s-DRN: Stabilized Developmental Resonance Network

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Abstract—Online incremental clustering of sequentially incoming data without prior knowledge suffers from changing cluster numbers and tends to fall into local extrema according to given data order. To overcome these limitations, we propose a stabilized developmental resonance network (s-DRN). First, we analyze the instability of the conventional choice function during node activation process and design a scalable activation function to make clustering performance stable over all input data scales. Next, we devise three criteria for the node grouping algorithm: distance, intersection over union (IoU) and size criteria. The proposed node grouping algorithm effectively excludes unnecessary clusters from incrementally created clusters, diminishes the performance dependency on vigilance parameters and makes the clustering process robust. To verify the performance of the proposed s-DRN model, comparative studies are conducted on six real-world datasets whose statistical characteristics are distinctive. The comparative studies demonstrate the proposed s-DRN outperforms baselines in terms of stability and accuracy.

Index Terms—Online incremental learning, clustering, adaptive resonance theory (ART), scalability, stability

I. INTRODUCTION

CLUSTERING, one of unsupervised learning algorithms, aims to group data instances into a number of categories. Clustering algorithms allow the analysis of data characteristics without prior knowledge, which can be applied to memory design [1], [2], [3], [4]. Clustering includes two main types of approaches: 1) batch learning and 2) online learning. The batch learning approaches, whose representative algorithms include k-means [5] and GMM [6], are straightforward and simple to implement. However, they, in general, require a predefined cluster number from the user and all the training data to be given in advance. These features limit the application of batch learning algorithms in real-world applications where data are observed sequentially and continuously.

On the other hand, online learning approaches can handle the varying number of clusters and incrementally process continuous data. Thus, we focus on developing an effective online incremental clustering algorithm in this paper. Previous online learning approaches such as distance metric learning (DML) [7] and self-organizing incremental neural network (SOINN) [8] memorize all the given input and processing each input instance takes $O(n)$ computation. Fusion adaptive resonance theory (ART) [9] and Fuzzy ART [10] networks are efficient in the perspective of computation and memory usage, but they demand inputs to be normalized in the range of [0, 1] and the problem of node proliferation lingers [11]. Developmental resonance network (DRN) [12] has attempted to solve the two limitations, although its remedy for the normalization problem works for a certain range of input and it suffers from an inefficient grouping algorithm which is to solve the node proliferation problem.

To overcome the limitations mentioned above, we propose a stabilized developmental resonance network (s-DRN) [7]. The proposed s-DRN, free from the normalization problem, handles inputs with all scales and shows superior clustering performance. For the design of s-DRN, we first analyze the normalization problem remaining in the DRN model and solve the normalization problem by proposing a normalized node activation function. The node activation function proposed in DRN utilizes an exponential function and the activation value rapidly shrinks as the input scale increases. In such cases, DRN does not function as expected after a particular threshold scale. We propose to normalize input by the global weight vector which varies over time and the normalization problem disappears.

Next, we design a node grouping algorithm to alleviate the node proliferation problem. Since DRN and s-DRN allow unrestricted input scales, they cannot employ the complement coding scheme to prevent node proliferation and a node grouping algorithm for inhibiting node proliferation is essential. Three criteria, distance, intersection over union (IoU) and size criteria, are devised for the node grouping algorithm to effectively exclude unnecessary clusters from incrementally created clusters. In particular, we define and formulate the concept of IoU criterion for the node grouping algorithm. With the proposed IoU criterion, the node grouping algorithm becomes both scalable and stable in that the performance dependency on the vigilance parameter decreases. The proposed node grouping algorithm of s-DRN is computationally more efficient than that of DRN and s-DRN displays more effective clustering performance than conventional methods due to the proposed node grouping algorithm.

The remainder of this paper is structured as follows. Section II summarizes DRN as a preliminary. Section III proposes the s-DRN model and Section IV presents the experiment results with a thorough analysis. Concluding remarks follow in Section V.

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1Source code available at https://github.com/Uehwan/Incremental-Learning
II. DEVELOPMENTAL RESONANCE NETWORK

In this section, we briefly delineate the computation flow of the DRN model as a preliminary.

