Monolithic Integration of Neuromorphic Electronic Skin and In-Memory Computing Chips for Fine Manipulation in Embodied Intelligent Agents

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ABSTRACT For fine manipulation in embodied intelligent agents, tactile systems are required not only to provide highly sensitive perception, but also to support low-latency information processing and highly integrated hardware implementation. To address the large data-movement overhead, delayed response, and limited compactness caused by the separation of sensing, transmission, and computation in conventional tactile architectures, this work proposes a monolithically integrated platform that combines neuromorphic electronic skin with an in-memory computing chip to establish an efficient task-oriented tactile information processing pathway. Within a unified hardware architecture, the platform couples mechanical stimulus perception, neuromorphic encoding, and on-chip computing, enabling external tactile inputs to be dynamically represented at the sensory source and further processed for feature extraction and pattern discrimination in the in-memory computing array. The structural design, operating principle, and electrical, neuromorphic, and computing characteristics of the integrated platform are systematically investigated. In addition, representative fine-manipulation-related tasks, including contact-state recognition, slip warning, and texture classification, are employed to validate the system. The results demonstrate that the proposed platform effectively preserves the temporal information embedded in tactile events and outperforms conventional discrete architectures in terms of task-processing accuracy, real-time capability, and data-movement efficiency. This study provides a promising route toward highly integrated, low-latency, and task-driven tactile intelligence hardware, and lays the groundwork for the co-design of tactile sensing and on-chip processing in next-generation embodied intelligent systems.

INDEX TERMS neuromorphic, monolithic, tactile, manipulation

I. INTRODUCTION

THE rapid development of embodied intelligence is driving robotic systems beyond conventional coarse grasping and pre-programmed actions toward more adaptive, autonomous, and interaction-intensive fine manipulation [1], [2]. In this context, tactile perception is becoming as indispensable as vision for enabling intelligent agents to interact effectively with the physical world [3]. In contact-rich and dynamically changing manipulation scenarios, vision alone is often insufficient to reliably capture critical information such as contact states, local force distribution, incipient slip, and surface texture [4], [5]. By contrast, electronic skin offers distributed tactile sensing capabilities that provide a crucial foundation for stable grasping, dexterous manipulation, and real-time physical interaction [6]. However, as tactile arrays continue to increase in scale and spatiotemporal resolution, conventional separated architectures based on sensing, transmission, and computation are increasingly constrained by excessive data movement, high latency, and limited system compactness, making them poorly suited to the stringent hardware requirements of fine manipulation [7]. In practical fine-manipulation tasks, what is needed is not merely more accurate tactile measurement, but tactile intelligence hardware capable of rapidly representing and processing dynamic events such as contact onset, incipient slip, local vibration, and short-term force variation. Therefore, how to compress, preserve, and efficiently utilize task-relevant tactile information at the sensory source has become one of the central questions in the development of embodied tactile systems [8].

In recent years, substantial progress has been made in electronic skin, neuromorphic sensory devices, and in-memory computing hardware. On the one hand, research on electronic skin has evolved from merely pursuing high sensitivity and multimodal perception toward neuromorphic paradigms capable of dynamic stimulus encoding and bioinspired tactile representation, endowing tactile front ends with event-driven operation, spike-based output, and synaptic-like response characteristics [9], [10]. On the other hand, the emergence of in-memory computing has provided an attractive route to reducing data-transfer overhead and improving edge-side processing efficiency, allowing sensory information to be processed closer to its source. These advances have laid an important foundation for next-generation tactile intelligence hardware. Nevertheless, most existing studies still rely on discrete device integration, board-level interconnections, or serial combinations of separate functional modules, and therefore lack a unified hardware framework that tightly couples sensing, encoding, and computation. More specifically, existing electronic skin studies often emphasize sensing capability itself, neuromorphic devices mainly demonstrate temporally correlated response behaviors, and in-memory computing chips are largely optimized for general computational efficiency, leaving the collaboration among these three components relatively weak in realistic embodied manipulation scenarios [11]. This limitation becomes particularly pronounced in fine manipulation, where tactile information is typically high-dimensional, sparse, temporally sensitive, and strongly task-dependent. Under conventional continuous-sampling and external post-processing schemes, such information inevitably leads to substantial data redundancy and reduced real-time responsiveness to critical dynamic events. Therefore, the monolithic integration of neuromorphic electronic skin with in-memory computing chips, together with an efficient closed-loop pathway from mechanical stimulus perception to task-relevant output, remains a critical and largely unresolved challenge.

