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Deep learning algorithm featuring continuous learning for modulation classifications in wireless networks

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Abstract： Although modulation classification based on deep neural network can achieve high Modulation Classification(MC) accuracies, catastrophic forgetting will occur when the neural network model continues to learn new tasks. In this paper, we simulate the dynamic wireless communication environment and focus on breaking the learning paradigm of isolated automatic MC. We innovate a research algorithm for continuous automatic MC. Firstly, a memory for storing representative old task modulation signals is built, which is employed to limit the gradient update direction of new tasks in the continuous learning stage to ensure that the loss of old tasks is also in a downward trend. Secondly, in order to better simulate the dynamic wireless communication environment, we employ the mini-batch gradient algorithm which is more suitable for continuous learning. Finally, the signal in the memory can be replayed to further strengthen the characteristics of the old task signal in the model. Simulation results verify the effectiveness of the method.

Keywords： Deep Learning(DL)；modulation classification；continuous learning；catastrophic forgetting；cognitive radio communications

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1 Introduction

In the 21st century, DL technologies emerge with the continuous expansion of big data and the constant improvement of computing power[1]. By learning the inherent laws and representation features from raw data, DL enables agents to 'imitate' human activities, such as visual recognition, logical reasoning, and the performance is often much better than that of the traditional Machine Learning(ML) algorithms[2]. Therefore, the world enters an era of Artificial Intelligence(AI). Naturally, scientists begin to import DL methodologies into the field of wireless radio communications, aiming to design an intelligent communication system. MC is one of the attempts equipping the wireless communication system with cognitive abilities.

More explicitly, MC is the intermediate link of signal detection and demodulation, which helps the radio transceiver to recognize the surrounding wireless signals. Traditional MC algorithms, such as K-Nearest Neighbor(KNN)[3], Decision tree classifier[4], Support Vector Machine(SVM)[5] etc., often rely on experts' knowledge to establish decision rules for distinguishing various signaling. Generally speaking, MC algorithms can be divided into two categories: Likelihood-Based (LB) methods and Feature-Based(FB) methods[6]. The LB approaches calculate the statistical characteristics of the received signals, which are compared with appropriate thresholds to reach a decision[7]. Whereas, the FB methods can be regarded as a cognitive process. After extracting the various features of the incoming data, the classifier facilitates the cognition process through distinguishing data attributes[8].

The breakthrough of DL enables a new perspective in achieving MC. More explicitly, Neural Network(NN) classifiers can establish multi-layer perception networks for complex time domain radio signals, which can learn intricate features and realize effective signal classifications through the estimation of feature posteriori probability[9-10]. In order to extract complex data features more accurately, experts begin to play with various neural network models, such as Residual Network(ResNet), Dense convolution Network(DenseNet), Long-and Short-Term Memory(LSTM) neural network, etc. The accuracy of recognition is usually utilized to reflect the effectiveness across different DL models[11-13]. Furthermore, DL models designed for MC that combine the temporal and spatial layers are also investigated in[14].

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Although these DL models demonstrate a super–human ability in individual tasks, such as AlphaGo[15], the above–mentioned DL models suffer from the problem of 'catastrophic forgetting'[16–17]. That is, when a model learns multiple tasks at different time, the model almost completely forgets what it has learned before. Ideally, the learning system must be able to continuously acquire new knowledge, at the meantime it should also prevent new data input from significantly interfering with existing knowledge. This problem is also defined as the Stability–Plasticity problem[18]. Therefore, the aim of this paper is to overcome the fatal issue of catastrophic forgetting in MC tasks when using DL models. We will use a technique called continuous learning to address this problem. Continuous learning is also known as lifelong learning[19], sequential learning[20], or incremental learning[21].

At first, people use multi–task training methods to solve catastrophic forgetting, which means training samples are scrambled and randomly selected. Thus, data distribution would be approximately independent and identically distributed (i.i.d.). However, new tasks' data are unpredictable and essentially non–i.i.d. in the time domain[22]. Later, experts try a number of techniques, such as reducing overlap[23], replaying the past samples or virtual samples[24], introducing a dual architecture[25]. However, these works are mainly designed for a small dataset, while using a shallow neural networks architecture. In addition, the effects of dropout and different activation functions on catastrophic forgetting are studied[26].