A. Global Weight Update

DRN utilizes a global weight vector \( \mathbf{w}_g = [w_{g1}, ..., w_{cg}] \), where \( c \) is the number of channels and \( k \mathbf{w}_g = [w_{g1}, ..., w_{g2}] \) to cope with unknown scales of multi-channel inputs, which gets updated as follows:

\[
k_{\mathbf{w}_g}^{(\text{new})} = \begin{cases} 
    k_{\mathbf{x}_i}^{(\text{old})}, & \text{if } i = 1 \\
    k_{\mathbf{w}_g}^{(\text{old})}, & \text{if } i \neq 1 \text{ and } d(k_{\mathbf{w}_g}^{(\text{old})}, k_{\mathbf{x}_i}) = 0 \\
    (1 - k_{l_g})k_{\mathbf{w}_g}^{(\text{old})} + k_{l_g}(k_{\mathbf{x}_1} \land k_{\mathbf{w}_g}^{(\text{old})}, k_{\mathbf{x}_i} \lor k_{\mathbf{w}_g}^{(\text{old})}), & \text{if } i \neq 1 \text{ and } d(k_{\mathbf{w}_g}^{(\text{old})}, k_{\mathbf{x}_i}) 
eq 0
\end{cases}
\]

where \( \mathbf{k}_x_i \) is the \( i \)-th step input of the \( k \)-th channel and \( k_{l_g} \in (0, 1] \) is the learning rate of \( k_{\mathbf{w}_g} \).

B. Node Activation

The input \( k_{\mathbf{x}_i} \) activates the \( j \)-th node as follows:

\[
T_j = \sum_{k=1}^{c} (k_{\gamma} f(d(k_{\mathbf{x}_i}, k_{\mathbf{w}_j}))) = \sum_{k=1}^{c} (k_{\gamma} \exp(-\alpha d(k_{\mathbf{x}_i}, k_{\mathbf{w}_j}))),
\]

where \( k_{\gamma} \) is a contribution parameter and \( \alpha \) is a slope parameter, \( f(x) = \exp(-\alpha x) \) is the choice function that normalizes the activation value \( T_j \) to \( T_j \in [0, 1] \), and \( d(k_{\mathbf{x}_i}, k_{\mathbf{w}_j}) \) is the distance between \( k_{\mathbf{x}_i} \) and the weight vector \( k_{\mathbf{w}_j} \).

C. Template Matching

The template matching process identifies if the node with the largest activation value (say \( J \)-th node) resonates with the activity vector \( \mathbf{x}_i \). First, the ratio \( L_{c}(k_{\mathbf{x}_i}, k_{\mathbf{w}_j}) = S_{c}(k_{\mathbf{x}_i}, k_{\mathbf{w}_j})/k_M \) between the two vectors \( k_{\mathbf{x}_i} \) and \( k_{\mathbf{w}_j} \) for each element \( e \) (\( e = 1, 2, ..., k_{z} \) and \( k_{z} \) is the dimension of the \( k \)-th channel) is calculated using the global diagonal vector \( k_M = k_{\mathbf{w}_g2} - k_{\mathbf{w}_g1} \) of the \( k \)-th channel and the decision diagonal vector \( S_{c}(k_{\mathbf{x}_i}, k_{\mathbf{w}_j}) = k_{x_i} \land k_{\mathbf{w}_j2} - k_{x_i} \lor k_{\mathbf{w}_j1} \) of the \( J \)-th node.

Then, the resonance condition is defined as

\[
k_{m_{j}} = \frac{k_2 - |L(k_{\mathbf{x}_i}, k_{\mathbf{w}_j})|}{k_2} \geq k_{\rho},
\]

where \( k_{m_{j}} \in [0, 1] \) is a resonance value, \( L(k_{\mathbf{x}_i}, k_{\mathbf{w}_j}) = [L_{c}(k_{\mathbf{x}_i}, k_{\mathbf{w}_j}) | e = 1, ..., k_z] \), and \( k_{\rho} \in [0, 1] \) is a vigilance parameter.