To address these challenges, this work presents a monolithically integrated platform that combines neuromorphic electronic skin with an in-memory computing chip for fine manipulation in embodied intelligent agents. Within a unified hardware architecture, the platform couples mechanical stimulus perception, neuromorphic encoding, and on-chip computing, allowing external tactile inputs to be dynamically represented at the sensory source and further processed for feature extraction and pattern discrimination in the in-memory array, thereby establishing a continuous tactile information pathway oriented toward task execution. Specifically, we first develop an electronic skin unit capable of converting external tactile stimuli into neuromorphic response signals, and then monolithically integrate it with an in-memory computing module to reduce system-level data movement and improve real-time processing capability. We subsequently investigate the structural design, operating mechanism, and electrical, neuromorphic, and computing characteristics of the integrated platform. Finally, through representative fine-manipulation-related tasks, including contact-state recognition, slip warning, and texture classification, we validate the comprehensive advantages of the proposed platform in task-processing accuracy, latency reduction, and data-movement efficiency. These results indicate that monolithic integration is not merely a strategy for structural compactness, but a system-level approach for coordinating sensing, encoding, and computation around task requirements. This work provides a promising route toward highly integrated, low-latency, and task-driven tactile intelligence hardware, and lays the groundwork for the co-design of tactile sensing and on-chip processing in next-generation embodied intelligent systems.

II. SYSTEM ARCHITECTURE AND OPERATING PRINCIPLE

In this work, we develop a monolithically integrated tactile intelligence platform for fine manipulation in embodied intelligent agents, with the central objective of tightly coupling tactile sensing, neuromorphic encoding, and in-memory processing within a unified hardware architecture. As illustrated in Fig. 1, the proposed platform mainly consists of a neuromorphic electronic skin unit, a signal interfacing and coupling module, an in-memory computing array, and a task-oriented output terminal. In contrast to conventional separated architectures based on discrete sensors, readout circuits, and external processors, the present system pushes the acquisition, representation, and preliminary processing of tactile information as close as possible to the sensing source. This design minimizes the data-movement overhead associated with large-scale array readout and enhances the real-time responsiveness of the system to dynamic contact events. At the architectural level, external mechanical stimuli are first perceived by the electronic skin unit and induce corresponding changes in its internal electrical states. These changes are then transformed into neuromorphic response signals and mapped directly onto the input of the in-memory computing chip, where task-relevant information is extracted and processed in situ. The final output of the system is used to represent contact states, stimulus categories, or manipulation-related features, thereby providing hardware support for fine manipulation. In this sense, the proposed platform is not merely a compact rearrangement of a conventional tactile system, but rather a continuous information-processing pathway from physical contact to task-oriented output.

From the perspective of operating principle, the system follows a processing pathway of "mechanical stimulus–neuromorphic encoding–array computing–task output." [12], [13] If the external mechanical stimulus is denoted by $S(t)$ and the system output by $Y(t)$, the overall information flow can be abstracted as:

$$Y(t) = G\left(C\left(\mathcal{E}(S(t))\right)\right) \tag{1}$$

where $\mathcal{E}(\cdot)$ represents the sensing and encoding process of the neuromorphic electronic skin, $C(\cdot)$ denotes the feature mapping and information processing process in the in-memory array, and $G(\cdot)$ refers to the task-oriented output generation process. This expression indicates that the key advantage of the present platform does not lie in optimizing only a single module, but in ensuring that the output of each stage is naturally matched to the input requirements of the next stage, thereby minimizing unnecessary intermediate conversion and information loss. Specifically, when external stimuli such as pressure, dynamic contact, microvibration, or slip-related perturbations are applied, the electronic skin unit converts mechanical inputs into modulated electrical responses through the coupling effect between its sensing layer and functional layer. Unlike conventional continuous analog outputs, the neuromorphic electronic skin in this work emphasizes event-driven representation of tactile information, where stimulus intensity, duration, and temporal variation are encoded through spike frequency, spike timing, response amplitude, or other synaptic-like dynamic parameters. To further describe this process, the output of the neuromorphic front end can be expressed as:

$$R(t) = f\left(P(t), \dot{P}(t), \tau\right) \tag{2}$$

where $P(t)$ is the mechanical stimulus intensity, $\dot{P}(t)$ denotes the stimulus variation rate, and τ is the characteristic time constant associated with intrinsic device dynamics. This relationship indicates that the electronic skin output is determined not only by contact magnitude, but also by how rapidly the stimulus changes and how the device preserves short-term temporal information, making it particularly suitable for describing dynamic tactile events such as transient contact, incipient slip, and vibration-mediated texture.

At the neuromorphic encoding stage, the present work places greater emphasis on preserving temporal information than on simple amplitude-based sampling of tactile signals. For a typical event-driven response, the output spike frequency can be further expressed as:

$$f_{\mathrm{spike}} = f_0 + \alpha P + \beta \frac{dP}{dt} \tag{3}$$

where f_0 is the baseline spike frequency, and α and β represent the response coefficients to stimulus intensity and stimulus variation, respectively. This relationship indicates that when external contact becomes stronger or changes more rapidly, the system can actively highlight more task-relevant dynamic information through variations in spike emission behavior. Such a representation not only more closely resembles the information-transfer mechanism between mechanoreceptors and neurons in biological tactile systems, but also significantly reduces the prolonged output of static redundant information, allowing the downstream computing module to focus more effectively on task-relevant temporal features. On this basis, the neuromorphic response signals are directly coupled to the in-memory computing array, where memory-computing units perform operations such as feature accumulation, weighted mapping, and pattern discrimination, thereby enabling efficient transformation of raw tactile stimuli into high-level task representations. Because the input signals have already been compressed and encoded at the front end, the back-end array no longer needs to process large amounts of raw sampled data, but can instead perform local computation directly at the feature level. This is a key reason why the system can simultaneously achieve high efficiency and low latency.

