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RESEARCH ARTICLE

Semi-Supervised Learning for Spiking Neural Networks Based on Spike-Timing-Dependent Plasticity

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ABSTRACT In this study, we propose a semi-supervised learning method for spiking neural networks based on spike-timing-dependent plasticity (STDP). The spiking neural network structure of the proposed method incorporates teacher neurons and synapses, which serve the same purpose as real-life teachers, who ensure that the actions of their students do not transcend social norms. In the first stage of the proposed learning method, STDP-based supervised learning is applied. In the second stage, STDP-based unsupervised learning is conducted in the absence of any input signal to the teacher neuron. The proposed learning method classified handwritten characters with higher accuracy than the existing method. On the MNIST dataset, the proposed method was approximately 5%, 1%, and 3% more accurate than the conventional algorithm on 100, 400, and 1600 excitatory neurons, respectively.

INDEX TERMS Spiking neural network, semi-supervised learning, spike-timing dependent plasticity, image classification.

I. INTRODUCTION

Recently, neural network-based structures have been extensively studied and applied to various tasks, such as image/video classification, object detection, and recognition in the field of computer vision [1], [2], [3], [4], [5], [6], [7]. Owing to the development of high-performance hardware, extensive research has been conducted on the training of deeper networks using large amounts of data. However, although deep networks exhibit good performance in certain applications, they are difficult to apply in limited environments because of their power consumption. On the other hand, multiple studies have pointed out that mammalian neocortical neurons communicate with each other using spikes, thereby achieving complex brain functionality while consuming only 10-20 W of power [8], [9], [10], [11], [12], [13]. This has motivated the adoption of neural structures in the modeling of each node in artificial neural networks (ANNs), notably, spiking neural networks (SNNs), which have been developed to mimic the spike-based model of information transmission exhibited in the human brain. SNNs are more efficient in terms of power consumption because they replace matrix multiplications, which are essential components of existing neural networks, by simple additions of the weights of the synapses where input signals are generated. In other words, SNNs have the property to handle spatio-temporal asynchronous inputs very efficiently. These features allow the use of SNNs for applications that use sensors such as the dynamic vision sensor (DVS) and LiDAR. Sensors such as DVS and LiDAR are expected to be used in autonomous vehicles, unmanned aerial vehicles, and drones, which require high-speed and low-power processing. Therefore, SNNs are expected to be used in many fields in the future.

In general, neuromorphic engineering can be categorized into three primary subfields—neuron modeling, inference methods, and synaptic learning. Neuron modeling aims

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to model each node of an artificial network following the template of a human neuron. Inference methods use post-processing to infer output, e.g., based on the distribution of output spikes and statistics, because of the unavailability of the exact inferencing mechanism of the human brain. Post-processing algorithms have been developed based on the statistics of spikes in neurons to ascertain the output of specific signals fed to the SNNs [8], [10], [13]. However, the aforementioned studies designate meaning to each neuron and assume the value or meaning mapped to that neuron to have been inferred if the proportion of the spike trail corresponding to that neuron is the greatest. Finally, active research is also being conducted on synapse learning. Methods for increasing or decreasing the connectivity at human synapses have been modeled based only on massive experiments, and a concrete approach remains to be established. In this context, several researchers have investigated learning methods by analyzing empirical outcomes [14], [15], [16], [17], [18], [19].

The learning methods for SNNs are of two types—supervised and unsupervised. The use of supervised learning based on backpropagation is commonplace and it is applied in conventional neural networks by optimizing the values of the synapse weights. However, the requirement of pre-training for these approaches makes biological modeling impractical. In contrast, unsupervised learning has been studied based on spike-timing-dependent plasticity (STDP). STDP is a learning method for SNNs in which the weights of synapses have been empirically shown to be dependent on the duration between spikes at the pairs of constituent neurons. When two neurons exhibit strong connectivity, the duration between their respective spikes is small. Conversely, if the connection is weak, the duration is large. Therefore, STDP-based training algorithms can be considered more suitable to mimic the functioning of biological neurons.

To demonstrate the usefulness of SNNs, several attempts have been made to apply them to the classification and recognition of Modified National Institute of Standards and Technology (MNIST) datasets [20]. The two-layer SNN model based on STDP-based unsupervised learning proposed by Diehl and Cook [8] exhibited an accuracy of approximately 82% in recognizing MNIST datasets with 78,400 parameters. Hazan et al. [10] achieved an approximate accuracy of 85% on an MNIST dataset by maintaining the number of parameters using the self-organizing map, which is primarily used for unsupervised learning of deep neural networks. However, its accuracy was significantly lower than those of various ANN-based networks using supervised learning, some of which achieved accuracies of approximately 91% using approximately 100 parameters only. Another study used backpropagation optimization to conduct supervised learning of SNNs to increase their accuracy. Backpropagation algorithms can be used to train SNNs both indirectly and directly [11]. For direct backpropagation, Wu et al. [11] and Tavanaei and Maida [12] proposed approximations of derivatives of membrane potentials to solve the non-differentiable problem. On the other hand, trained ANNs can be converted to SNNs for inference as indirect approaches [21], [22]. Further, the use of additional neurons for supervision has also been proposed. Hao et al. [13] first proposed the use of output neurons and symmetric STDP to construct two-layer SNNs for supervised learning.

Neural networks are known to frequently encounter overfitting during their learning stage. For SNN learning, several studies on STDP-based learning mimic the process of biologically plausible learning with ultra-low power in the human brain. However, these STDP-based learning methods are particularly prone to overfitting due to noise spikes or over-response of output neurons to some specific patterns. For example, if one output neuron overreacts, the weight of all synapses connected to the neuron is significantly affected, causing spikes to occur only in the same neuron for the next data sample. In addition, if a noise spike accidentally occurs in the output neuron that is not a correct answer, the weights of the synapse connected to the neuron are inappropriately updated.