D. Template Learning

If the \( J \)-th node has resonated in the template matching process, the weight \( k_{\mathbf{w}_j} \) gets updated by

\[
k_{\mathbf{w}_j}^{(\text{new})} = (1 - k_l)k_{\mathbf{w}_j}^{(\text{old})} + k_l[(k_{\mathbf{x}_i} \land k_{\mathbf{w}_j}^{(\text{old})}, k_{\mathbf{x}_i} \lor k_{\mathbf{w}_j}^{(\text{old})})],
\]

where \( k_l \in (0, 1] \) is the learning rate of the \( k \)-th channel.

E. \( \nu \)-Node Selection and Connection

After the node activation process, DRN selects the largest \( \nu \) nodes and connects them to improve the efficiency of the following grouping process. \( \nu C_2 \) connections are created if \( x_i \) has updated \( w_j \) or \( \nu + 1 \) \( C_2 \) connections if \( x_i \) has created a new node. Moreover, DRN defines the center point vector for the \( i \)-th node \( p_i = (1/2)(w_{i1} + w_{i2}) \) and the concept of synaptic strength \( T_{i,j} = \exp(-\alpha |p_i - p_j|) \) that represents the strength of the connection between \( i \)-th and \( j \)-th nodes.

F. Node Grouping

In the final computation step, DRN iterates through the connected nodes in the order of the synaptic strength. DRN groups a pair of nodes if the two nodes in the pair resonate satisfying the condition in (3) and stops iteration.

III. s-DRN

In this section, we describe the proposed s-DRN, summarized as Algorithm 1 with the proposed activation function for scalability and the node grouping algorithm for stability. Moreover, we analyze the computational efficiency of the proposed s-DRN.

A. Scalability

First, we analyze the normalization problem that remains with (2). For the exponential function to perform as a distance normalization function, it should satisfy the following condition:

\[
k_{\gamma} \exp(-\alpha d(k_{\mathbf{x}_i}, k_{\mathbf{w}_j})) \geq \delta,
\]

where \( \delta \) is the minimum value a processor supports. (5) reduces to

\[
d(k_{\mathbf{x}_i}, k_{\mathbf{w}_j}) \leq \frac{1}{\alpha} \ln\left(\frac{k_{\gamma}}{\delta}\right).
\]

As modern 64-bit processors support \( \delta = 10^{-310} \) and \( (\alpha, \gamma) = (0.1, 0.1) \) represents a commonly-used value set, the distance \( d(k_{\mathbf{x}_i}, k_{\mathbf{w}_j}) \) should be approximately less than 10,000 for the conventional activation function to perform normally. Otherwise, the clustering performance degrades dramatically (Fig. 1).

To overcome the limitation and the normalization problem, we propose a scalable activation function as follows.

\[
T_j = \sum_{k=1}^{c} k_{\gamma} \exp\left(-\frac{\alpha d(k_{\mathbf{x}_i}, k_{\mathbf{w}_j})}{k_M}\right).
\]

With the proposed activation function, s-DRN can handle all scales of input since \( k_{\gamma} \exp\left(-\frac{\alpha d(k_{\mathbf{x}_i}, k_{\mathbf{w}_j})}{k_M}\right) > \delta \) is invariably satisfied.
B. Node Grouping

We propose a node grouping algorithm to mitigate the performance instability attributed to data input order and the dependency on vigilance parameters. The proposed node grouping process compares the activated cluster with nearby clusters when an input vector arrives and groups a pair if two clusters in the pair satisfy three criteria: distance, IoU and size criteria. The three conditions are examined over all channels and all the channels should satisfy each condition for the examination of the next condition.