FIGURE 1. System Architecture and operating principle

Monolithic integration is one of the defining features that distinguishes the proposed system from conventional discrete implementations. In traditional architectures, the sensing unit, signal-conditioning module, and computing unit typically belong to different hardware levels, and the total system latency can be expressed as:

$$T_{\mathrm{sys}} = T_{\mathrm{sense}} + T_{\mathrm{read}} + T_{\mathrm{transfer}} + T_{\mathrm{compute}} \tag{4}$$

where T_{sense} is the sensing establishment time, T_{read} is the signal readout time, T_{transfer} is the data transmission time between the front end and the back end, and T_{compute} is the back-end computing time. For high-density tactile arrays, T_{transfer} often increases rapidly with channel count, accompanied by higher power consumption and interface complexity. In the present architecture, however, the neuromorphic electronic skin and the in-memory computing module are not merely connected through long external interconnects; instead, they are tightly integrated within a unified process and structural design framework, allowing the output of the sensing front end to be delivered to the computing units through a shorter path, with lower latency and reduced parasitic loss. As a result, while maintaining high sensitivity to dynamic contact events, the system can also reduce T_{read} and T_{transfer} at the overall architecture level, thereby achieving a level of real-time performance better suited to fine-manipulation tasks. For embodied intelligent agents, contact events in fine manipulation are often transient, localized, and strongly time-dependent. Therefore, the system must not only sense such events, but also process them in a timely and efficient manner. Motivated by this requirement, the proposed monolithically integrated architecture establishes an efficient information pathway from mechanical perception to on-chip computation by tightly combining a neuromorphic tactile front end with an in-memory computing back end, thereby laying the system foundation for subsequent tasks such as contact recognition, slip warning, texture discrimination, and manipulation-state perception.

Overall, the system architecture presented in this section is not merely a compact reconstruction of a conventional tactile hardware chain, but a reorganization of how tactile information is captured, compressed, and utilized from the earliest stage of the signal pathway. It is precisely this continuous collaborative mechanism from source-end sensing to on-chip processing that gives the proposed platform its structural advantages and functional foundation for fine-manipulation scenarios.

III. DESIGN AND MONOLITHIC INTEGRATION OF NEUROMORPHIC ELECTRONIC SKIN AND IN-MEMORY COMPUTING CHIP

To enable efficient tactile information acquisition and on-chip processing for fine manipulation in embodied intelligent agents, this work adopts a system-level co-design strategy to jointly develop the neuromorphic electronic skin front end, the in-memory computing back end, and the monolithic integration pathway between them [14]. Unlike conventional approaches in which sensors and processors are designed separately and later coupled through peripheral circuits, the present study emphasizes front-end/back-end co-optimization at the levels of device structure, signal representation, and process compatibility, so that tactile responses triggered by mechanical stimuli can be delivered to the downstream computing module with reduced loss and latency, thereby improving the overall information-processing efficiency and structural compactness of the system. Conceptually, the proposed platform is not a simple combination of an "electronic skin" and a "computing chip"; rather, it is constructed around how tactile information is generated, represented, and utilized in fine-manipulation tasks. Accordingly, this section discusses the design of the neuromorphic electronic skin unit, the architecture of the in-memory computing chip, and the monolithic integration strategy that unifies them, while also clarifying the intrinsic mapping relationship among the different functional modules.

The neuromorphic electronic skin serves as the tactile sensing and neuromorphic representation front end of the system, and its design is centered on establishing a stable mapping from mechanical input to dynamic electrical response [15]. To this end, the electronic skin unit is constructed with a multilayer device architecture composed of a sensing layer, a functional layer, and electrode structures. The sensing layer is responsible for perceiving external mechanical stimuli such as pressure, contact, and microvibration, while the functional layer modulates carrier transport, interfacial polarization, or localized charge distribution, thereby converting mechanical perturbations into dynamic response signals that can be directly read by the downstream circuit. From a structural perspective, the electronic skin unit must simultaneously provide mechanical compliance and response reproducibility, while also generating temporal output features suitable for neuromorphic processing, such as stimulus-dependent spike-frequency variation, temporal accumulation effects, short-term retention, or synaptic-like dynamic modulation. Formally, if the external mechanical stimulus is denoted by $P(t)$, the front-end response can be expressed as:

$$R(t) = f\left(P(t), \dot{P}(t), \tau\right) \tag{5}$$

where $\dot{P}(t)$ denotes the stimulus variation rate, τ represents the characteristic time constant associated with charge transport, interfacial polarization, or short-term memory behavior in the device, and $f(\cdot)$ is the mechanical-electrical-neuromorphic mapping determined by the device structure. This expression indicates that the front-end output depends not only on stimulus intensity itself, but also on the dynamic evolution of the stimulus and the intrinsic temporal behavior of the device. As a result, the tactile front end no longer outputs only continuous analog voltage or current signals; instead, it encodes the intensity, duration, and temporal evolution of tactile stimuli in an event-driven manner, thus providing a more task-relevant input representation for the subsequent in-memory computing module. Furthermore, to better match the back-end array, the neuromorphic output of the front end can be implemented in the form of frequency coding, amplitude modulation, or inter-spike-interval encoding, such that dynamic tactile events undergo a preliminary stage of information compression and feature highlighting before entering the computing core.