In previous studies, several efforts were made to prevent overfitting. Diehl and Cook [8] proposed a winner-take-all STDP-based unsupervised learning method to prevent noise spikes. The method proposed by Diehl and Cook [8] suppresses the occurrence of additional noise spikes by forcing only the synapse connected to the first responding neuron to update the weights rather than updating the weights of all synapses. However, this method often overreacts to the first firing neuron that responds, which could lead to overfitting in learning. The approach by Hao et al. [13] uses biologically plausible STDP-based supervised learning to effectively avoid overreacting with dopamine-STDP-based weight updates. This method shows higher classification performance than the prior work by Diehl and Cook [8], but cannot handle noise spikes, which could lead to problems of overfitting in the learning process. In conclusion, to avoid overfitting during SNN learning, both overresponse and noise spikes should be addressed, but existing studies are not able to solve both problems simultaneously. Therefore, in this study, we proposed a relatively simple but effective semi-supervised learning method that can effectively avoid overreaction and noise spikes. The first step of the proposed method—STDP-based negative supervised learning—generates a negative label signal through the teacher neuron, which can suppress the occurrence of noise spikes that may accidentally occur. At the same time, STDP-based unsupervised learning—the winner-take-all learning method— is also performed on the correct neurons. Therefore, even if an overreaction occurs during the learning process, it is helpful for learning because the overreaction occurs in one of the correct neurons. In the second stage—STDP-based unsupervised learning—differences between classes are learned, resulting in improved classification performance. The existing STDP-based unsupervised learning method requires label mapping for all output neurons after learning, to obtain an inference result. Although the most accurate mapping method is manual labeling, it is impractical when there are many output neurons required to achieve high classification performance. Taking this into account, Diehl and Cook [8] employed an inference method by mapping classes based on spike statistics of output neurons in the learning process. However, the mapping method based on spike statistics has the disadvantages of overreaction and noise spikes, which cause inconsistencies and consequently, inaccuracy. However, since the semi-supervised learning method proposed in this paper learns a pattern for a predetermined class from each neuron through supervised learning at the initial stage of learning, inference can be simply performed without manual label mapping. The proposed method first divides the output neurons into groups of the same size as the number of classes in the dataset before training. Subsequently, the proposed method maps each group to a corresponding class and the proposed STDP-based negative supervised learning method generates a negative label signal through the teacher neuron during learning. Note that the negative label signal can suppress the occurrence of noise spikes that could accidentally happen. If the output neuron group does not receive the negative label signal, STDP-based unsupervised learning is performed within the correct neuron group. If an overreaction occurs, the overreaction is found on one of the correct neurons, allowing it to train faster. The second training step improves classification performance without degradation due to negative learning because it learns differences between classes. As a result, the proposed semi-supervised learning method executes more stable training and outperforms the existing unsupervised learning method. On MNIST datasets, the proposed method is approximately 5%, 1%, and 3% more accurate than the existing algorithm [8] on 100, 400, and 1600 excitatory neurons, respectively. The remainder of this paper is organized as follows. In Section II, the network architecture and learning method of the proposed methodology are presented. The classification performance of the proposed method is compared with that of the existing alternative in Section III. Finally, the concluding remarks are presented in Section IV.

II. PROPOASED METHOD

The proposed network structure is illustrated in Fig. 1. The SNN consists of input neurons, excitatory neurons, inhibitory neurons, teacher neurons, input-excitatory synapses, excitatory-inhibitory synapses, inhibitory-excitatory synapses, and teacher-excitatory synapses. To begin with, an input image is vectorized and signalized into a spike signal using a Poisson probability distribution and inputted into the input neurons. During the learning stage, the label is simultaneously inputted into the teacher neurons via a one-hot coded process and signalized, and the weights of the input-excitatory synapses are learned. The weights of the other two synapses are affixed without learning. During the inference phase, only the input image is inputted into the input neuron, and the spike incidence statistics of the excitatory neuron are used to derive the inference results. As input-excitatory and excitatory-inhibitory synapses have positive weights, the potential energies of postsynaptic neurons are increased [23]. In contrast, the membrane potential energies of postsynaptic neurons are decreased because the inhibitory-excitatory and teacher-excitatory synapses exhibit negative weights [24]. For the proposed supervised learning, teacher neurons are connected to excitatory neurons via inhibitory synapses. Teacher-excitatory synapses with negative weights are essential for STDP-based supervised learning, and excitatory neurons that do not correspond to the label suppress the response. STDP-based supervised learning is accomplished by applying input spikes and label spikes to the proposed networks.

By conducting supervised learning, the mapping of the output semantics of excitatory neurons is omitted compared to the procedure of the conventional method. This makes its application to tasks such as image classification, object detection, etc. more convenient. For example, if an SNN is trained using a dataset with a very large number of labels, such as the ImageNet [25] and MS-COCO [26] data sets, the number of output neurons must also be increased in keeping with the number of labels. Increasing the number of output neurons complicates the process of mapping the output neurons of the SNN learned via unsupervised learning to the labels of each neuron. Further, the supervised learning of the proposed method outputs the same result even in parallel learning, so it is particularly effective in cases involving datasets with large numbers of labels. In addition, as supervised learning can increase the learning rate, quicker convergence of learning is ensured. Following the completion of supervised learning, we apply STDP-based unsupervised learning to the teacher neurons using only the input spikes instead of label spikes.