For the formulation of the criteria, let \( R_i \) and \( R_j \) denote a pair of neighboring clusters (Fig. 2). The weight vectors representing each cluster for the \( k \)-th channel are:

\[
R_i = \{ k w_i; w_{i1}; ...; w_{ik} \} \quad \text{and} \quad R_j = \{ k w_j; w_{j1}; ...; w_{jk} \},
\]

where \( c \) is the number of channels and semicolon represents concatenation. We define the distance vector between a pair of clusters as

\[
d_{ij} = ( d_{i1}, d_{i2}, ...; d_{c} ),
\]

where each element of the vector is defined as

\[
k d_{ij} = \min( |k w_i - k w_j|; |k w_i1; ...; k w_{ik} - k w_{jk}| ),
\]

where \( \min() \) operator chooses the minimum element of a vector. The proposed distance criterion is

\[
\max(d_{ij}) < 1 - \rho,
\]

where \( \max() \) operator chooses the maximum element of a vector and \( \rho \) is a vigilance parameter for the template matching. Note that in s-DRN, \( \rho \) is used instead of \( k \rho \) due to unnecessity of vigilance parameter for each channel.

We propose the IoU criterion since the distance criterion can become loose and combine all the clusters when a low valued vigilance parameter is used. The IoU criterion tests if the hypothetically grouped cluster could encompass the two compared clusters with the least extension. This guarantees the grouped cluster does not occupy un-investigated feature space substantially. The below represents the hypothetically grouped cluster for the \( k \)-th channel:

\[
k R_i \oplus k R_j = \{ k w_i; w_{i1}; ...; w_{ik} \} \cup \{ k w_j; w_{j1}; ...; w_{jk} \},
\]

For each category cluster, we define the volume of the \( k \)-th channel as

\[
k V_j = \prod_{y=z}^{dim(k w_j)} (k w_{j2} - k w_{j1} y),
\]

Next, we define the IoU criterion for the \( k \)-th channel as

\[
\text{IoU}(k R_i, k R_j) = \frac{k V_i + k V_j}{k V_{i \oplus j}} > \tau,
\]

where \( \tau \) determines the final threshold for the grouping process. The range of IoU value is in \([0,2]\) and we set \( \tau \) as 0.85.

The size criterion limits the maximum size of a category cluster. Excessively large clusters resulted from node grouping hinder the normal template matching process. Thus, we limit the size of a cluster. The maximum size of the \( j \)-th cluster for the \( k \)-th channel \( |k w_{j2} - k w_{j1}| \) is limited to \( k M(1 - \rho) \), which is congruent to \( c \).

C. Computational Efficiency

The computational complexity of fusion ART on which DRN is based is \( T(n) = h z n \), where \( h \) is the number of categories, \( z \) is the dimension of the input, and \( n \) is the number of data samples. With its grouping algorithm, the computational complexity of DRN becomes

\[
T(n) = (h z + v(v - 1)/2) n + m q,
\]

Fig. 1. Clustering results of DRN and s-DRN on example 2D synthetic data. Black lines indicate the global weight areas and blue lines represent each cluster weight boundary. As the input scale increases, DRN could not perform due to the instability with \( c \) while s-DRN shows robust performance.
where \( m \) and \( q \) are the average numbers of global weight updates and connected category pairs, respectively.

On the other hand, the computational complexity of s-DRN is

\[
T(n) = (hz)n + hz. 
\] (16)

The increase of computation \( hz \approx O(h) \) with s-DRN is minuscule compared to that of DRN which is \((1/2)v(v - 1)n + mq \approx O(n)\).

### Algorithm 1 s-DRN algorithm

Input: Training data \( x_i \), hyper-parameters: \( \rho, \tau, l \)

Output: Clustered data

1. Calculate the distance \( d(x_i, w_g) \)
2. if \( d(x_i, w_g) \neq 0 \) then
3. Update the global weight vector \( w_g \) by (1)
4. end if
5. Calculate the activation value \( T_j(x_i) \) using (7)
6. Select the node \( J \) with the largest activation value
7. Calculate the resonance value \( m_J \) using (3)
8. if \( m_J \geq \rho \) then
9. Update the weight \( w_J \) by (4)
10. break
11. else
12. Generate a new cluster, and initialize the value of the weight to \( x_i \)
13. end if
14. for \( j = 1 \) to \( h \) do
15. Calculate criteria values between clusters \( J \) and \( j \)
16. Achieve grouping flag \( flag_{gr} \) from grouping criteria
17. end for
18. if \( flag_{gr} \) then
19. Group cluster \( J \) and the indexed cluster
20. end if

### IV. Experiments

In this section, we illustrate the experiment setting for performance verification and establish the effectiveness of the proposed s-DRN model.