Furthermore, Silver et al. in [27] first proposed the idea of using the output of previous task model to improve the performance of new tasks, the proposed Task Rehearsal Method(TRM) uses previously learned tasks as the source of inductive bias. Later, the replaying method is inspired by TRM. This family of algorithms use the stored samples of previous task or use the generative models to prevent the interference of previous tasks[28–29]. Moreover, Incremental Classifier and Representation Learning(ICaRL) is the first playback method, which selects and stores the samples closest to the characteristic average value of each class[30], whereas Gradient based Sample Selection(GSS) selects the sample subset closest to the feasible area of historical data to constrain the optimization of new tasks[31].

In addition, regularization methods can also solve the problem of catastrophic forgetting. By estimating the importance of different parameters of NN, new model parameters are encouraged to be as close to old model parameters as possible, which strengthens the role and mechanism of synapse in memory preservation. From a computational point of view, it is actually modeling the loss function of the new task by adding a regular term, which can punish the change of the neural network mapping function[32–33]. Elastic Weight Consolidation(EWC)[34] is the first method to build on this idea, and the first continuous learning algorithm migrated to address the challenge of MC. However, EWC still has the dilemma that learning new knowledge comes with the price of forgetting the old. It just happens slower. On the other hand, Memory Aware Synapses(MAS) redefines the parameter importance measurement as an unsupervised setting[35]. In [36], the parameter subset is iteratively assigned to continuous tasks by constructing binary masks, which is called parameter isolation method. It is also of great significance to the field of continuous learning.

In this paper, we envisage a continuous learning algorithm for MC that learning between different tasks should promote each other. That is, the proposed learning algorithm can prevent new data input from interfering with the existing knowledge. More explicitly, this paper solves the problem of catastrophic forgetting by creatively applying the concept of Gradient Episodic Memory(GEM)[37]. The contributions of this paper are listed as follows:

1) To the best of our knowledge, this paper is the first DL algorithm that embodies the spirit of GEM to facilitate continuous learning, which is specifically tailored for MC.

2) Firstly, a memory storing selective data of previous tasks is established at the MC classifier, which will be used by the proposed GEM to evaluate the proper gradient update direction with the consideration of both the old and new tasks.

3) Secondly, in order to further improve the MC accuracy of old tasks, the data in memory can be replayed during the training of new tasks.

4) Finally, the proposed GEM algorithm can work with any DL neural networks, because it focuses on gradient update for continuous learning tasks, rather than DL architecture.

2 Deep learning based on MC

2.1 Problem formulation

In this paper, we study two continuous learning tasks, and define the old task as Task–A and the new task as Task–B.

When there is only Task-A in the classification task, the receiver can use a DL based MC classifier to do the work with high precision giving adequate training data. At this time, the neural network model structure contains the characteristics of Task-A signal. However, when a new set of signals is introduced, catastrophic forgetting will occur. In other words, the neural network model learning new Task-B will cover the characteristics of old Task-A. At this time, the receiver mainly contains the features of new Task-B and some features of old Task-A, as shown in Fig.1.