The in-memory computing chip is responsible for in situ processing of the neuromorphic tactile signals generated by the front end, with the aim of completing information accumulation, feature mapping, and pattern discrimination as close as possible to the sensing source. To overcome the data-transfer bottleneck inherent to conventional von Neumann architectures, in which memory and computation are physically separated, the present work employs an array of memory-computing units as the back-end processing core, allowing input tactile signals to directly participate in internal state modulation and weighted computation. The chip consists of a memory-computing core array, an input mapping module, and an output readout module. The core array performs operations such as parallel weighting, response accumulation, and pattern projection, while the input mapping module translates the neuromorphic outputs of the electronic skin into electrical stimuli suitable for array operation. The output module then extracts discrimination results relevant to specific tactile tasks. For a typical array structure, the output can be expressed as:

$$I_j = \sum_{i=1}^{N} G_{ij} V_i \tag{6}$$

where V_i denotes the i-th input signal from the front end, G_{ij} represents the weight or effective conductance of the memory-computing unit located at the i-th row and j-th column, and I_j is the j-th output response. This relationship indicates that neuromorphic tactile signals can be directly subjected to weighted summation and feature projection inside the array, thereby avoiding the large number of sampling, buffering, and data-movement steps required in conventional digital processing chains. Importantly, the in-memory computing chip is not treated as a generic standalone processor that passively receives arbitrary inputs; rather, it is specifically optimized to match the output characteristics of the electronic skin front end, including input dynamic range, temporal scale, and interface compatibility. For example, if the front end employs spike-frequency coding, the back-end array can adapt directly to the input pattern through time-window accumulation or spike-count mapping; if the front end uses amplitude-modulated signals, the array input can realize weighted computation through equivalent voltage mapping. Such co-design not only improves the efficiency of dynamic tactile information processing, but also makes the chip back end more suitable as a task-specific tactile computing core rather than a general-purpose processing unit.

The monolithic integration of the neuromorphic electronic skin with the in-memory computing chip constitutes the central element of the proposed system architecture. To avoid the performance penalties associated with conventional discrete implementations, such as long-distance interconnection, complicated signal conditioning, and inter-module mismatch, the present platform integrates the tactile sensing unit and the computing array within a unified process and structural framework. Specifically, the neuromorphic electronic skin is arranged in an on-chip region compatible with the in-memory array, and its output nodes are directly coupled to the back-end input ports through short-range interconnects, thereby significantly shortening the signal transmission path and reducing parasitic capacitance and noise interference. From the viewpoint of system overhead, the burden associated with interconnection and data movement can be approximately expressed as:

$$D_{\text{sys}} \propto N \cdot B \cdot L \tag{7}$$

where N is the number of effective channels, B is the data width transmitted per channel, and L is the interconnect length or an equivalent transmission-load factor. In conventional discrete systems, both L and B are typically large because raw tactile signals must be externally acquired, conditioned, and transmitted before entering the downstream processor. In contrast, in the monolithically integrated architecture proposed here, the front end compresses the input representation through neuromorphic encoding and the back end shortens the transmission path through direct on-chip coupling, thereby reducing both B and L and significantly lowering system-level data-movement overhead. Meanwhile, the integration strategy also explicitly considers structural matching between the mechanically responsive layer and the chip substrate, electrical compatibility between the flexible functional front end and the back-end computing units, and the stability and scalability of the on-chip interface. In this context, “monolithic integration” refers not merely to compact spatial stacking, but to unified design across materials, structures, interconnects, and functional pathways. Through this monolithic integration strategy, the system realizes a continuous information flow from mechanical stimulus sensing and neuromorphic encoding to in-memory processing on a highly compact platform, greatly reducing reliance on external acquisition, conversion, and transmission modules. This design not only provides a viable route toward cooperative operation between high-density tactile arrays and on-chip computing units, but also establishes a hardware foundation for future tactile intelligence systems featuring low power consumption, high real-time capability, and practical deployment in embodied manipulation scenarios.

Overall, the design methodology presented in this section reflects a hardware construction strategy driven backward from task requirements. The front-end electronic skin is no longer optimized solely for high-sensitivity sensing, but rather for neuromorphic representation of dynamic tactile events; the back-end chip is no longer intended merely to provide generic computing power, but is instead tailored for efficient on-chip mapping of temporal tactile features; and monolithic integration further elevates the relationship between the two from functional coupling to deep collaboration at the levels of structure and information flow.

