IUST
Iran University of Science and Technology

Iranian Journal of Electrical and Electronic Engineering

Journal Homepage: ijeee.iust.ac.ir

Efficient Tactile Perception in Robotics: Reducing Data Redundancy through Compression and Normalization in Spiking Convolutional Graph Networks

E.Rezaei Ahvanooii* S. Abolmaali*(C.A).

Abstract:
Touch, one of the fundamental human senses, is essential for understanding the environment by enabling object identification and stable movements. This ability has inspired significant advancements in artificial neural networks for object recognition, texture identification, and slip detection applications. However, despite their remarkable capacity to simulate tactile perception, artificial neural networks consume considerable energy, limiting their broader adoption. Recent developments in electronic skin technology have brought robots closer to achieving human-like tactile perception by enabling asynchronous responses to temperature and pressure changes, thereby enhancing robotic precision in tasks like object manipulation and grasping.
This research presents a Spiking Graph Convolutional Network (SGCN) designed for processing tactile data in object recognition tasks. The model addresses the redundancy in spiking-format input data by employing two key techniques: (1) data compression to reduce the input size and (2) batch normalization to standardize the data. Experimental results demonstrated a 93.75% accuracy on the EvTouch-Objects dataset, reflecting a 4.31% improvement, and a 78.33% accuracy on the EvTouch-Containers dataset, representing an 18% improvement. These results underscore the SGCN's effectiveness in reducing data redundancy, decreasing required time steps, and optimizing tactile data processing to enhance robotic performance in object recognition.

Keywords:
Tactile Perception, Graph Convolutional Network, Spiking Neural Network, Redundancy Reduction, Batch Normalization.

Introduction

Tactile sensors play a crucial role in object recognition and performing many everyday tasks, such as driving and food preparation. The tactile pixels in these sensors provide robots with remarkable capabilities for better object recognition. These tactile sensors can offer vital information, such as texture, roughness, and friction, which are used in applications like object identification, slippage detection, and texture analysis [1]. This study addresses the challenges of object recognition using event-driven tactile sensors. Prior research has predominantly utilized conventional tactile sensors and machine learning techniques, including convolutional neural networks. [2]. However, event-driven sensors differ significantly in performance and the type of data they provide, these tactile asynchronously report environmental changes, offering data in the form of event-driven "spikes," where each taxel operates independently [3]. Compared to frame-based traditional sensors, event-driven sensors offer advantages such as enhanced energy conservation, improved scalability, and reduced latency. However, learning from these event-driven systems is still in its infancy and demands further investigation and development. [4].
Despite these advancements, artificial neural networks still consume significantly more energy than the human brain, especially in robotics applications that require rapid and accurate environmental perception. The sense of touch is essential for various robotic tasks, including object manipulation and grasping. Recent advancements in electronic skin technology are bringing robots closer to achieving tactile perception comparable to that of humans. Electronic skins can respond to various stimuli, including temperature and pressure, simultaneously, thereby enhancing the precision and efficiency of robotic systems [5].
The model used in this study utilizes Spiking Graph Convolutional Networks (SGCN), which offer unique

Iranian Journal of Electrical & Electronic Engineering, YYYY.
Paper first received DD MONTH YYYY and accepted DD MONTH YYYY.
*The authors are with the Electrical and Computer Engineering Department, Semnan University, Semnan, Iran
E-mail: e_rezaee@semnan.ac.ir
Author: E.Rezaei Ahvanooii
E-mail: shabolmaali@semnan.ac.ir. Corresponding Author: S. Abolmaali.
https://doi.org/....

capabilities for sensing and perceiving objects through touch. The input data for this model is received in a spiking format, meaning that the information is processed dynamically and at high speed. An analysis of the input data revealed that a significant portion of this data contained redundancy. Addressing this issue requires optimization techniques to improve system efficiency and ensure optimal resource utilization [4].

TactileSGNet [6] is a network based on event-driven tactile data that reacts asynchronously to environmental changes such as pressure or temperature. This network processes data in real-time and is more energy-efficient than traditional methods. Due to the irregular arrangement of sensors in robotic devices, this network is more suitable for tactile learning than conventional convolutional methods. It addresses this challenge by organizing tactile data into a graph structure, allowing the network to effectively leverage local connections between tactile sensors. The main ideas of this research are divided into two key phases. First, the input data is compressed using specialized compression techniques to reduce the data size and eliminate redundancy. This step helps decrease the data volume and improve processing speed. Next, the data is normalized using batch normalization in Spiking Graph Convolutional Networks to ensure balanced data distribution. This normalization process enhances learning quality, reduces training time, and increases prediction accuracy [2].

This study utilized two different datasets, and the results show high accuracy in classifying various household objects using the proposed methods. These findings suggest that the use of compression and normalization techniques can significantly improve classification accuracy and reduce the time required for data processing. The application of these methods, particularly in the identification and classification of household objects, demonstrates significant advancements in the fields of image processing and machine learning [5]. This research aims to reduce the redundancy in input data and improve the efficiency of information processing systems.