A. NETWORK ARCHITECTURE

The proposed network employs the leaky integrate and fire with an adaptive threshold (LIF-AT) neuron model proposed by Diehl and Cook [8]. LIF-AT was designed by applying an adaptive threshold [27], [28] to the commonly used neuron model, leaky integration, and fire (LIF) [29]. LIF-AT is a neuron model that adds the weight of the synapse to the membrane voltage of the postsynaptic neuron corresponding to every presynaptic spike, and it is transferred to it. LIT-AT produces a post-synaptic spike whenever the membrane voltage exceeds the membrane potential threshold. Subsequently, the membrane voltage then gradually decreases over time. Further, the threshold value increases whenever a spike occurs during training [27]. On the other hand, following the transfer of the spikes, the threshold value decays exponentially to the initial threshold [8], [28]. This model mimics the pre-threshold phenomenon of biological neurons, which prevents the learning of specific synapses to ensure equal learning of the synapses between input neurons and excitatory neurons. The application of an SNN requires the encoding of input data with scalar values into spike trains. Spike encoding converts scalar values into a Poisson-distributed spike train with a specific frequency. In the proposed network, each of N

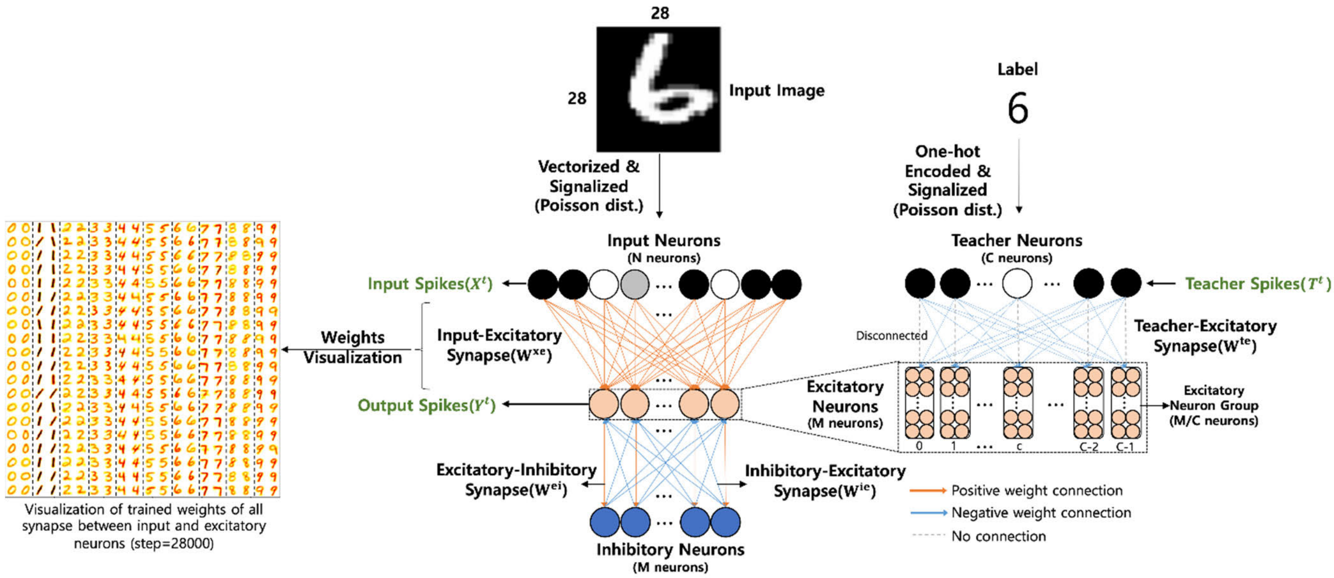


FIGURE 1. Proposed network structure for semi-supervised learning.

input neurons independently generates the following Poisson-distributed input spike, X^i,

$$X^i = \{x_0^i, x_1^i, \ldots x_n^i, \ldots, x_{N-1}^i \,|\, x_n^i \in \{0, 1\}\}', \tag{1}$$

where x_n^i denotes the spike at the nth input neuron at the time i. The input spikes are transmitted to M excitatory neurons via input-explanatory synapses. Simultaneously, teacher neurons generate Poisson-distributed teacher spikes, T^i given by

$$T^i = \{t_0^i, t_1^i, \ldots, t_c^i, \ldots, t_{C-1}^i \,|\, t_c^i \in \{0, 1\}\}', \tag{2}$$

where t_c^i denotes the spike at the cth teacher neuron at the time i. The teacher spikes are transmitted to M excitatory neurons via teacher-excitatory synapses. Each spike transmitted to excitatory neurons increases or decreases their membrane potential depending on the weight of the synapse through which it passes. The membrane potential, V_e, of the excitatory neurons is given by

$$\tau \frac{dV_e}{dt} = (E_{rest} - V_e) + g_e(E_e - V_e) + g_i(E_i - V_i), \tag{3}$$

where τ denotes the time constant associated with the membrane potential; E_{rest}, E_e, and E_i denote the resting membrane potential and the equilibrium potentials of excitatory and inhibitory synapses, respectively; g_e and g_i denote the excitatory conductance and inhibitory conductance, respectively. In the proposed model, g_e and g_i in the LIF-AT model can be denoted by

$$\tau_{g_e} \frac{dg_e}{dt} = -g_e + W_{xe} \cdot X^i, \tag{4}$$

$$\tau_{g_i} \frac{dg_i}{dt} = -g_i + W_{ie} \cdot D^i + W_{te} \cdot T^i, \tag{5}$$

where τ_{g_e} and τ_{g_i} denote the time constants of the excitatory and inhibitory synapse conductance; W_{xe}, W_{ie}, and W_{te} denote the matrices of input-excitatory, inhibitory-excitatory, and teacher-excitatory synapse weights, respectively; and D^i denotes inhibitory spike. Excitatory neurons generate output spikes, Y^i, given by

$$Y^i = \{y_0^i, y_1^i, \ldots, y_m^i, \ldots, y_{M-1}^i | y_m^i \in \{0, 1\}\}'. \tag{6}$$