IV. ELECTRICAL, NEUROMORPHIC, AND COMPUTING CHARACTERISTICS OF THE INTEGRATED PLATFORM

To comprehensively evaluate the proposed monolithically integrated platform for tactile sensing and on-chip processing, we systematically characterize its performance from three complementary perspectives: electrical response, neuromorphic behavior, and in-memory computing capability. First, in terms of basic electrical characteristics, the integrated platform exhibits stable and repeatable responses to external mechanical stimuli. As the intensity of applied pressure, dynamic contact, or microperturbation varies, the neuromorphic electronic skin front end produces clearly modulated electrical outputs, including variations in response amplitude, reconstruction of conductive states, and temporal response differences under different stimulation conditions. These observations confirm that the tactile front end is capable of reliably converting mechanical inputs into electrical information. To quantitatively describe the tactile response capability, the sensing sensitivity can be defined as:

$$S_X = \frac{\Delta X / X_0}{\Delta P} \tag{8}$$

where X_0 denotes the initial output, ΔX is the signal variation induced by the external stimulus, and P represents the mechanical stimulus intensity. When the output is expressed in terms of current, voltage, or conductance, this equation describes the conventional electrical sensitivity; when the output is represented by spike frequency, it can also be extended to quantify frequency sensitivity. Furthermore, under repeated loading and releasing cycles, the device maintains good response consistency and reversibility, indicating sufficient stability for repetitive tactile sensing tasks. Owing to the close coupling between the front-end structure and the back-end computing chip, the output signals from the sensing unit can be delivered directly to the downstream module without requiring long-distance transmission or complicated signal conditioning, thereby reducing system-level distortion and latency introduced by external interfaces. For dynamic stimuli, the overall response delay of the system can be further expressed as:

$$t_{\text{total}} = t_{\text{sense}} + t_{\text{encode}} + t_{\text{transfer}} \tag{9}$$

where t_{sense} is the time required for mechanical stimulation to generate an electrical response, t_{encode} is the time associated with neuromorphic representation formation, and t_{transfer} denotes the signal-transmission time from the front end to the back end. A key advantage of the monolithic architecture is that it can significantly reduce t_{transfer}, thereby improving overall real-time performance.

In terms of neuromorphic response characteristics, the platform demonstrates a major advantage over conventional electronic skin systems by representing external tactile stimuli in an event-driven and temporally correlated manner. Specifically, when subjected to mechanical stimuli with different amplitudes, durations, and rates of variation, the neuromorphic electronic skin generates response outputs featuring frequency modulation, timing dependence, and short-term accumulation effects. To describe the relationship between tactile stimuli and spike output, the spike frequency can be expressed as a function of both stimulus intensity and variation rate:

$$f_{\mathrm{spike}} = f_0 + \alpha P + \beta \frac{dP}{dt} \tag{10}$$

where f_0 is the baseline spike frequency, and α and β represent the response coefficients to stimulus amplitude and dynamic variation rate, respectively. This expression indicates that the tactile front end can encode not only how strong the external contact is, but also how rapidly it changes, making it particularly suitable for capturing dynamic events such as contact onset, incipient slip, and vibration-mediated texture cues. Compared with conventional continuous analog output, this representation more faithfully reflects the dynamic evolution of contact events rather than providing only an instantaneous signal value. In particular, under continuous or pulsed stimulation, the system exhibits pronounced temporal modulation behaviors, including increases in response frequency under stronger stimulation, history-dependent effects induced by changes in stimulation interval, and synaptic-like potentiation or depression caused by repeated stimuli. To further quantify such short-term neuromorphic modulation, the paired-pulse facilitation index can be introduced as:

$$PPF = \frac{A_2 - A_1}{A_1} \times 100\% \tag{11}$$

where A_1 and A_2 denote the first and second response peaks induced by two adjacent stimuli, respectively. A higher PPF value indicates enhanced sensitivity to temporally neighboring tactile events, which is particularly meaningful for describing continuous contact, local vibration, and slip-precursor signals. These results suggest that the electronic skin front end not only possesses basic mechanosensory capability, but also offers the potential to compress and preprocess temporal information at the sensory source, thereby strengthening sensitivity to transient contact and dynamic tactile patterns.

With regard to computing performance, the back-end processing module in the monolithically integrated platform is capable of effectively mapping, accumulating, and processing the signals generated by the neuromorphic electronic skin. Through the cooperative operation of memory-computing units within the array, the system can perform tactile-task-relevant feature extraction or pattern discrimination near the sensing source, without transferring all raw high-dimensional tactile data to an external processor. For a typical in-memory computing array, the output can be expressed as:

$$I_j = \sum_{i=1}^{N} G_{ij} V_i \tag{12}$$

where V_i denotes the i-th input signal from the front end, G_{ij} represents the weight or effective conductance of the corresponding memory-computing unit, and I_j is the j-th output response. This relationship indicates that neuromorphic tactile signals can be directly subjected to weighted accumulation and feature projection inside the array, enabling efficient mapping of task-relevant patterns. Because the input signals have already been transformed into a neuromorphic representation by the front end, the array-level processing can focus more directly on temporally meaningful features and task-effective information, thereby reducing the data redundancy and computational burden associated with conventional continuous-sampling schemes. To further characterize this advantage, the system-level data-compression efficiency can be defined as:

$$\eta = \frac{N_{\mathrm{raw}}}{N_{\mathrm{encoded}}} \tag{13}$$

where N_{raw} is the amount of raw data that would need to be transmitted under a conventional continuous-sampling scheme, and N_{encoded} is the amount of data delivered to the back-end array after neuromorphic encoding. When $\eta > 1$, the system achieves effective data compression and information condensation. From a broader system-integration perspective, the tight monolithic coupling of sensing, encoding, and computation not only improves signal-transmission efficiency and processing real-time performance, but also reduces power consumption, interface complexity, and area overhead to a certain extent. Overall, the proposed integrated platform exhibits strong performance in electrical stability, temporally correlated neuromorphic representation, and efficient on-chip tactile information processing, thereby establishing a solid foundation for subsequent system-level validation in fine-manipulation-oriented tasks.

V. TACTILE INFORMATION PROCESSING FOR FINE MANIPULATION

To validate the application potential of the proposed monolithically integrated platform in fine manipulation for embodied intelligent agents, we further performed a system-level analysis of tactile information processing in tasks closely related to manipulation. Rather than evaluating the system solely in terms of sensing sensitivity or isolated classification accuracy, this section emphasizes whether the platform can support efficient perception, rapid encoding, and low-latency processing under task-oriented requirements.

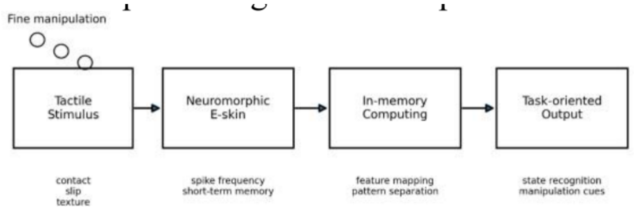

FIGURE 2. Schematic illustration of tactile information processing for fine manipulation based on the proposed monolithically integrated platform

Based on representative tactile demands in fine manipulation, three tasks were selected for validation: contact-state recognition, slip warning, and texture classification, corresponding respectively to static/dynamic contact judgment, manipulation-stability monitoring, and surface-feature discrimination. As illustrated in Figure 2, the overall processing pathway consists of four stages: tactile stimulus, neuromorphic electronic skin, in-memory computing chip, and task-oriented output. External mechanical stimuli are first converted by the electronic skin front end into neuromorphic responses with temporal characteristics, which are then fed into the on-chip computing array for feature mapping and pattern discrimination, ultimately yielding task-level outputs relevant to manipulation decisions. This workflow indicates that the present study does not simply connect sensing and computing modules in series, but instead establishes a task-oriented closed-loop information pathway on a unified hardware platform, thereby providing a structural basis for real-time tactile processing in fine manipulation.

At the task-performance level, the monolithic integrated platform exhibits substantially improved tactile information processing capability compared with a conventional discrete architecture. Figure 3 summarizes the classification accuracy for the three representative tasks. For contact-state recognition, the monolithic platform achieves an accuracy of 96.2%, significantly higher than the 88.5% obtained by the discrete architecture. For slip warning, the proposed platform reaches 93.4%, whereas the conventional system achieves only 84.7%. Similarly, in texture classification, the monolithic platform delivers 91.1%, outperforming the comparison architecture, which yields 82.6%. These improvements do not arise merely from the optimization of any single module, but rather from system-level synergy. On the one hand, the neuromorphic electronic skin preserves dynamic temporal information from contact events directly at the sensory source, allowing incipient slip, microvibration patterns, and stimulus-duration features to be effectively represented at the input stage. On the other hand, the in-memory computing chip processes these temporally correlated signals directly, reducing information loss associated with intermediate conversion, transmission, and reconstruction. As a result, the monolithically integrated platform exhibits superior pattern separability and feature fidelity across different task types.

To further reveal the system-efficiency advantages of the monolithic architecture, Figure 4 compares the processing latency and data-movement overhead between the two system types. The results show that the discrete architecture requires 38 ms, 46 ms, and 52 ms for the three tasks, respectively, whereas the monolithically integrated platform reduces these values to 14 ms, 17 ms, and 19 ms, corresponding to latency reductions exceeding 60% in all cases. Meanwhile, when the data movement of the discrete architecture is normalized to 1, the monolithic platform exhibits normalized values of only 0.31, 0.28, and 0.35 for the three tasks. These results indicate that by moving neuromorphic encoding and in-memory processing on-chip and tightly coupling them to the sensing front end, the system significantly reduces the need for external transmission of raw high-dimensional tactile data, thereby improving overall processing efficiency. Such an advantage is especially critical for fine manipulation, where contact events are often highly transient and localized. If the system cannot complete sensing and decision-making in a timely manner, even a highly sensitive sensor would be insufficient to support real-time manipulation. Therefore, the proposed platform not only improves task-level recognition performance, but also demonstrates hardware characteristics that are more suitable for embodied intelligence, particularly in terms of real-time response and system compactness.