1 Background and Related Work

This study examines Spiking Graph Convolutional Networks (SGCNs) for object recognition, employing event-driven tactile data. In this section, we provide a concise overview of the background and pertinent literature in this area. Given the extensive nature of research in this field, we will only present a selection of representative works due to space constraints.

To date, various tactile sensors have been designed and developed, including widely used sensors such as PPS, BioTac, and Tekscan [7]. In this study, we utilized the NeuTouch sensor, an event-based tactile sensor recently introduced in research [8]. Research into learning from event-based tactile data has been limited so far [9]. Recent studies have introduced a multi-faceted spiking neural network based on the SLAYER model [10]. However, our work differs from these studies; instead of using fully connected layers, we employ Spiking Graph Neural Networks with LIF neurons [11]. Tactiles, which function as tactile sensor units, are similar to image pixels but process information such as contact and pressure instead of images [12]. The greater the number of tactile on the sensor surface, the higher the accuracy of the robot in recognizing tactile details [13]. These tactile allow robots to sense characteristics like roughness, softness, and temperature of objects similar to human touch. This capability enables robots to perform tasks including object recognition, preventing slippage, and analyzing surface textures more effectively. [14].

1.1 Graph Convolutional Networks

In these networks, convolutions operate not on conventional data but on the nodes of a graph [15]. These networks can be classified into two main types: spatial graph convolutional networks and spectral graph convolutional networks [16]. Spatial methods are directly applied to graphs, while spectral methods utilize spectral decomposition of the Laplacian matrix to better model the relationships among nodes [17]. The Laplacian matrix is employed in spectral methods for graph analysis and to enhance the understanding of node relationships [18]. These networks have applications in various fields due to their ability to process structured data such as graphs, including applications in object detection and classification in images and videos [19].

1.2 Spiking Graph Convolutional Networks

These networks leverage event-based spike processing and feature extraction from sparse input data to identify important patterns and process event-based tactile sensor data [20]. A key feature of this architecture is its ability to perform transfer learning and process spatiotemporal data, akin to brain computations [21]. However, using these networks comes with significant challenges. The diversity of data, including dimensions, sizes, textures, and colors of objects, can impact accuracy and performance, leading to generalization issues [22]. Environmental noise, such as low light and vibrations, can reduce detection accuracy [23]. Additionally, the non-separable nature of the spike function complicates training and necessitates solutions like converting deep neural networks to spiking networks and approximating spike function derivatives [24]. Despite these challenges, the biological similarity of spiking graph networks makes them more suitable and biologically plausible for real-world applications [25]. Their ability to learn from limited training data and effectively process tactile information makes them a promising approach for event-based tactile object recognition [26]. These networks are increasingly recognized for their unique ability to model and process complex information, especially in object recognition and touch-based learning [27]. Numerous studies continue to focus on enhancing the performance of spiking neural networks, including the creation of spatial and temporal spiking networks. An innovative model is a hybrid model that integrates both spatial and temporal spiking neurons to accurately capture intricate spatiotemporal features. [28]. This model has achieved 92% accuracy in object recognition and 89% accuracy in container content identification, demonstrating its high efficiency in these areas [30]. Furthermore, the use of k-nearest neighbor methods to enhance accuracy has also been explored [31]. However, these models face challenges such as high computational complexity and the need for fine-tuning, which must be considered in their design and implementation [30]. Another innovative technique that enhances the stability of training spiking neural networks is threshold-dependent batch normalization [32]. This method normalizes neuron outputs and adjusts their firing thresholds to prevent excessive or insufficient firing, helping spiking neural networks perform complex tasks like image classification with greater accuracy [33]. This technique is particularly effective in deep networks that may encounter issues such as vanishing or exploding gradients [34]. Hybrid models in spiking neural networks, combining graph networks and biologically inspired neural models, enable more effective processing of spatiotemporal information [35]. These models offer high accuracy and flexibility but also face challenges such as computational complexity and the need for high-quality data [36]. Ultimately, this review emphasizes that finding the right balance between accuracy and efficiency in selecting and designing spiking models is crucial. The choice of the appropriate approach should be based on the specific needs of each project, and new techniques like threshold-dependent batch normalization can play a significant role in enhancing the performance of spiking neural networks [37].

2.3 One-dimensional Max Pooling Compression

One-dimensional Max Pooling is a data compression technique used to reduce dimensionality and computational load. This technique aims to reduce redundancy in input data and extract features. In One-dimensional Max Pooling, a sliding window moves over the data, selecting the maximum value from each segment. This process reduces the number of time steps or input data while preserving important features.