Based on the thresholds, each neuron independently has $V_{th_m}^i$, where y_m^i is the spike of the ith time of the mth excitatory neuron, and we can obtain an output spike, y_m^i, which can be denoted by

$$y_m^i = f(x) = \begin{cases} 1, & v_m^i > V_{th_m}^i, \; v_m^i \in V_e^i \\ 0, & otherwise \end{cases} \tag{7}$$

where $V_{th_m}^i$ increases in the presence of spikes and decreases gradually in their absence. Therefore, it contributes to the suppression of responses to signals of similar sizes and patterns, such as the threshold of human neurons [30], [31]. The output spikes are transmitted to the inhibitory neurons via excitatory-inhibitory synapses. Excitatory-inhibitory and inhibitory-excitatory synapses use the same connection and weights as the two-layer SNN. Inhibitory neurons share a one-to-one connection with excitatory neurons and are modeled to output inhibitory spikes D^i whenever they receive spikes. Inhibitory spikes inhibit the responses of excitatory neurons by implementing inhibitory-excitatory synapses with negative weights, W_{ie}. The input spike encoding, and the synaptic connections implemented in the proposed learning method are discussed in greater detail in the following subsections.

B. SPIKE ENCODING

The classification of images or handwritten symbols using an SNN requires the conversion of scalar images into input

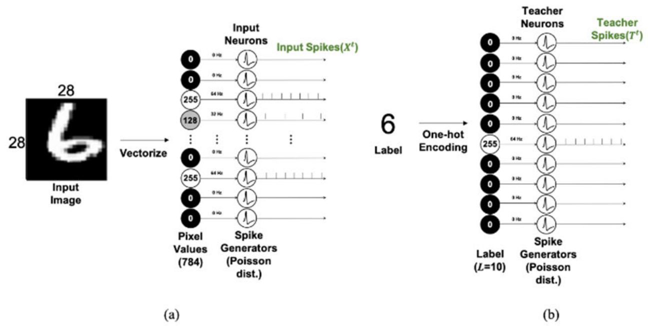


FIGURE 2. Example of input and teacher spike encoding on MNIST dataset (L = 6 labels). (a) Example of spike encoding of an image to input spikes with Poisson-distributed frequency. (b) Example of spike encoding of a label to teacher spikes with Poisson-distributed frequency.

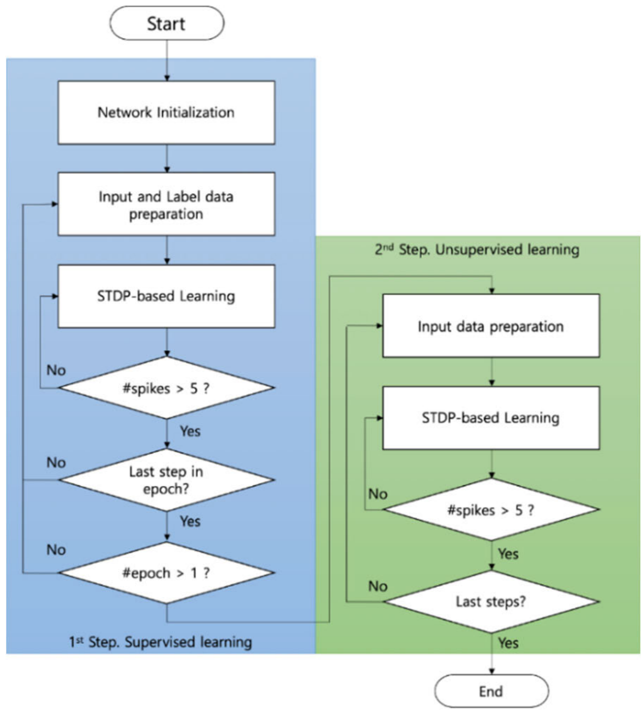


FIGURE 3. Proposed semi-supervised learning method for an SNN.

spikes. An example of such conversion into input and teacher spikes is depicted in Fig. 2. MNIST datasets contain 8-bit scalar values and pairs of 28 × 28 images with handwritten class labels. A 2D image is used as the initial frequency of the input neuron, where each pixel is mapped to exactly one input neuron and the corresponding pixel value is scaled to generate a spike. A firing rate of 255 is transmitted to the teacher neuron corresponding to the target label to ensure that the teacher neuron exhibits a firing speed similar to that of the input neurons that received the 8-bit input image. As shown in Fig. 2, the input neuron is a Poisson spike generator that modulates the input frequency into a spike train in unit time. The Poisson spike generator proposed by Heeger [32] is used to receive the firing rate, divide it by 4, and generate a spike train following the Poisson distribution for 350 ms. If less than 5 spikes are generated by excitatory neurons, the firing rate is doubled to generate a spike train again, and the simulation is performed for 350 ms, as proposed by Diehl and Cook [8]. As illustrated in Fig. 2(b), this frequency can be gradually increased during the learning process. In the figure, L denotes the number of classes, one-hot encoding is the method used to convert into a vector, and teacher spikes, T^i, are created following the procedure used in the input image.