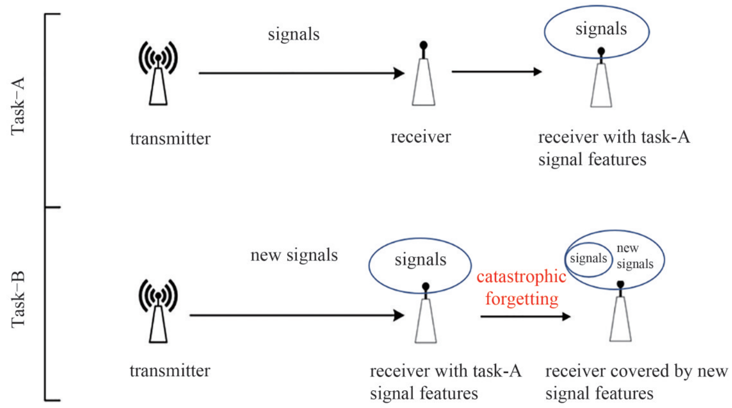

Fig.1 The problem of catastrophic forgetting

For the sake of comparison, the open-source RadioML2016.10b dataset[38] is employed to evaluate the classification tasks of Table 1, which covers the range of SNR from −20 dB to 18 dB in 2 dB increments. For each SNR, each modulation type contains 6 000 frames and the length of the frame is 128 samples. We consider different modulation schemes used by different types of users transmitting on a single channel, as seen in Fig. 1. Different user types are known and we categorize modulations into four types, which are listed in Table 1.

Table1 Allocation of modulation types

tasks	Task-A	Task-B
primary user	AM-DSB, BPSK, GFSK	QAM64, WBFM
secondary user	8PSK, PAM4	CPFSK
idle	no signal	no signal
illegal user	QAM16	QPSK

There are primary users(granted with top priority in channel usage), secondary users(granted access when the channel is idle), idle and illegal users. The receiver in Fig. 1 is responsible for monitoring the channel state(idle or not) and coordinating the primary and secondary users, while denying the access of illegal users. The classifier basically computes a likelihood score for classifying signals as idle, primary user, secondary user, and illegal user, respectively. If one score is larger than the other three, the instance is classified as the corresponding case in MC.

2.2 **DL classifier**

The research of this paper is based on the background of dynamic wireless modulation signal transmission, which means that there are many signals to send and receive. In addition, dynamic continuous learning puts forward higher requirements for the feature level of the signal to be extracted.

Therefore, we design a custom deep neural network that takes I/Q samples from RadioML2016.10b as input, which is plotted in Fig. 2. Firstly, the input signals are processed using LSTM layers having 128 units, so that the signal correlations and dependencies in time domain can be explored in this recursive neural network layer. Then, high level signal features are extracted by convolution layers consisting of 256 stacked filters having kernel size of 3, which means the signal features are jointly considered both in spatial and temporal domains. This architecture is referred as Long and short-term memory Convolution fully connected Depth Neural Network(LCDNN)[14]. The output layer has 4 neurons representing four classification types of Table 1.

The LCDNN model outputs a probability distribution with a sum of 1 using Softmax operation, and then determines the proximity between the actual output and the expected output through the cross-entropy loss function. From the perspective of probability theory, the cross-entropy $L(\cdot)$ between the real classification distribution p and the estimated distribution q is defined as:

$$L(p,q)=-\sum_{x}p(x)\ln q(x) \tag{1}$$

where x represents data.

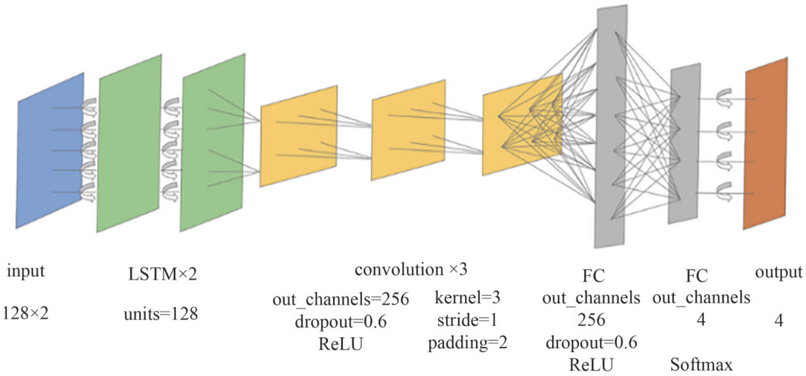

Fig.2 LCDNN designed for MC

2.3 Catastrophic forgetting

When the LCDNN model of Fig. 2 is assigned to only the Task–A of Table 1, the MC accuracy is plotted in Fig. 3. Not surprisingly, high MC accuracy can be achieved with the increase of SNR. The same is true, when only Task–B of Table 1 is shown to the LCDNN model. However, when the LCDNN or any conventional DL models have to learn a new task, i.e. first learn Task–A then trained with new Task–B, the MC accuracy of the old Task–A dropped sharply, as seen in the red solid circle line in Fig.3.