2.4 tdBN(tdBatchNorm)[38]

In spiking neural networks, inputs are presented as discrete spikes, and neurons activate only when their membrane potential exceeds a specific threshold. While this spike-based mechanism has its advantages, it also presents significant challenges, particularly in adjusting neuron firing rates and addressing issues like vanishing or exploding gradients during training. To mitigate these challenges, threshold-dependent batch normalization is employed. This method is similar to conventional batch normalization in artificial neural networks but with specific adaptations for the unique features of Spiking Neural Networks (SNNs). A key modification is channel-wise normalization. In this process, the mean and variance of inputs are computed for each channel of pre-synaptic activations. The pre-activations are then normalized based on the threshold voltage to maintain stability and control over input signal variations.

Channel Normalization Calculation: The channel normalization calculation is performed as follows for each channel *m*:

$$z^m = \frac{\gamma W_{tr}(z_m - E|z_m|}{\sqrt{Var[z_m] + \sigma}}$$

In this formula:

- W_{tr} is the neuron firing threshold.
- γ is a hyperparameter depending on the network structure.
- E[z_m] is the mean of the channel mmm inputs.
- Var[z_m] is the variance of the channel mmm inputs.
- σ is a small value used to prevent division by zero.

This formula adjusts inputs based on neuron firing thresholds to prevent vanishing or exploding gradients. Consequently, this technique aids in optimizing the network and enables more effective execution of models on neuromorphic hardware. After normalization, the final output is optimized using trainable parameters. This process significantly improves network firing rate adjustment and training stability, leading to more effective and stable learning.

A new method combining threshold-dependent normalization techniques and the aforementioned compression techniques has been introduced. This approach aims to reduce redundancy in input data and enhance overall efficiency.

3. Methodology

This section explores a method that utilizes Spiking Graph Convolutional Networks (SGCNs), originally introduced in [38], These establish the basis for our research. Unlike pixel-based networks in vision sensors, tactile taxels (sensory units) are analogous to

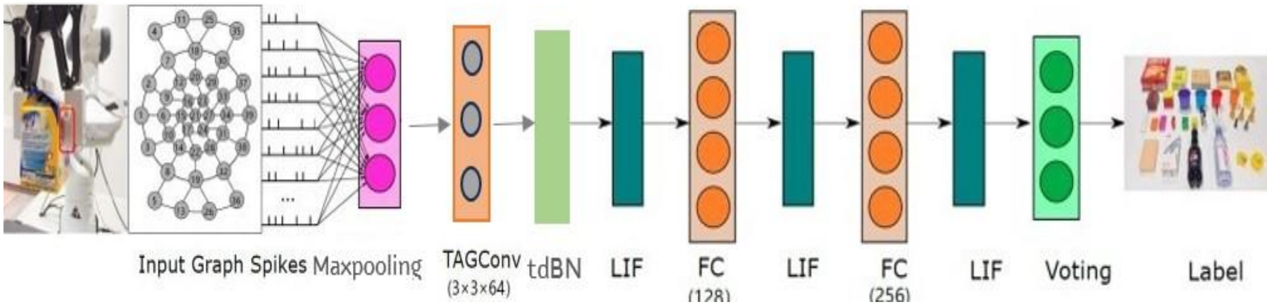


Figure 1: Our network is a spiking neural network based on TactileSGNet [6]. A spiking neural network (SNN) processes input spikes from tactile sensors (taxels), specifying their connectivity by an input graph. The network consists of a graph convolutional layer (TAGConv) with max pooling and a normalization layer, two fully connected (FC) layers, and a voting layer, in addition to the LIF layers.

human sensory receptors; they are distributed unevenly, with each one carrying different neural importance [40]. Advances in artificial electronic skins have enabled the development of flexible tactile sensors that can simulate or even surpass human tactile perception [41]. These sensors can be mounted on existing robotic limbs or feature irregularly arranged taxels [42]. One such example is the NeuTouch sensor, biologically inspired and equipped with 39 taxels in a radial pattern [43]. Although NeuTouch serves as a primary example, the developed methods for tactile sensors apply to sensors with varying taxel configurations and arrangements, enabling a wide range of applications in robotics and prosthetics [44].

zTo process touch-based graph data effectively, we introduce the Neural Spiking Tactile Graph Network (TactileSGNet) architecture. This network incorporates Leaky Integrate-and-Fire (LIF) neurons and features a Topology-Adaptive Graph Convolutional (TAGConv) layer, fully connected (FC) layers, and a final voting mechanism for classification. [45].

LIF Activations[46]: In conventional neural networks, activation functions such as ReLU are used [47]. However, these functions are not suitable for spiking neural networks. Instead, we utilize the Leaky Integrate-and-Fire (LIF) model which outlines these neural dynamics as follows:

$$\tau \frac{du(v)}{du} = -u(v) + \sum_{n} k_n y_n$$

Where u_v represents the membrane potential and τ is the time constant. To update this potential, we use the Euler method, and its simplified form is as follows:

$$u(v+1) = \alpha u(v) + \sum_{n} n k'_n y_n$$

The LIF activation function generates a spike when the membrane potential attains a specific threshold, after which it resets.