C. INPUT-EXCITATORY SYNAPSES

The input-excitatory synapse weight matrix is defined by

$$W_{xe} = \begin{bmatrix} w^{xe}_{0,0} & \cdots & w^{xe}_{N-1,0} \\ \vdots & \ddots & \vdots \\ w^{xe}_{0,M-1} & \cdots & w^{xe}_{N-1,M-1} \end{bmatrix}, \quad w_{max} > w^{xe}_{n,m} > 0, \tag{8}$$

where w^{ax}_{m} and $w^{xe}_{n,m}$ denote the maximum synapse weights and the STDP-based trainable scalar value, respectively. Following the execution of learning using the proposed method, $W_x e$ can be visualized as a 2D image, as depicted in Fig. 1. As is evident from the visualized image, the numbers of excitatory neurons assigned to the labels are equal. Each small 2D image represents the average image of the input data corresponding to the label assigned to the mth neuron.

D. TEACHER-EXCITATORY SYNAPSES

A teacher-excitatory synapse is defined by

$$W_{te} = \begin{bmatrix} w^{te}_{0,0} & \cdots & w^{te}_{C-1,0} \\ \vdots & \ddots & \vdots \\ w^{te}_{0,M-1} & \cdots & w^{xe}_{C-1,M-1} \end{bmatrix}, \quad -w_{max} < w^{te}_{c,m} < 0, \tag{9}$$

where $w^{te}_{c,m}$ is negative and is defined by

$$w^{te}_{c,m} = \begin{cases} 0 & c = [c/m] \\ w_{inh} & otherwise \end{cases} \tag{10}$$

where $c \in \{0, \ldots, C-1\}, m \in \{0, \ldots, M-1\}$, w_{inh} denotes the inhibition weight. As illustrated in Fig. 1, $[M/C]$ excitatory neurons constitute a group that is mapped to a specific label. If the group index coincides with the class value, the synapses are not connected. However, synaptic connections with different indices and class values suppress the response of the other neuronal groups via teacher spikes.

E. TRAINING

The proposed method of network training uses a two-step supervised and unsupervised learning approach, as illustrated in Fig. 3. In the SNN constructed to classify handwritten digits, the weights of the input-excitatory synapses are learned during the learning process using post-pre STDP [8]. The conventional method uses the power-law weight dependence for the STDP rule. During the evaluation of the performance of the proposed method, the post-pre STDP learning rule is employed to evaluate the classification accuracies of both the proposed and conventional algorithms to ensure a fair comparison. The updating of weights in post-pre STDP learning is triggered by the post-synaptic and pre-synaptic traces. To approximate synaptic dynamics, synaptic weights are updated based on the synaptic traces [33]. The alteration in weight corresponding to a pre-synaptic trace is defined as follows:

$$\Delta w = -\eta_{pre} x_{post}, \tag{11}$$

where η_{pre} denotes the learning rate corresponding to a presynaptic spike and x_{post} denotes the postsynaptic trace. Similarly, the alteration in weight corresponding to a post-synaptic spike is defined as follows:

$$\Delta w = \eta_{post} x_{pre}, \tag{12}$$

where η_{post} denotes the learning rate corresponding to a post-synaptic spike and x_{pre} denotes the presynaptic trace. This approximate updating rule is commonly used in synapse learning. In this study, η_{pre} and η_{post} were set to 5×10^{-5} and 2×10^{-3}, respectively. Both STDP-based unsupervised learning and conventional STDP-based unsupervised learning are competitive learning methods because the weights of all synapses connected to the neurons exhibiting the fastest response are simultaneously updated [16]. For this reason, if different handwritten digits share a similar shape, the excitatory neuron mapped to different labels exhibits the fastest response. Therefore, in the proposed method, intra-class variation learning is conducted by inhibiting the response of neurons that are not mapped to a label, and competitive learning is simultaneously conducted between the mapped neurons. After one or two epochs of supervised learning, all connections in the network are maintained, preventing the occurrence of teacher spikes in teacher neurons. This is because, in the absence of teacher spikes, unsupervised learning is conducted, as in the case of a two-layer SNN [8]. This unsupervised learning method is also conducted for one to two epochs. Via unsupervised learning, competitive learning is carried out via inhibitory spikes among the complete excitatory neurons as the absence of teacher spikes induces excitatory and intra-class variation learning. In this case, intra-class and inter-class variations are simultaneously learned. However, because of the execution of supervised learning, intra-class variation remains relatively small. Consequently, inter-class variation learning is primarily used.

F. INFERENCE

In unsupervised learning, output nodes are typically mapped to labels following the completion of learning. The data are inputted into the network and predictions are based on the observed values of the output nodes. Following STDP-based unsupervised learning, excitatory neurons and labels are mapped based on the statistical characteristics of spikes generated at the output nodes during learning [8]. However, whenever new data are required to be learned for other applications, remapping of labels is required with certain exceptions. In contrast, the mapping for supervised learning is completed for the proposed method, thereby eliminating the necessity of artificial label mapping. The network proposed in this paper then outputs a prediction class, C_{pred}, based on the statistics of spikes in excitatory neurons during the simulation. Here, the predicted class, C_{pred}, is calculated as follows:

$$C_{pred} = \frac{C}{M} \times \underset{m}{argmax} \left(\sum_{i=0}^{T-1} y_m^i \right) \tag{13}$$

where C and M denote the number of classes and the number of excitatory neurons, respectively.

TABLE 1. Comparison of classification accuracies on MNIST.