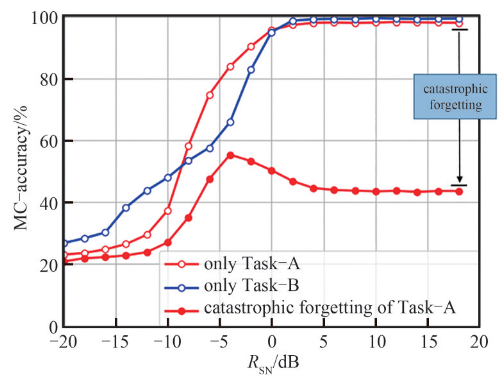

Fig.3 The classification accuracy using LCDNN model, when trained with only Task–A or Task–B, and the catastrophic forgetting of Task–A when trained with Task–B after Task–A

On one hand, it is difficult to change the applied neural network model once it is determined in the training process, which means that the model capacity is limited. When the model has new input, the limited capacity will be divided. On the other hand, the optimization objectives of different tasks are different, and the parameters of neural network are related to the characteristics of each dimension of input. Because neurons can be defined as global variables, the subtle changes of neurons may change the parameters and output of the whole neural network. This is the catastrophic forgetting problem we intend to address in this paper.

3 Proposed continuous learning algorithm

In this section, we introduce the improved GEM algorithm to facilitate continuous learning for MC using the LCDNN model of Section 2. Please notice that the proposed GEM method can work with any DL classifiers. For the sake of simplicity, we just use the LCDNN model to illustrate the idea of GEM.

The primary idea of GEM is to have a Memory(M) at the DL classifier storing part of Task–A's data, which can be employed to limit the gradient update direction of new tasks, i.e. Task–B, during continuous learning. Besides, we can also replay specially selected memory data during the training of future tasks to further combat the problem of catastrophic forgetting. When selecting representative data for storing in memory, we use NearMiss–3 under–sampling algorithm[39], which selects the nearest K majority samples for each minority sample. Hence, each minority sample is surrounded by the majority samples. The loss function $L(\cdot,\cdot)$ for M of previous task is defined as:

$$L(f_\theta, M) = \frac{1}{|M|} \sum_{(x_i, y_i) \in M} L\left[f_\theta(x_i), y_i \right] \tag{2}$$

where f_θ is the parameterized neural network, x_i represents data and y_i represents the corresponding label.

In the process of learning new task(Task–B), we ensure that the data in the memory(Task–A)'s gradient descending direction is roughly the same as that of the new task, so as to ensure that M always presents an optimized working mechanism to avoid catastrophic forgetting. In this way, the training of Task–B is not contradicting with the interest of Task–A, which can be mathematically written as:

$$\begin{cases} \min L(f_\theta(x_{\text{Task}-\text{B}_{\text{train}}}), y_{\text{Task}-\text{B}_{\text{train}}}) \\ \text{s.t.} \;\; L(f_\theta^{T-1}, M) \geqslant L(f_\theta^{T}, M) \end{cases} \tag{3}$$

where ${f_\theta}^T$ is the model state at the T–th gradient update epoch. Equation (3) ensures that the loss for memory data of previous task demonstrates a downward trend every time after the gradient of Task–B $\boldsymbol{g}$ is updated.