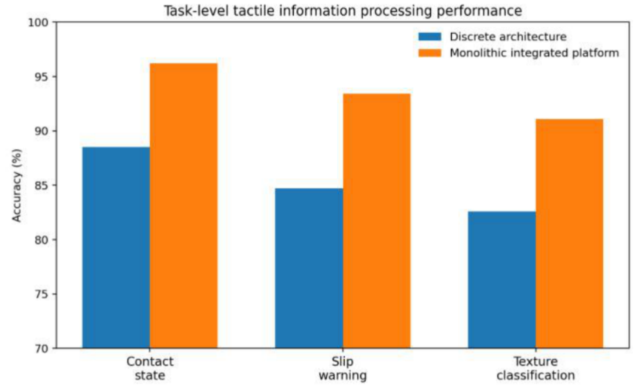

FIGURE 3. Accuracy comparison between the proposed monolithic integrated platform and a conventional discrete architecture for three representative fine-manipulation-related tactile tasks

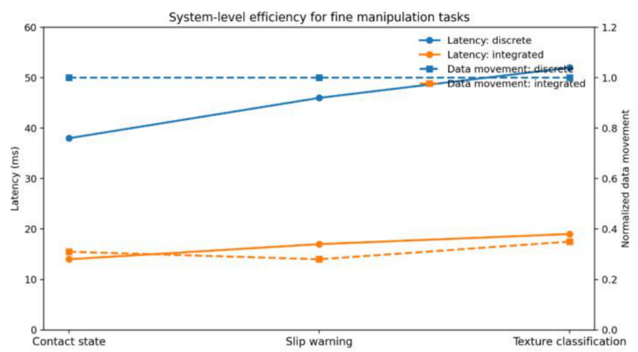

FIGURE 4. Comparison of task-processing latency and normalized data movement between the monolithically integrated platform and a conventional discrete architecture

For a more intuitive summary of the task-level results, Table 1 compares the input cues, output evaluation metrics, and performance differences between the two architectures across the three tactile tasks. Contact-state recognition mainly relies on static and dynamic pressure-distribution information, slip warning depends more strongly on transient force fluctuations and indicators of contact instability, and texture classification is closely associated with temporally structured microvibration patterns. Although the three tasks differ in their dependence on tactile cues, the proposed platform consistently delivers both higher accuracy and lower latency, indicating strong adaptability to different forms of tactile spatiotemporal information. This observation further suggests that the monolithically integrated architecture is not effective only for a single specific tactile mode, but instead possesses broader potential for task transfer across fine-manipulation-related scenarios.

TABLE 1. PERFORMANCE COMPARISON FOR REPRESENTATIVE TACTILE INFORMATION PROCESSING TASKS RELATED TO FINE MANIPULATION

Task	Input cue	Output metric	Discrete architecture	Monolithic integrated platform	Improvement
Contact-state recognition	Static/dynamic contact pressure	Recognition accuracy	88.5% / 38 ms	96.2% / 14 ms	+7.7% acc.; -63.2% latency
Slip warning	Transient force fluctuation	Warning accuracy	84.7% / 46 ms	93.4% / 17 ms	+8.7% acc.; -63.0% latency
Texture classification	Microvibration-induced temporal pattern	Classification accuracy	82.6% / 52 ms	91.1% / 19 ms	+8.5% acc.; -63.5% latency

Overall, the results in this section demonstrate that the proposed monolithically integrated platform combining neuromorphic electronic skin and an in-memory computing chip enables a continuous closed loop from tactile stimulus sensing and neuromorphic encoding to on-chip processing in multiple tasks closely related to fine manipulation. Its advantages are reflected not only in improved task-level recognition accuracy, but also in reduced system-level data movement and lower processing latency. Compared with conventional discrete architectures, the present platform is better suited for constructing low-latency, highly integrated, and task-oriented tactile-intelligence hardware systems, thereby laying a solid foundation for future closed-loop validation in robotic grasping, in-hand manipulation, and complex physical interaction scenarios.

VI. DISCUSSION

The central significance of the proposed monolithically integrated platform, which combines neuromorphic electronic skin with an in-memory computing chip, lies not merely in the physical co-integration of tactile sensing and on-chip processing, but in establishing a new hardware organization paradigm for tactile information processing in fine manipulation by embodied intelligent agents. Unlike conventional tactile systems that rely on continuous sampling, external data transmission, and back-end centralized computation, the present platform moves neuromorphic encoding toward the sensory source and tightly couples it with an in-memory computing module, allowing tactile information to undergo task-relevant compression and efficient processing at an early stage of the signal pathway. This is particularly important for fine manipulation, because tactile cues relevant to manipulation are often not expressed simply as static pressure distributions, but rather as dynamic events such as contact onset, incipient slip, vibration-mediated texture signatures, and localized force variation. The architecture presented in this work suggests that only when sensing, encoding, and computation are organized into a continuous pathway within a unified platform can tactile hardware truly evolve from being merely measurable to being directly useful for manipulation.