# Neurons	100	400	900	1600	6400
Semi-SNN (S0-U3)	87.24 %	91.08 %	92.24 %	93.25 %	93.79 %
Semi-SNN (S1-U2)	**88.56 %**	**92.88 %**	**94.16 %**	**94.95 %**	95.08 %
Semi-SNN (S2-U1)	88.36 %	92.72 %	93.91 %	94.03 %	93.91 %
Semi-SNN (S3-U0)	29.67 %	39.90 %	43.99 %	49.44 %	56.54 %
Two-layer SNN [8]	82.90 %	87.00 %	-	91.90 %	95.00 %
Sym-STDP [13]	83.11 %	91.31 %	-	91.33 %	**95.81 %**

III. EXPERIMENTAL RESULTS

To evaluate the classification performance of the proposed semi-supervised learning method, we developed the proposed network and learning method using Python 3.6 [34] on a Windows 10 PC with an Intel i7-8700 (3.2 GHz) and 32 GB of RAM. On the MNIST [20] and Fashion-MNIST [35] datasets, an objective comparison was conducted in terms of the classification accuracy. MNIST and Fashion-MNIST datasets consist of 60,000 training data and 10,000 test data samples. For simulation, dt was set to 0.5 ms, the simulation time was set to 350 ms, and rest time was set to 150 ms, with $\tau = 100$, $E_{rest} = -65mV$, $E_e = 0mV$, $E_i = -100mV$, $\tau_{g_i} = 1$, $\tau_{g_i} = 1$, $w_{ei} = 10.4$, $w_{ie} = 17$, $w_{inh} = 17$. W_{xe} is initialized to uniform distribution [0, 1] and then each synapse is normalized to 78. We used the training dataset to train the proposed method for 20 epochs. Table 1 depicts the accuracy of the classification of handwritten digits using the proposed method with respect to various numbers of excitatory neurons. These accuracies were compared to those of the conventional methods.

In Table 1, the ‘S1-U2‘ indicates that the ratio of supervised and unsupervised learning used in the proposed semi-supervised learning method is 1:2. In this notation,