In the process of optimizing the neural network model, the gradient descent method is usually employed to solve the minimum loss, so as to obtain the model parameters. Therefore, we use the relationship between gradient and loss function to achieve the goal of equation (3). From a mathematical point of view, we can calculate the angle between $\boldsymbol{g}$ and the gradient in memory $\boldsymbol{g}_{\text{m}}$(Task–A) as the following,

$$\left\langle \boldsymbol{g}, \boldsymbol{g}_{\text{m}} \right\rangle = \left\langle \frac{\partial L(f_\theta(x_{\text{Task}-\text{B}_{\text{train}}}), y_{\text{Task}-\text{B}_{\text{train}}})}{\partial \theta}, \frac{\partial L(f_\theta(x_m), y_m)}{\partial \theta} \right\rangle \geqslant 0 \tag{4}$$

When the equation (4) is satisfied, it indicates that the included angle between $\boldsymbol{g}$ and $\boldsymbol{g}_{\text{m}}$ is an acute angle, and the $\boldsymbol{g}$ direction is the loss decreasing direction, which means that the loss in M shows a downward trend. Hence, the requirement of equation (3) is guaranteed. On the contrary, when the included angle between $\boldsymbol{g}$ and $\boldsymbol{g}_{\text{m}}$ is an obtuse angle, the $\boldsymbol{g}$ direction is the loss increasing direction. However, when equation (4) cannot be satisfied, we project $\boldsymbol{g}_{\text{m}}$ to the nearest direction in order to satisfy equation (4). The projection region is the right–angle feasible region outlined by $\boldsymbol{g}_{\text{m}}$, so the included angle between $\boldsymbol{g}_{\text{m}}$ and the gradient of Task–B is an acute angle, as shown in Fig.4.

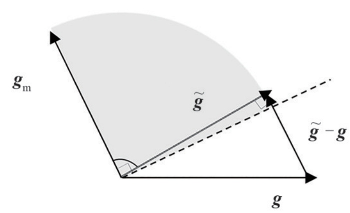

Fig.4 The projection of the gradient of Task–B in order to satisfy equation (4)

Algorithm: proposed GEM

Procedure function(TRAIN, VALIDATE, TEST)

  for p=epoch 1, epoch 2,$\cdots$,epoch 80

    TRAIN (f_θ, Task–B$_{\text{train}} \cup M$)

      $M \in$Task–A$_{\text{train}}$

      for t=batch 1,batch 2,$\cdots$,batch X

        (x, y) in Task–B$_{\text{train}}$ U $M(t)$ & (x_m, y_m) in $M(t)$

        $\boldsymbol{g} \leftarrow \nabla_\theta l(f_\theta(x), y)$

          $\boldsymbol{g}_m \leftarrow \nabla_\theta l(f_\theta(x_m), y_m)$

            if $\boldsymbol{g} \cdot \boldsymbol{g}_m \geqslant 0$

              $\theta \leftarrow \theta - lr \cdot \boldsymbol{g}$

            else

              $\tilde{\boldsymbol{g}} \leftarrow$PROJECT $\boldsymbol{g}$

              $\theta \leftarrow \theta - lr \cdot \tilde{\boldsymbol{g}}$

      end for t

    VALIDATE (f_θ, Task–B$_{\text{val}}$)

      if Evaluate(f_θ, Task–B$_{\text{val}}(p-1)$)<(f_θ, Task–B$_{\text{val}}(p)$)

return $f_\theta(p)$
end for p
return f_θ
TEST (f_θ, Task-A$_{test}$,Task-B$_{test}$)
Task-A$_{continual_learning}$←Evaluate(f_θ, Task-A$_{test}$)
Task-B$_{continual_learning}$←Evaluate(f_θ, Task-B$_{test}$)
return Task-A$_{continual_learning}$, Task-B$_{continual_learning}$
end Procedure

The projection vector $\tilde{\boldsymbol{g}}$ is located by minimizing the vertical distance, which is defined as follows:

$$\begin{cases}\min|\tilde{\boldsymbol{g}}-\boldsymbol{g}| \\ \text{s.t. } (\tilde{\boldsymbol{g}},\boldsymbol{g}_m)\geqslant 0\end{cases} \tag{5}$$