From an architectural perspective, one of the key implications of this work is that it elevates the relationship between neuromorphic electronic skin and in-memory computing chips from simple functional concatenation to task-oriented information collaboration. In many existing studies, electronic skin primarily focuses on mechanical-stimulus detection, multimodal sensing, or mechanical compliance, while neuromorphic devices are often used to demonstrate synaptic-like behavior or temporal response dynamics, and in-memory computing chips mainly emphasize array-level parallelism and reduced data movement. By contrast, the present work highlights the system-level unification of these three components in the context of embodied manipulation. The front end is not designed merely to output raw sensory signals, and the back end is not treated as a passive processor for arbitrary inputs; instead, both are jointly engineered around the dynamic tactile features required for fine manipulation. This design philosophy implies that future tactile hardware should not be advanced simply by increasing sensor sensitivity or enlarging computing-array scale, but by more carefully considering how task requirements can shape both sensory representation and chip architecture. In this sense, the present study demonstrates not only an integration strategy, but also a co-design framework for tactile systems in embodied intelligence.

Nevertheless, several aspects of the current work warrant further development. First, from the perspective of system scale, the advantages of the present platform are mainly demonstrated at the unit or limited-array level, and there remains considerable room for extension toward larger-area, higher-density, and more highly distributed tactile systems. For practical robotic fingertips, dexterous hands, or full-hand electronic skin deployment, scaling up the array will inevitably intensify challenges associated with interconnection complexity, fabrication uniformity, and signal drift. Second, from the task perspective, the current validation primarily demonstrates tactile information processing capabilities that are directly relevant to fine manipulation, but it has not yet fully reached the level of real closed-loop manipulation control. In particular, tighter real-time coupling with grasp adjustment, adaptive force redistribution, and in-hand reorientation strategies remains to be established. Third, from the standpoint of device and system reliability, the long-term stability of the monolithically integrated platform under repeated deformation, complex contact conditions, and multi-source noise disturbances still requires more systematic evaluation. When the mechanically responsive front-end layer and the back-end chip array operate in long-term coupled conditions, issues such as interfacial stability, packaging reliability, and parameter drift may all influence practical deployment.

These considerations point to several important future directions. One is the extension toward more complex multimodal tactile scenarios, where shear force, temperature, humidity, or even proprioception-related information could be incorporated on top of pressure and dynamic-contact sensing, thereby enriching the physical interaction space represented by the system. Another is the further development of the monolithic platform toward higher density and stronger scalability, enabling distributed deployment that more closely matches the structural requirements of realistic robotic hands. A third direction is deeper cross-modal coupling with vision, proprioception, and motion-control modules, such that on-chip tactile processing results can be used directly in closed-loop embodied decision-making. A fourth is the evolution of the present task-driven processing architecture toward tactile intelligence systems capable of online learning, adaptive updating, and improved environmental generalization. Overall, the platform proposed in this work provides a viable route toward tactile hardware with high real-time capability, strong integration density, and reduced data-movement overhead, while also offering insight into future embodied systems in which sensing, computation, and decision-making are more tightly fused.

VII. CONCLUSION

In this work, we proposed and developed a monolithically integrated platform that combines neuromorphic electronic skin with an in-memory computing chip to address the demand for efficient tactile information acquisition and processing in fine manipulation by embodied intelligent agents. Within a unified hardware architecture, the platform enables the seamless linkage of mechanical stimulus perception, neuromorphic representation, and on-chip information processing, thereby establishing a continuous tactile-information pathway oriented toward task execution. Compared with conventional discrete tactile systems, the significance of the present work lies not only in improving individual device or module performance, but also in achieving tight front-end/back-end collaboration through monolithic integration, allowing tactile information to be transformed from physical input to task-level output in a more compact and efficient manner.

On this basis, we systematically investigated the electrical response characteristics, temporally correlated neuromorphic behaviors, and tactile-task-processing capability of the integrated platform, and validated its application potential in representative fine-manipulation-related tasks, including contact-state recognition, slip warning, and texture classification. The results demonstrate that the proposed system can maintain reliable tactile-response performance while enabling more task-relevant signal representation and more efficient on-chip computation, thereby exhibiting clear advantages in recognition accuracy, processing real-time capability, and reduced data-movement overhead. These findings indicate that monolithic integration of neuromorphic electronic skin with an in-memory computing chip provides a feasible route toward improving the overall effectiveness of tactile-intelligence systems.

Overall, this work offers a new design strategy for high-integration, low-latency, and task-driven tactile hardware aimed at next-generation embodied intelligent systems. More importantly, the present study suggests that future tactile systems should not evolve through the isolated optimization of sensors or computing units alone, but through deeper system-level coupling among sensing, encoding, computation, and manipulation requirements. The monolithic integration strategy and task-oriented architecture presented here may provide useful guidance for the development of high-performance robotic electronic skin, brain-inspired tactile-processing hardware, and embodied intelligence platforms designed for complex physical interaction scenarios.

DECLARATION OF CONFLICTING INTERESTS

The author(s) declared no potential conflicts of interest with respect to the research, author-ship, and/or publication of this article.

DATA SHARING AGREEMENT

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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