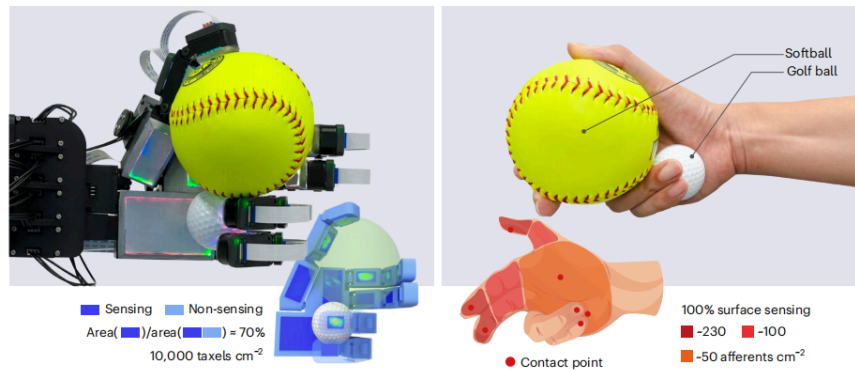


Figure 11. Overview of F-TAC Hand

4.3. VT-SNN achieves low-power object recognition in tactile sensors

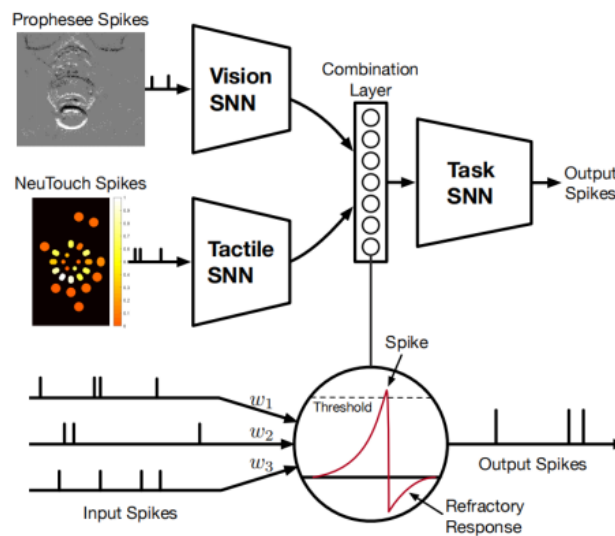


Figure 12. VT-SNN working principle diagram

Researchers from the National University of Singapore have developed a VT-SNN system that combines touch sensing with brain-like computing, achieving real-time object recognition with milliwatt-level power consumption.

The system uses 39 bio-inspired touch sensors to detect pressure changes when touching objects. Its graphene-based sensors respond quickly and provide precise signals to the neural network. In container sorting tests, the touch-based SNN model achieved 71% accuracy - much better than traditional MLP-GRU models (50%) - while using 1,000 times less power [9].

5. Conclusion and challenges

This review has examined the integration of machine learning (ML) with tactile sensing, demonstrating significant improvements in data processing efficiency, feature extraction, and real-world applications. Supervised learning enables high-accuracy pattern recognition [5], unsupervised methods efficiently extract spatio-temporal features from unlabeled data [6], and Spiking Neural Networks (SNNs) provide ultra-low-power, event-driven processing [7, 9]. Applications like dexterous manipulation (F-TAC Hand [8]), Braille recognition [5], and neuromorphic object classification (VT-SNN [9]) highlight ML's transformative role in robotic interaction with complex environments.

Key challenges persist: (1) ML models demand extensive labeled tactile data, limiting real-world generalization; (2) Hardware-algorithm co-design (e.g., taxel-SNN synchronization) is needed for power-efficient information capture [10]; (3) Processing high-bandwidth spatio-temporal sensor data (e.g., FBG arrays) requires lightweight expressive models [2]; (4) Robustness against environmental variables (texture/slippage/temperature) remains problematic; (5) Scaling neuromorphic systems (e.g., SNNs) necessitates breakthroughs in on-chip learning and spike routing [9].

Future efforts focus on cross-modal sensor fusion, explainable ML interpretations, edge-compatible lightweight models, and bio-inspired adaptive algorithms. Addressing these challenges will advance autonomous, dexterous robots capable of operating efficiently in unstructured environments.

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