The above problem can be solved by Quadratic Programming(QP) of inequality[40]. Namely,

$$\begin{cases}\min f(\boldsymbol{x})=\dfrac{1}{2}\boldsymbol{x}^{\mathrm{T}}\boldsymbol{P}(\lambda)\boldsymbol{x}+\boldsymbol{q}(\lambda)\boldsymbol{x} \\ \text{s.t. } \boldsymbol{A}\boldsymbol{x}\geqslant\boldsymbol{b} \\ \boldsymbol{x}=Q_F(\boldsymbol{P},\boldsymbol{q},\boldsymbol{A},\boldsymbol{b})\end{cases} \tag{6}$$

where $\boldsymbol{P}\in\mathbf{R}^{n\times n},\boldsymbol{q}\in\mathbf{R}^n,\boldsymbol{A}\in\mathbf{R}^{m\times n},\boldsymbol{b}\in\mathbf{R}^m$. Furthermore, for our GEM QP problem, equation (5) can be transformed into：

$$\begin{cases}\min\dfrac{1}{2}\|\tilde{\boldsymbol{g}}-\boldsymbol{g}\|_2^2 \\ \text{s.t. } \left\langle\tilde{\boldsymbol{g}}\cdot\boldsymbol{g}_m\right\rangle\geqslant 0\end{cases} \tag{7}$$

which is equivalent to:

$$\begin{cases}\min\ \dfrac{1}{2}\boldsymbol{u}^{\mathrm{T}}\boldsymbol{u}-\boldsymbol{g}^{\mathrm{T}}\boldsymbol{u}+\dfrac{1}{2}\boldsymbol{g}^{\mathrm{T}}\boldsymbol{g} \\ s.\text{t. } \boldsymbol{G}\cdot\boldsymbol{u}\geqslant 0,\boldsymbol{G}=-\boldsymbol{g}\end{cases} \tag{8}$$

Thus, the gradient projection problem is transformed into a dual form as follows, where $\boldsymbol{u}=\boldsymbol{G}^{\mathrm{T}}\boldsymbol{\lambda}+\boldsymbol{g}$：

$$\begin{cases}\min\ \dfrac{1}{2}\boldsymbol{\lambda}^{\mathrm{T}}\boldsymbol{G}\boldsymbol{G}^{\mathrm{T}}\boldsymbol{\lambda}+\boldsymbol{g}^{\mathrm{T}}\boldsymbol{G}^{\mathrm{T}}\boldsymbol{\lambda} \\ \text{s.t. } \boldsymbol{\lambda}\geqslant 0 \\ \boldsymbol{\lambda}=Q_F(\boldsymbol{G}\boldsymbol{G}^{\mathrm{T}},\boldsymbol{g}^{\mathrm{T}}\boldsymbol{G}^{\mathrm{T}},\boldsymbol{e},\boldsymbol{0}+margin)\end{cases} \tag{9}$$

Firstly, the $\boldsymbol{\lambda}$ value satisfying equation (7) is obtained, and calculates the gradient $\tilde{\boldsymbol{g}}$ after projection, while margin is set to 0.5 in this paper. Then, equation (4) and (9) are calculated at each update of the model.

By projecting the gradient $\boldsymbol{g}$ of the Task-B into the feasible region outlined by the gradient $\boldsymbol{g}_m$ of the Task-A, the $\boldsymbol{g}$ update direction is modified by inequality constraints, see equation (4), so as to ensure that the included angle between the old and new task gradients is an acute angle, which not only ensures the training of the new Task-B, but also makes the loss of the old Task-A decline as a whole, so as to slow down the forgetting of the old Task-A.

4 Simulation results

In this paper, the LCDNN architecture of Fig.2 is used for MC with continuous learning using GEM of Section 3, although the proposed GEM algorithm can work with any DL models. In addition, we divide the 10 modulation signals of RadioML2016.10b dataset into 4 classification types for each task, as shown in Table 1. For each task, 37.5% of the data was used as the training set, 12.5% as the validation set and the remaining 50% data are used as the test set. We also select NUM_M number of representative data of previous task stored in memory, which will be used for continuous learning. It is worth emphasizing that data is grouped into mini-batch containing 1 024 sampling during training, compared with the global-batch training method. The learning-rate is set to 0.001. Finally, cross-entropy loss function is employed to measure the dissatisfaction with the results.