#### A. Experiment Setting

1) Datasets: We retrieved six real-world benchmark datasets from the UCI machine learning repository encapsulating a variety of problems, including credit approval, bank note authentication, car evaluation, wholesale customers and informed customers datasets. We attentively selected the set of datasets so that each dataset fairly differs in the size of the dataset, the number of clusters, input dimensions, and scale ranges.

2) Metrics: For quantitative analysis, we employed three performance metrics. First, Davies-Bouldin index (DBI) [14] estimates the ratio of within-cluster scatter to between-cluster separation as follows:

\[
DBI = \frac{1}{K} \sum_{k=1}^{K} \max_{j \neq k} \left( \frac{\sigma_k + \sigma_j}{d(\mu_k, \mu_j)} \right),
\] (17)

where \( K \) is the cluster number, \( \mu_k \) is the center point of cluster \( k \), \( \sigma_x \) is the average distance of every element \( x \) in a cluster to \( \mu_x \) and \( d(\mu_k, \mu_j) \) is the distance between \( \mu_k \) and \( \mu_j \). The lower value of DBI indicates higher clustering performance.

Next, clustering purity (CP) [15] matches each output cluster to the ground-truth cluster as follows:

\[
CP(\Omega, C) = \frac{1}{N} \sum_{k=1}^{K} \max_{j=1}^{C} |w_k \cap c_j|,
\] (18)

where \( \Omega = \{w_1, w_2, ..., w_K\} \) is the set of clusters and \( C = \{c_1, c_2, ..., c_J\} \) is the set of ground-truth classes. Since a large number of clusters can bias CP, we complemented CP with normalized mutual information (NMI) [16] which is defined as

\[
NMI(\Omega, C) = \frac{2 \times I(\Omega; C)}{H(\Omega) + H(C)},
\] (19)

where \( H \) is entropy and \( I(\Omega; C) \) is mutual information between \( \Omega \) and \( C \). Both CP and NMI lie in the range \([0, 1]\), where a larger value implies higher performance.

3) Baseline: For comparative studies, we employed three baseline algorithms: \( k \)-means [5], GMM [6] and DRN [12]. \( k \)-means and GMM are two representative batch-based clustering algorithms and the number of clusters should be given in advance. On the other hand, DRN and s-DRN are online learning algorithms and the number of clusters increases in an incremental manner.

[https://archive.ics.uci.edu/ml/index.php](https://archive.ics.uci.edu/ml/index.php)
4) Implementation Detail: To reduce the effect of randomness, we conducted each experiment 100 times and report the average and the standard deviation of each metric. In addition, each experiment received the data instances in different orders. For k-means and GMM, we split the datasets into train and test sets with the ratio of 5:5. We set the ratio, which showed the best performance for k-means and GMM after sweeping the ratio from 1:9 to 9:1. Moreover, we provided k-means and GMM with the ground-truth cluster numbers.

For DRN and s-DRN, we sequentially input data instances and did not provide the ground-truth cluster numbers. We set one vigilance parameter, \( \rho \) for both DRN and s-DRN. Parameters were obtained using the follow metric:

\[
T_j = \sum_{k=1}^{c} (\xi_d(DBI) + \xi_c(1 - CP) + \xi_n(1 - NMI))
\]

where \( \xi_d, \xi_c \) and \( \xi_n \) are reciprocals of standard deviations of DBI, CP and NMI, respectively. We swept the vigilance from 0.1 to 0.9 and found the best value (0.7 and 0.5 for DRN and s-DRN, respectively) according to (20). We use one vigilance parameter since vigilance parameter cannot be fine-tuned in the real-world setting. In the real-world setting, no prior knowledge of dataset is given and data instances come sequentially.