TAGConv-Layer [48]: This layer adjusts to the topology of the input graph, with its convolution operation represented as follows:

$$y_g = \sum_{d=1}^{D} H_{d,e} * p_d + q_e$$

Where $H_{d,e}$is the graph filter, and q is the normalized adjacency matrix.

Fully ConnectedLayer:
This layer functions similarly to standard layers in neural networks:

$$y = Az + c$$

Here, z denotes the inputs from the previous layer, A represents the weight matrix, c is the bias vector, and y signifies the output feature.

Voting Layer: This layer facilitates the final classification, where the neuron that generates the highest number of spikes within a designated time window determines the predicted class.

Training: To train the network, a loss function is established. This function computes the mean squared error between the vector z and the voting results from the output layer, averaged over a specified time step.

$$n = \left\| r_t - \frac{1}{T} \sum_{t=1}^{T} M_0 \right\|^2$$

In this context, M represents the decision matrix, and y_t represents the output feature from the final layer at time t. In conventional neural networks, the network is trained by reducing the error function using standard backpropagation methods. However, Spikes are non-differentiable; however, we can approximate the derivative of the spike function, demonstrating effectiveness across a range of tasks. In this research, we utilize the box function g(n) to estimate the derivative of the spike function, owing to its simplicity and demonstrated effectiveness

$$g(n) = sign\left(|n - n_T| < \frac{\theta}{2}\right)\frac{1}{\theta}$$

In this formula, θ is recognized as the width parameter.

4) Result of Expriments:

The primary aim of our experiments was to assess various architectures for event-based tactile object recognition. The main objective of this research is to improve the efficiency and processing speed of spiking tactile data. To showcase the advantages of the proposed method compared to existing approaches, we compared our model with two similar methods: Hybrid Graph Neural Networks and Event-Based Tactile Learning using position-spiking neurons. This research was carried out using the PyTorch library

a) Datasets

We compared the methods using two event-driven tactile datasets, which were gathered using a Franka Emika Panda robotic arm fitted with a NeuTouch sensor:

- **EvTouch -Containers**: This dataset includes tactile data from four types of containers with five different fill levels, resulting in 300 samples.
- **EvTouch - Objects**: This dataset consists of tactile data from 36 object classes with 720 samples.

The input size for EvTouch_Objects is specified as a tensor of shape [39, 2, 325]. In this structure, the first dimension, 39, the Number of taxels, indicates the number of samples processed concurrently during training or evaluation. The second dimension, 2, corresponds to the compression or release of the taxels. The third dimension, 325, indicates the time steps involved in the experiment, during which the taxels grasp and release the object.

For EvTouch-Container, the input size is a tensor of shape [39, 2, 250]. This structure is similar to the previous one, but the number of time steps involved in the experiment, during which the taxels grasp and release the object is 250. These datasets were used to evaluate object recognition performance with tactile sensors.

b) Methods:

To reduce redundancy in the input data, we employed compression and normalization techniques. Below, we outline the proposed methods for compression and normalization

Proposed Compression Method: One-dimensional Max Pooling: In our proposed method, we defined window sizes ranging from 2 to 5 and step sizes from 2 to 5. The window size and step size can be adjusted across different dimensions within the specified ranges. The table below shows the step sizes and window sizes used.

Table 1: Window Size and Step Size

Window-size	Stride
2	2
3	3
4	2
4	3
4	4
5	2
5	3
5	5

4 tdBN Normalization Method(tdBatchNorm)[38]

In our proposed method, normalization was carried out using the tdBN normalization technique. This method improved accuracy and reduced training and testing loss, leading to faster processing and more efficient computations. In the following sections, the accuracy of the proposed method will be compared with other similar techniques in the field, along with a detailed comparison of training and testing loss with the original paper.

4-2-1 Comparison of Methods:

We compared our proposed method with four different approaches that utilized the same datasets. Each of these methods and their resulting accuracy are described below:

- **Tactile SGNet [6]**: In this study, we compared the training loss and test loss results obtained with those reported in this paper, which forms the basis for our work, as our primary objective is to enhance the network proposed in this article.

- **Hybrid-SRM-FC [49]**: This is a hybrid model used for event-based tactile data learning, consisting of TSRM and LSRM models. This approach is more energy-efficient than traditional ANN networks.

- **Hybrid-LIF-GNN [49]**: Similar to the previous model, this hybrid approach processes event-based tactile data using a combination of Graph Convolutional Networks (GNN) and LIF models. LIF is employed to simulate the characteristics of spiking neurons and process event-driven spiking data. LIF neurons periodically activate or deactivate, mimicking the behavior of biological neurons. GNNs are used to learn from graph-structured data and complex relationships.