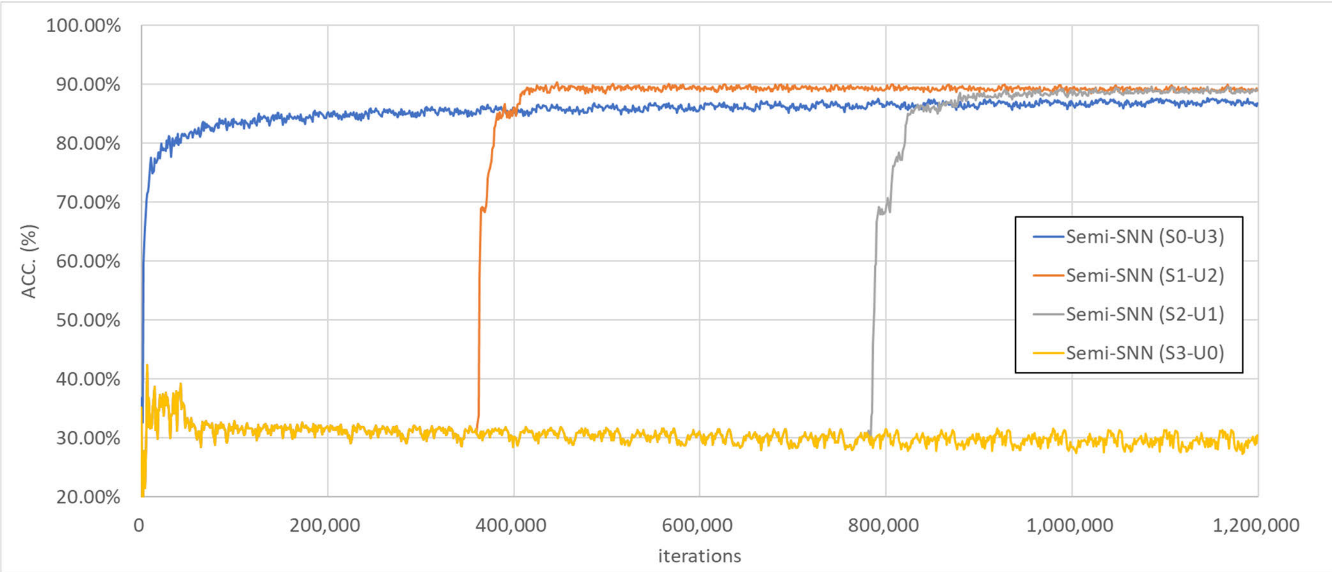


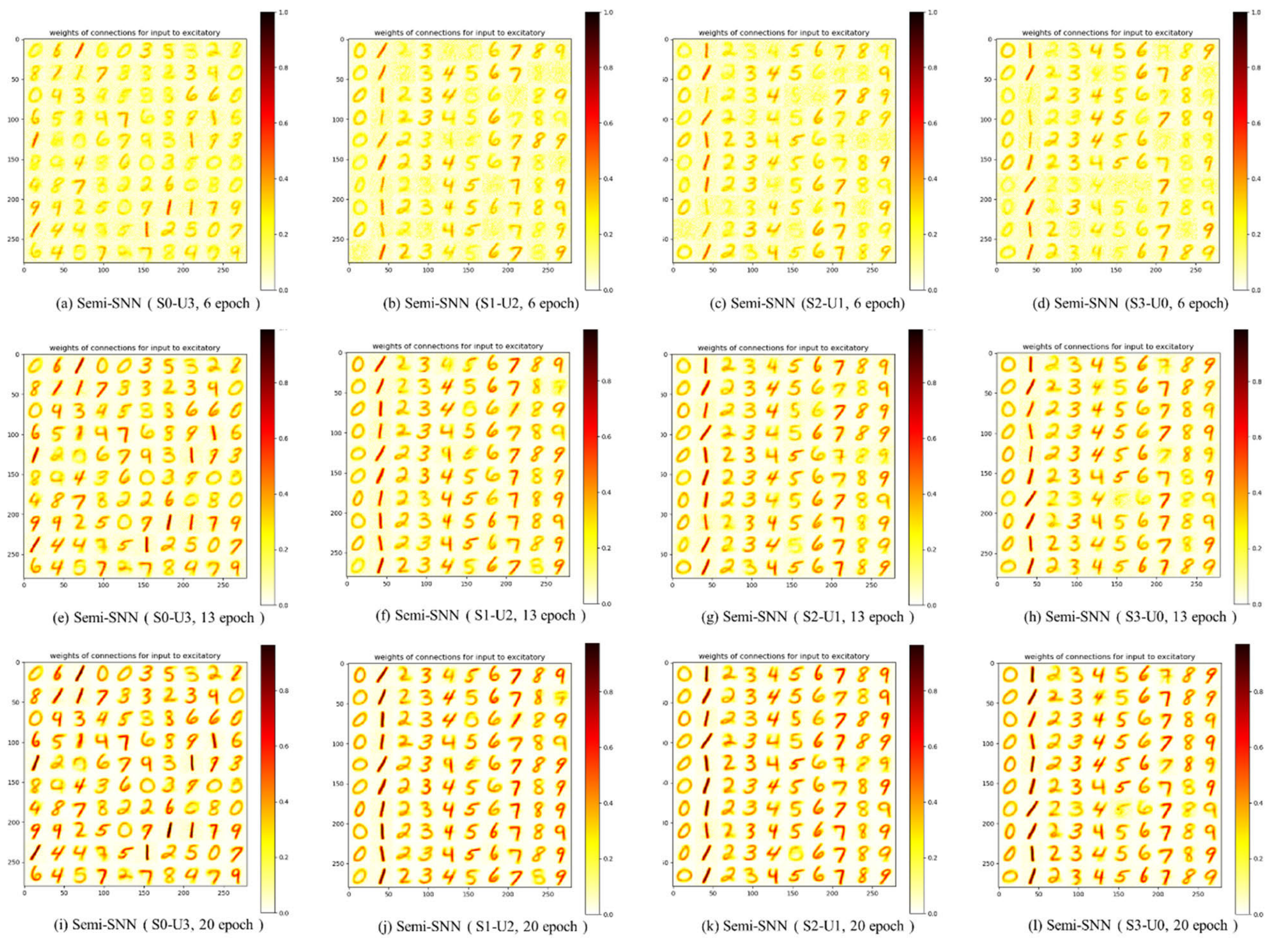
FIGURE 4. Comparison of classification accuracies of the proposed methods with networks of 100 excitatory neurons on the MNIST test dataset for every 1,000 iterations of training.

Semi-SNN (S0-U3) denotes the same network and learning method described by Diehl and Cook [8]. In the last row, Sym-STDP is the architecture proposed by Hao et al. [13]. In terms of accuracy, Semi-SNN (S1-U2) outperforms all the methods in the case of 100, 400, 900, and 1600 excitatory neurons. On the other hand, Sym-STDP [13] exhibits the highest accuracies corresponding to 6400 excitatory neurons, followed by Semi-SNN (S1-U2) and Semi-SNN (S2-U1), respectively. Semi-SNN (S3-U0) uses only the proposed supervised learning method in all epochs, which degrades its accuracy compared to the others. This implies that networks trained for only an intra-class variation for three supervised sessions are incapable of handling inter-class variations effectively since two input spikes of similar patterns can respond to excitatory neurons mapped to different classes. LIF-AT, the neuron model used in this paper, is modeled to increase the membrane potential threshold of post-synaptic neurons whenever a spike is detected. Subsequently, the membrane potential threshold gradually decreases over time to prevent the occurrence of a spike at only one neuron in unsupervised learning as in the case of competitive learning. In addition, the supervised learning method carries out training in a way that suppresses the occurrence of spikes at all the excitatory neurons except those mapped to a target label (class). This makes it useful to train variance within the same class because competitive learning is actively performed between neurons mapped to the same class. On the other hand, since only the neurons mapped to one class are trained while other neurons are not influenced, this type of exclusive learning cannot induce the learning of inter-class variation using only supervised learning. Simultaneous responses of two classes of excitatory neurons corresponding to similar patterns, for example,‘1’ and ‘7’, can complicate the reasoning of the correct answer. On the contrary, the proposed learning method makes more accurate inference possible by training the variance between classes using at least two phase of unsupervised learning following supervised learning.

TABLE 2. Comparison of classification accuracies on Fashion-MNIST.

# Neurons	100	400	900	1600	6400
Semi-SNN (S0-U3)	72.85 %	77.33 %	79.17 %	79.68 %	80.95 %
Semi-SNN (S1-U2)	74.22 %	79.42 %	81.02 %	81.11 %	81.76 %
Semi-SNN (S2-U1)	**74.74 %**	**80.09 %**	**81.05 %**	**81.54 %**	81.35 %
Semi-SNN (S3-U0)	41.36 %	52.60 %	53.13 %	55.84 %	59.36 %
Sym-STDP [13]	-	77.61 %	-	-	**84.89 %**