B. Results and Analysis

Table I summarizes the results of comparative studies. s-DRN consistently displays superior performance over all six datasets achieving small values for DBI and large values for CP and NMI. We note that s-DRN outperforms k-means and GMM on average although k-means and GMM were given the ground-truth cluster numbers and half of each dataset was given as a training set. The comparative studies corroborate that s-DRN guarantees satisfactory clustering performance in an online incremental manner compared to batch-based clustering algorithms. Moreover, the performance of s-DRN surpasses that of DRN over all six datasets, which verifies the effectiveness of the proposed node grouping algorithm.

Particularly, the performance gap between DRN and s-DRN is the largest for the wholesale customer dataset. The large input scale of the dataset interrupts DRN’s activation function and its performance deteriorates sharply. The result of the wholesale customer dataset confirms that the proposed activation function truly resolves the normalization problem. Fig. 3 further investigates the effect of input scale on the clustering performance. We tested each algorithm on the liver disorder dataset and varied the scale from \( \times 1 \) to \( \times 100,000 \). The effect of input scale on other algorithms including s-DRN is insignificant while the performance of DRN gets sensitively affected.

Fig. 4 illustrates the effect of the vigilance parameter on clustering performance for DRN and s-DRN. For all six datasets, we varied the vigilance parameter from 0.1 to 0.9 and observed the performance variation in DBI. As the figure exhibits, the clustering performance of s-DRN is stable over all vigilance values in all six datasets. However, the clustering performance of DRN strongly depends on the value of the vigilance parameter. For quantitative analysis, we report the averages of standard deviations of DBI scores for DRN and s-DRN, which are 0.307 and 0.143, respectively.

V. Conclusion

In this paper, we proposed a resonance-based online incremental clustering network, s-DRN, which is a stabilized model of DRN. The proposed s-DRN model resolves the normalization problem remaining in conventional methods with the proposed activation function. Thus, s-DRN can effectively handle all input scales. Moreover, s-DRN equipped with the proposed node grouping algorithm becomes robust to variation of vigilance parameter, and the need for fine-tuning vigilance parameter disappears. In addition, the clustering performance improves with the proposed node grouping algorithm. A thorough examination of s-DRN through experiments on six real-world benchmark datasets established the effectiveness of s-DRN. We expect s-DRN can be applied to various real-world settings where no prior knowledge on sequentially incoming data is given.

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TABLE I

| Algorithm | Balance Scale | Liver Disorder | Blood Transfusion |
|-----------|---------------|----------------|-------------------|
|           | DBI | CP | NMI   | DBI | CP | NMI   | DBI | CP | NMI   |
| $k$-means | 1.6059 | 0.6805 | 0.1592 | 1.1229 | 0.3526 | 0.1483 | 0.4588 | 0.7620 | 0.0535 |
|           | (0.0266) | (0.0198) | (0.0510) | (0.1690) | (0.0176) | (0.0121) | (0.0416) | (0.0146) | (0.0048) |
| GMM       | 1.6562 | 0.6899 | 0.1383 | 1.7940 | 0.3364 | 0.1069 | 0.8218 | 0.7534 | 0.0130 |
|           | (0.0475) | (0.0265) | (0.0625) | (0.3177) | (0.0025) | (0.0180) | (0.0065) | (0.0004) | (0.0011) |
| DRN       | 1.0865 | 0.6734 | 0.1459 | 1.0624 | 0.3426 | 0.0594 | 0.5851 | 0.7614 | 0.0264 |
|           | (0.1546) | (0.0425) | (0.0280) | (0.5307) | (0.0037) | (0.0190) | (0.1452) | (0.0029) | (0.0081) |
| s-DRN     | 1.0707 | 0.8137 | 0.2572 | 0.6951 | 0.3642 | 0.1309 | 0.4802 | 0.7679 | 0.0306 |
|           | (0.0622) | (0.0230) | (0.0185) | (0.1266) | (0.0134) | (0.0341) | (0.0609) | (0.0010) | (0.0029) |

Fig. 4. Effect of vigilance parameter on clustering performance for DRN and s-DRN. Vigilance parameter value was varied from 0.1 to 0.9 for performance measurement.

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