The research of this paper is based on the simulation of dynamic wireless communication environment, there are many signals sent and received every day, see 2.1 for details. If the global-batch are used, on one hand, it is difficult to read into memory at one time. On the other hand, the difference between adjacent batches is too small and the gradient is basically no difference, resulting in an increase in the loss of memory in Fig.5. In addition, in continuous learning phase, each mini-batch will trigger an included angle verification and judge whether projection is required, see equation (9), which more accurately ensures that the gradient shows a downward trend.

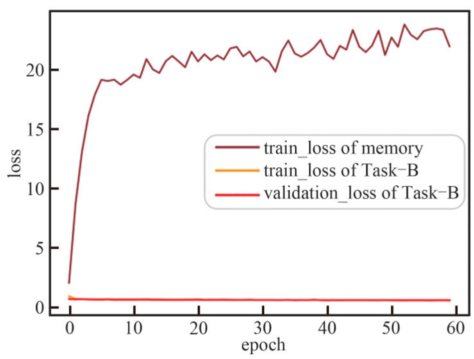

Fig.5 The training loss and validation loss of Task-B, and the loss of Task-A calculated using data in memory during continuous learning with global-batch

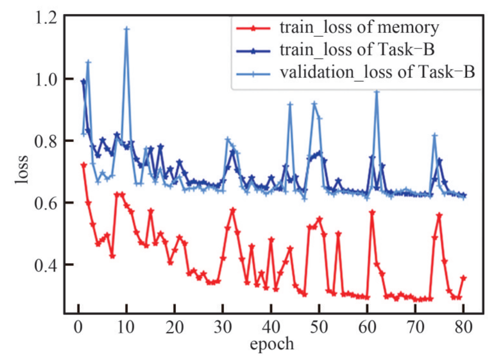

Fig.6 The training loss and validation loss of Task-B, and the loss of Task-A calculated using data in memory during continuous learning with mini-batch, NUM_M=30 000

In order to further unveil the power of continuous learning using GEM, Fig.6 plots the loss of Task-A calculated using stored data in memory, while the LCDNN model is trained with Task-B, as seen in the training and validation loss of Task-B. Fig.6 shows that the loss of Task-A satisfies equation (3), which ensures a downward trend, indicating the learning of a new Task-B in fact can cooperate with the old Task-A. Moreover, the loss curves in Fig.5 demonstrate a volatile movement, although the overall trend is decreasing. Again, that is because the mini-batch update method is used during training, rather than global-batch training.

Fig.7 shows the achievable MC accuracy with/without continuous learning using GEM. When learning a new Task-B after the previous Task-A of Table 1, Task-A suffers from catastrophic forgetting having a MC accuracy of merely 54%. However, when we deploy the proposed GEM algorithm, Task-A's MC accuracy dramatically increase to about 70%, as seen in Fig.6. What is more, the classification accuracy of the new Task-B achieves about 97% in high SNR region. That is because, the LCDNN is trained with Task-B's data, hence achieving a high accuracy is reasonable.

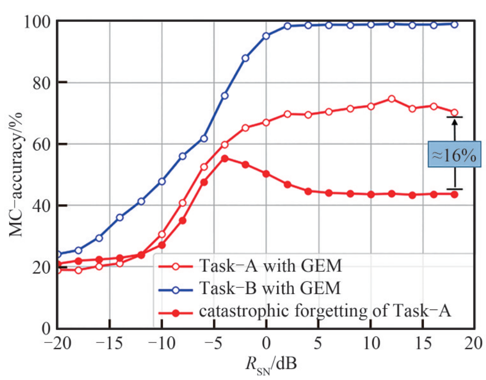

Fig.7 The classification accuracy of Task-A and Task-B after continuous learning using LCDNN model with mini-batch, while compared with the catastrophic forgetting of Task-A without GEM, $NUM_M = 30\,000$