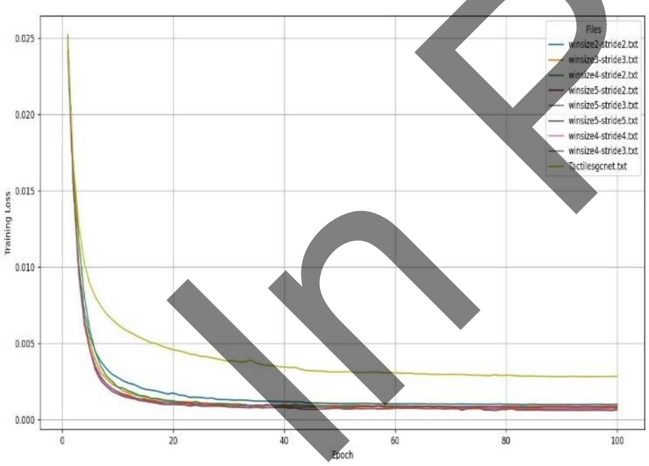
- **Work [50]**: This model employs spiking neurons that function similarly to biological neurons. These neurons respond asynchronously to stimuli by firing spikes, making the network ideal for processing event-driven, sparse tactile data. The network uses a graph-based structure to organize and process data from tactile sensors, effectively utilizing local communication between the sensors.

Table 2:The parameters used in this paper will be detailed in the following sections

Parameter	Value	Description
Number of Network Layers	3	Number of layers in the neural network
Gradient Width Approximation (β)	0.5	Parameter for adjusting the approximate gradient
Batch Size	1	Number of samples processed in each batch
Membrane Potential DecayConstant	0.2	Rate of membrane potential decay over time
Learning Rate	1×10^{-3}	Learning rate for updating weights in the network
MembranePotentialRecovery(u_R)	0	Membrane potential value after neuron activation
MembranePotentialActivationThreshold	0	The membrane potential threshold at which the neuron activates

5 Training Preparation and Evaluation

The parameters used in our model are listed in Table 1. We split the data into 80% for training and 20% for testing, with equal class distribution. The model is trained for 100 epochs, and as shown in Figures 2 and 3, our comparison metric is the precision on the test set. The study evaluated the training and testing process and found that our proposed method converged faster compared to the model used in TactileSGNet. Additionally, it achieved lower test loss and training loss than the reference method.



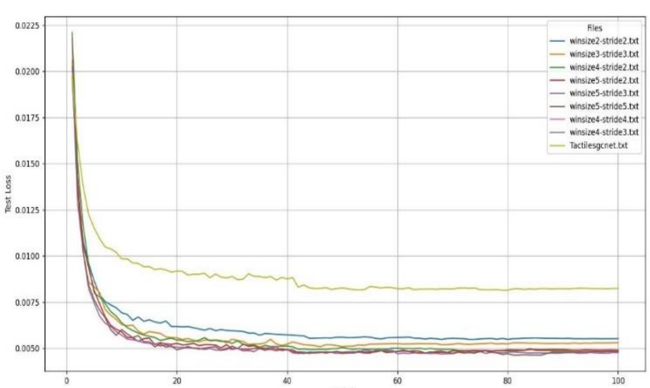
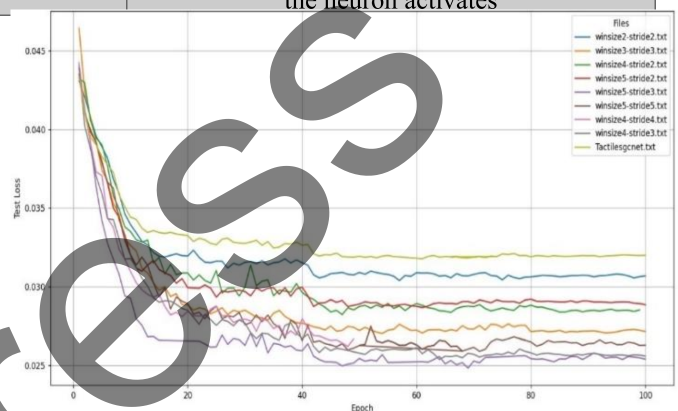


Fig.1: Training Losses and Test Losses as Training Progressed on EvTouch-Objects



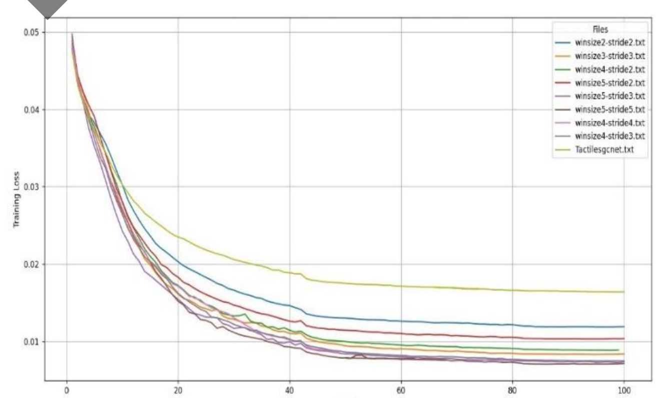


Fig. 2: Training Losses and Test Losses as Training Progressed on EvTouch-Containers.