Table 2 lists the accuracy of fashion-MNIST data [35]. The accuracy of fashion-MNIST is lower than that of MNIST overall, which means that it is a more challenging dataset to classify. Semi-SNN (S2-U1) outperforms all the methods in the case of 100, 400, 900, and 1600 excitatory neurons. On the other hand, Sym-STDP exhibits the highest accuracies corresponding to 6400 excitatory neurons, followed by Semi-SNN (S1-U2) and Semi-SNN (S2-U1), respectively. Semi-SNN (S3-U0) degrades its accuracy compared to the others. In the case of using 400 neurons, Semi-SNN (S3-U0), Semi-SNN (S2-U1), and Sym-STDP [13] have 77.33%, 80.09%, and 77.61% accuracy, respectively. In particular, the proposed Semi-SNN (S2-U1) has about 2% better accuracy than the



(a) Semi-SNN (S0-U3, 6 epoch) (b) Semi-SNN (S1-U2, 6 epoch) (c) Semi-SNN (S2-U1, 6 epoch) (d) Semi-SNN (S3-U0, 6 epoch)

(e) Semi-SNN (S0-U3, 13 epoch) (f) Semi-SNN (S1-U2, 13 epoch) (g) Semi-SNN (S2-U1, 13 epoch) (h) Semi-SNN (S3-U0, 13 epoch)

(i) Semi-SNN (S0-U3, 20 epoch) (j) Semi-SNN (S1-U2, 20 epoch) (k) Semi-SNN (S2-U1, 20 epoch) (l) Semi-SNN (S3-U0, 20 epoch)

FIGURE 5. Visualization of the trained weights of input-excitatory synapses.

biological supervised learning method Sym-STDP, and about 3% better accuracy than the existing method Semi-SNN (S3-U0). On the other hand, if 6400 neurons are used, the accuracy of Sym-STDP is higher than that of the proposed method.

Figure 4 shows the training accuracies of the proposed methods with a network of 100 excitatory neurons over every 1,000 iterations. To measure the classification accuracy, excitatory neurons were labeled by measuring the spike generation statistics of excitatory neurons after every 1,000 iterations. The accuracy of the conventional method, Semi-SNN (S0-U3) increased before the end of the first supervised learning session and converged to an approximate accuracy of 87.24%. For Semi-SNN (S1-U2) and (S2-U1), supervised learning was changed to unsupervised learning after one and two supervised sessions, respectively. In Fig. 4, the accuracy increases rapidly the moment the learning method is changed. This indicates that in the proposed semi-supervised learning method if sufficient intra-class changes have already been learned through supervised learning sessions, inter-class changes can be learned through a small number of iterations According to the results in Fig.4, the validity of the proposed semi-supervised learning method was confirmed through comparison with Semi-SNN.

The weights of the input-excitatory synapses of the proposed method with 100 excitatory neurons with respect to varying numbers of epochs and learning methods are presented in Fig. 5. The weight patterns in the arbitrarily learned excitatory neurons in the two-layer SNN are depicted in Figs. 5(a), 5(e), and 5(i). As mentioned earlier, mapping classes to excitatory neurons is essential for reasoning in this case. In the remaining cases, the patterns are learned from 0 to 9 according to the preset positions. The pattern learned in Fig. 5(l) is not significantly different from that in Fig. 5(j), but the corresponding test accuracies are greatly different, as presented in Table 1. This is because excitatory neurons have a different threshold, and the inter-class variation is determined by its value. Therefore, in the final learning session of the proposed method, unsupervised learning is essential to learn the threshold of excitatory neurons. Figs. 5(f) and 5(h) depict visualizations of the input-excitatory synapse weights learned using supervised learning using the same number of epochs. Therefore, if supervised learning is followed by a phase of unsupervised learning, the learning of already learned patterns is made more robust. Simultaneously, the differences between inter-classes are learned by varying the proper threshold. In the case of a network trained solely using supervised learning, the excitatory neurons mapped to class '7' can react to both class '1' and '7' input images with similar patterns. However, the excitatory neurons mapped to class '1' exhibit a relatively low threshold because they respond only to class '1'. In other words, neurons mapped to two classes react simultaneously at the beginning of the unsupervised learning session, but as the learning progresses, the classification accuracy of handwritten digits increases owing to the improvement in thresholds with the better learning of the variation between classes.

IV. CONCLUSION

In this study, we proposed an STDP-based semi-supervised learning method that sequentially applies both unsupervised and supervised learning. The proposed method employs a two-layer SNN. Additionally, inhibitory connections between teacher neurons and excitatory neurons suppress the reactions of neurons to conduct forced learning. Further, the sole execution of forced learning is the same as individual forced learning for one class. Therefore, the proposed method uses unsupervised learning in a network without teacher neurons to foster inter-class variation learning. Finally, in STDP-based learning, the difference between the spike occurrence times of a pre-synaptic neuron and a postsynaptic neuron exerts an extremely important effect on learning. The proposed method exerts a coercion effect on the connectivity but is more biologically plausible than the existing alternative as it does not enforce the normalization of synapse weights during the learning process. To measure the classification performance of the proposed method, MNIST handwritten classification, which is commonly used in existing studies, was conducted. Corresponding to identical numbers of neurons and connections, the classification performance of the proposed method was higher than that of the conventional one by 7%. Moreover, its classification accuracy converged slightly more slowly than that of the existing method during the learning process. However, in supervised learning, spikes are unconditionally generated, making learning faster than with unsupervised learning. Further, by forcing the learning to the desired position during the learning process corresponding to each occurrence of a spike at an excitatory neuron, the handwritten image recognized by the network is expressed as illustrated in Fig. 5. As a result, the class of input images is sequentially arranged and induces reactions at the desired position. Visualization of the weight values of the synapses confirms that the numbers are well represented. Finally, the proposed learning method can be applied to a heterogeneous learning model because parallel learning can be conducted on data from different fields and unsupervised learning can be applied to combine the learning results during the final learning session.

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