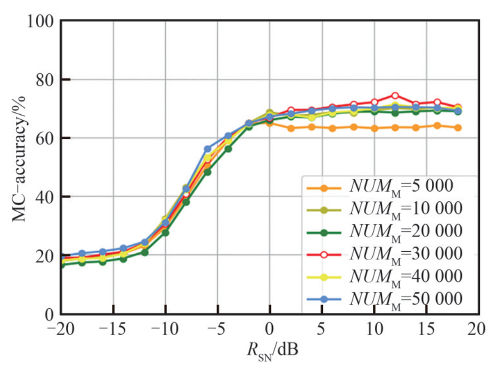

Fig.8 The classification accuracy of Task-A using GEM continuous learning, when having different memory size NUM_M

Moreover, Fig.8 studies the impact of memory size used in GEM of continuous learning of Task-A. Even when the memory size is very small, $NUM_M = 5\,000$, the proposed GEM algorithm already demonstrates a considerable improvement to the catastrophic forgetting of Task-A. When the memory size is gradually increased to $NUM_M =$ 10 000 to 50 000, the benefit of continuous learning begins to be saturated at high SNR region. This means

10 000 samples are adequate to evaluate equation (3), which only ensures the gradient descent direction of Task-A data in memory is roughly the same as that of the new task, not necessarily the ideal path.

In order to further improve the MC performance of GEM having a memory(NUM_M), we propose to replay the data in memory during continuous learning, namely, using the memory during the training of new tasks. As seen in Fig. 9, when having a memory size of $NUM_M = 30\,000$, the MC accuracy of Task-A using memory replay reaches 95% at high SNR, which is roughly 15% higher than that of the GEM learning of equation (3) based on gradient constraint strategy. That is to say, the memory data can guide the gradient descend of Task-A towards a lower direction. In addition, the classification accuracy of Task-B with memory replay decrease to 97% from 99% when using GEM, because memory data requires the loss function to optimize both Task-A and Task-B. In other words, the memory replay method allows us to strike a balance between both tasks, while using a small fraction of memory data.

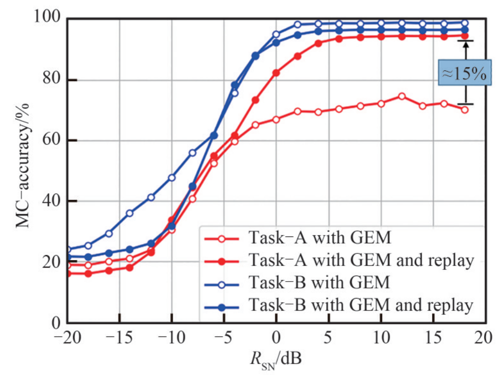

Fig.9 The classification accuracy of Task-A and Task-B after continuous learning using GEM constraint strategy, and the classification accuracy of Task-A and Task-B after continuous learning with memory replay $NUM_M = 30\,000$

5 Conclusion

In this paper, we propose a novel GEM algorithm to enable continuous learning for MC, and the proposed continuous learning algorithm is tested in a simulation of realistic wireless communication environment. We use the appropriate mini-batch update gradient for comparison and projection, which not only saves memory but also avoids falling into local optimization. In addition, compared with global-batch for small data sets, mini-batch is more effective in this complex signal environment. Secondly, we investigate the effect of memory capacity of the DL classifier and show that continuous learning can be achieved with limited data storage, i. e. $NUM_M = 30\,000$. Moreover, we show that the catastrophic forgetting problem can be further addresses if the data in memory is replayed during training. In summary, the novel proposed GEM algorithm can fulfil the duty of continuous learning by having a memory containing representative data of previous tasks and smartly use the memory to aid the gradient updating process of DL classifiers. It not only ensures the effective learning of new tasks, but also slows down the forgetting of old tasks. It is reasonable to believe that DL classifiers with continuous learning abilities will become a competitive solution for MC.

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