The precision attained by our method on the EVTouch-OBJECT dataset is 93.75%, obtained using a window size of 5 and a step size of 2. This represents an improvement of approximately 0.32% compared to the HYBRID_LIF_GNN method, which had the highest accuracy among the other approaches while requiring fewer computations. This outcome highlights the remarkable efficiency of our approach, where despite the count of time steps being reduced, our model's accuracy surpasses that of SOTA. On the EVTouch-CONTAINER dataset, our method shows an improvement of about 18%

over the original paper, with an accuracy of 78.333%, also obtained using a window size of 5 and a step size of 2. Table 3 presents the best accuracies achieved by various methods and our proposed approach. This table shows that the precision of the Hybrid_SRM_FC and HYBRID_LIF_GNN methods is more than our method for the EVTouch-CONTAINER dataset. Notably, these networks comprise two sub-networks, each containing a spiking graph layer and three spiking FC layers, and employ the baseline timing window sizes. Consequently, the computational demands of these structures far surpass those of our suggested method.

Table 3: Comparison of Methods

Method	EVTouch-OBJECTS	EVTOUCH-CONTAINER
TACTILSGNET[6]	89.44	60.17
Hybrid_SRM_FC[48]	91.00	86
HYBRID_LIF_GNN	93.33	79.33
Work[50]	90.28	-
Our work	93.750	78.333

Since the studies we compared our results with only report the highest accuracy and do not provide variations in accuracy values, statistical comparisons, such as ANOVA, for metrics like recall are not feasible. To illustrate the variability of the proposed method's results for the two datasets **EvTouch-Objects** (using the method with window size = 5 and time-step = 3) and **EvTouch-Containers** (using the same method) experiments were repeated multiple times. The best accuracies obtained from these experiments, as reported in Table 4, have been included:

Table 4: best results of each of the datasets

Experiment number	EvTouch-objects	EVTouch-containers
1	91.667	71.667
2	92.667	73.33
3	93.65	73.66
4	93.75	75.333
5	93.75	78.333

The mean and variance for the **EvTouch-Objects** dataset are **93.10** and **0.68**, respectively, and for the **EvTouch-Containers** dataset, they are **74.46** and **5.10**, respectively.

6Ablation Study:

The comparison of accuracy achieved under compression conditions without normalization, as shown in the table below, indicates that although normalization was not applied, the accuracy obtained surpasses that reported in the original paper for both datasets. For the EVTouch-object dataset with a window size of 5 and steps of 2, 3, and 5, the achieved accuracy is 91.666%, which represents an improvement of approximately 2.21% compared to the reference paper. For the EVTouch-Container dataset, the accuracy is 73.333%, which is consistent with window sizes 4 and step 4, and window size of 5 and step 3, reflecting an approximate improvement of 13.16% over the reference paper's accuracy.

Table 5: The Accuracy Achieved by Our Method without the Use of Normalization.

Method	EVTouch-objects (Accuracy/Converge Timestep)	EVTouch-containers (Accuracy/Converge Timestep)
2-2	89.583/(ep65)	70.000/ (ep43)
3-3	90.972/(ep50)	70.000/ (ep82)
4-2	91.666/(ep67)	70.000/ (ep52)
4-3	91.666/ (ep49)	70.000/ (ep52)
4-4	90.278 /(ep47)	73.333/ (ep76)
5-2	91.666 /(ep42)	70.000/(ep62)
5-3	91.666/ (ep49)	73.333/ (ep53)
5-5	91.666/ (ep90)	70.000/ (ep52)

7 Conclusion

Improving the accuracy and efficiency of neural networks used for receiving and processing tactile data remains a fundamental challenge. Enhancing the precision and performance of these networks not only accelerates advancements in deep learning but also represents a significant step toward optimizing artificial intelligence and automation systems. Additionally, input data often consists of long sequences of binary values that can be effectively compressed using advanced techniques. Such compression reduces the number of time steps and significantly decreases computational needs and energy consumption. Consequently, data compression enhances system efficiency and resource management, leading to reduced power consumption.

The proposed method resulted in an accuracy improvement of approximately 0.42% for the EvTouch-Objects dataset and 18% for the EvTouch-Container dataset, compared to the TactileSGNet method, which is the basis for our work. To achieve even better results in this field, applying new graph-based methods and innovative techniques can further enhance the accuracy and efficiency of machine learning models and spiking convolutional neural networks. This aspect will be addressed in future work.

References

[1] S. J. J. &. P. J. Kim, Tactile sensors for artificial skin applications: A review. Sensors, 20(9), 2756.

[2] Q. H. S. &. Z. Q. Liu, Spiking neural networks for object recognition in tactile sensing: A survey. Neural Computing and Applications, 34, 1793–181, (2022).

[3] J. K. D. C. H. &. P. S. Lee, . Advances in event-driven touch sensing for robotic perception. IEEE Transactions on Robotics,, 37(4), 1012-1021, (2021).

[4] J. H. D. K. H. &. P. J. Park, Efficient tactile object classification using event-based sensors and spiking neural networks. Frontiers in Neurorobotics,, (2020).

[5] X. Z. Y. &. Y. W. Gao, Enhanced tactile perception for robotic manipulation using spiking graph convolutional networks., IEEE Robotics and Automation Letters, 8(2), 2340-2347, (2023).

[6] W. S. T. T. a. H. S. o. C. S. S. o. C. U. o. S. Fuqiang Gu, TactileSGNet: A Spiking Graph Neural Network for Event-based Tactile Object Recognition, IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2020.

[7] L. G. R. P. A. M. &. C. M. T. Veiga, A review on tactile sensors for object recognition. Sensors, 20(18), 5264, (2020).

[8] C. S. &. P. J. ouganis, Event-based neuromorphic tactile sensing., . IEEE Robotics and Automation Letters, 6(2), 2490-2497, (2021).

[9] F. &. S. K. W. Paredes-Valles, . . Spiking neural networks for event-based tactile object recognition, IEEE Transactions on Neural Networks and Learning Systems, 31(6), 1792-1804, (2020).

[10] G. M. M. &. S. L. Tavernini, SLAYER: A supervised learning algorithm for spikingneural networks. Neurocomputing, 413, 147-156, Neurocomputing, 413, 147-156, (2021)..

[11] C. &. W. J. Hu, Graph neural networks with spiking neurons for tactile object recognition., IEEE Transactions on Neural Networks and Learning Systems, 33(5), 2032-2045, (2022)..

[12] Y. L. X. &. C. L. Lee, Tactile-based object recognition using event-drivenneuromorphic hardware. Nature Electronics, 3(9), 555-562, (2020)..

[13] Z. &. L. X. .. 8. 5. Li, Tactile sensing for robotic manipulation: A review. Frontiers in Robotics and AI,, (2021).

[14] X. &. H. J. .. Jin, Tactile sensor technologies for robotic manipulation: A survey Transactions on Robotics, 37(6), 2053-2071, IEEE, (2021)..

[15] H. L. Q. &. Z. Z. Zhou, Graph convolutional networks for event-based object recognition., IEEE Transactions on Neural Networks and Learning Systems, 32(7), 3245-3255, (2021).

[16] T. N. &. W. M. Kipf, Semi-supervised classification with graph convolutional networks., Proceedings of the International Conference on Learning Representations., (2020). .

[17] M. B. X. &. V. P. Defferrard, Convolutional neural networks on graphs with fast localized spectral filtering., Advances in Neural Information Processing Systems, 29,3844-3852, (2020). .

[18] a. U. D. A. A. Hesami Naghshbandy*K. Naderi*, Iranian Journal of Electrical and Electronic Engineering , 2022.

[19] Z. &. Z. J. Wu, A comprehensive review on graph convolutional networks., IEEE Transactions on Neural Networks and Learning Systems, 33(8), 3729-3749., (2022)..

[20] A. &. M. A. Tavanaei, Deep learning with spiking neurons: Principles, models, and applications., Neural Networks, 121, 305-322, (2020). .

[21] R. &. M. Perez, A.Event-based spiking neural networks for tactile object recognition., IEEE Robotics and Automation Letters, 6(3), 4211-4218, (2021). .

[22] C. &. W. J. Hu, Graph neural networks for tactile sensing and recognition. Sensors, 22(3),, Sensors, 22(3), 1032, (2022). .

[23] Z. &. L. F. Yi, Neuromorphic tactile sensing: Challenges and opportunities., Frontiers in Neurorobotics, 14, 64, (2020). .

[24] S. B. &. O. G. Shrestha, Approximating spike-timing-dependent plasticity using surrogate gradients., IEEE Transactions on Neural Networks and Learning Systems, 32(5), 2069-2082, (2021)..

[25] A. &. M. A. Tavanaei, Bio-inspired spiking neural networks for tactile data processing, IEEE Transactions on Robotics, 37(2), 492-503, (2021). .

[26] Z. &. L. X. Li, Tactile-based object recognition using event-driven neuromorphic hardware., Nature Electronics, 5, 449-457, (2022)..

[27] X. &. W. Y. Jin, Deep spiking neural networks for object recognition., IEEE Transactions on Neural Networks and Learning Systems, 32(8), 2924-2935, (2021).

[28] G. &. S. L. Tavernini, Spiking temporal convolutional networks for event-based tactile sensing., IEEE Transactions on Neural Networks and Learning Systems, 31(10), 4421-4433., (2021)..

[29] H. &. Z. Z. Zhou, Spiking neural networks for robotic perception and control., IEEE Robotics and Automation Letters, 7(1), 10-18, (2022).

[30] H. &. X. S. Peng, Integrating spiking neurons and k-nearest neighbors for tactile sensors., Sensors, 20(9), 2578, (2020)..

[31] Z. &. L. Y. Tan, Tactile object recognition with graph neural networks., Sensors, 22(7), 2411, (2022). .

[32] W. &. H. L. Fang, Threshold-dependent batch normalization for spiking neural networks., IEEE Transactions on Neural Networks and Learning Systems, 31(11), 4704-4716, (2020)..

[33] C. &. W. X.). Liu, Improving spiking neural network training with adaptive threshold normalization., Neural Processing Letters, 53(4), 2447-2460, 2021.

[34] S. &. M. W. Schmitt, Spiking deep networks: Neural processing and learning mechanisms., Nature Reviews Neuroscience, 22, 245-258, (2021). .

[35] A. &. C. F. Gomez, Combining graph neural networks and spiking neurons for tactile perception., IEEE Transactions on Robotics, 38(3), 881-891, (2022). .

[36] Y. &. H. T. Zhang, Neuromorphic graph spiking neural networks for spatial-temporal data analysis., Frontiers in Neuroscience, 14, 537, (2020)..

[37] V. &. M. Q. Vu, Spiking graph neural networks: A biologically plausible model for spatiotemporal data., Journal of Neural Engineering, 17(3), 036012, (2020). .

[38] L. D. 1. ,. Y. H. 1. a. G. L. 1. 1. C. f. B.-I. C. R. D. o. P. I. T. U. B. 1. B. I. C. f. F. C. T. U. Hanle Zheng 1Yujie Wu 1, Going Deeper With Directly-Trained Larger Spiking Neural Networks, arXiv:2011.05280v2 [cs.NE] 18 Dec 2020.

[39] J. &. W. J. Lin, TactileSGNet: Spiking graph neural networks for tactile object recognition., IEEE Transactions on Neural Systems and Rehabilitation Engineering, 29, 1592-1604, (2021)..

[40] M. &. W. C. Nelson, Tactile sensing and neuromorphic processing for robotics., Advanced Intelligent Systems, 4(6), 2100247, (2022). .

[41] A. &. B. Z. Chortos, Skin-inspired electronic devices. Nature Electronics,, 3(5), 263-273, (2020)..

[42] Q. &. Z. Y. .. Wang, Flexible tactile sensors for wearable electronic skins, Advanced Functional Materials, 31(7), 2006171, (2021)..

[43] A. &. S. T. (. haliq, Bioinspired tactile sensors: Current progress and future directions., IEEE Sensors Journal, 21(15), 17356-1736.

[44] H. &. W. X. Liu, Flexible tactile sensing systems for robotics and prosthetics., ACS Nano14(8), 9381-9388, (2020).

[45] J. &. C. K. Park, Tactile sensing with neuromorphic graph neural networks., IEEE Transactions on Robotics, 37(4), 1120-1134, (2021)..

[46] K. J. A. &. P. P. Roy, Towards Spike-Based Machine Intelligence with Neuromorphic Computing., (2019).

[47] X. B. A. &. B. Y. Glorot, Deep sparse rectifier neural networks., In Proceedings of the 14th International Conference on Artificial Intelligence and Statistics (pp. 315-323), (2011)..

[48] T. N. Kipf and M. Welling, Semi-supervised classification with graph convolutional networks, arXiv preprint arXiv:1609.02907, 2016.

[49] B. S. C. H. K. A. C. O. Kang P, Boost event-driven tactile learning with location spiking neurons., Frontiers in Neuroscience. 2023;17:1127537, 2023.

[50] J. X. L. S. D. H. L. T. Z. X. e. a. Yang J, Robot Tactile Data Classification Method Using Spiking Neural Network. 2021 China Automation Congress (CAC):, IEEE; 2021. p. 5274-9, 2021.

Sheis Abolmaali was born in Semnan, Iran, on August 21rd 1980. He received the B.Sc. in 2004, the M.Sc. degree in 2007, and the Ph.D. degree in 2018 all in Computer Engineering from the University of Tehran, Tehran. He is currently the assistant professor with the Electrical and Computer Engineering Department of the Semnan University, Iran. His current research interests include image and video processing, spiking neural networks, and neuromorphic systems.

Elahe Rezaeii Ahvanooii was born in Damghan, Iran, on September 29rd 1997. She received the B.Sc. in 2021, the M.Sc. degree in 2024, all in Computer Engineering from the University of Semnan, Semnan.
Her research interests include spiking neural networks and neuromorphic systems. She deeply studies advanced techniques aimed at improving the interpretation and

manipulation of visual data and also seeks to simulate the complex mechanisms of the brain using spiking neural networks and neuromorphic systems. This diverse combination of expertise places her at the forefront of technological innovation, driving progress in both theoretical and practical applications.