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Continual Learning-Based Selective Fixed-filter Active Noise Control

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***Abstract*—Selective fixed-filter active noise control (SFANC) has been widely applied in ANC systems due to its capability to dynamically select the most appropriate control filters based on the incoming noise. Existing SFANC algorithms are mainly trained on single specific noise dataset. Due to the diversity of noise types in real life, the continual learning (CL) technique could be applied to SFANC, which allows multi-task sequential training and helps to enhance the adaptability of SFANC to complex noise scenarios. However, catastrophic forgetting is an inherent problem in CL. The exact replay method was then employed to mitigate the effect of forgetting. Experimental results demonstrate that the proposed algorithm maintains satisfactory noise reduction results on previously learned tasks while effectively mitigating forgetting. Such improvement highlights the ability of the proposed algorithm to enhance the generalization capability of models across diverse noise types, achieving more robustness in complicated realistic scenarios.**

I. Introduction

Nowadays, with the increasing problem of environmental noise, the demand for effective noise control has also increased a lot. However, the traditional noise control methods are often passive and difficult to adapt to complex practical application scenarios, leading to the inability to achieve effective results [1], [2]. Active noise control (ANC) is a more powerful and effective technique compared to the traditional one, which is able to generate the anti-noise with the same amplitude and opposite phase to mitigate the undesired noise [2], [3]. Additionally, due to its better performance on low-frequency noise, ANC has been widely applied in common audio devices [4], [5].

However, the commonly used filtered-x least mean square (FxLMS) algorithm in traditional ANC systems sometimes can become a limitation when dealing with dynamic noise, leading to poor perceptions for users of the denoising effect due to its slow convergence [6]–[8]. The fixed-filter ANC is a method that uses the pre-trained control filter to reduce the impact of undesired noise, which is able to achieve rapid response and has been verified to be effective for realistic noise [9], [10]. Nevertheless, such a method has the problem that a pre-trained control filter is only effective for one specific noise type, which means its performance on other types of noise would be limited [11]–[13].

Considering the powerful classification ability of convolutional neural networks (CNNs), a CNN-based selective fixed-filter ANC (SFANC) method [14] was proposed to solve this problem, which was demonstrated in Fig. 1. The co-processor module in this algorithm is used for control filter selection. The network output is the filter index based on the incoming noise, which would be utilized later by the control filter database to make decisions. The selected control filter will then be used for further noise cancellation [15]. The CNN architecture was modified from ShuffleNet V2. The input noise spectrogram is first processed by the Conv0 module, which converts the one-channel input into a three-channel tensor, aligning it with the input requirement of the original ShuffleNet V2 architecture. The subsequent Stage2 and Stage3 modules are identical to those in the standard ShuffleNet V2, comprising primarily convolutional layers, batch normalization and ReLU activation functions. With the help of the powerful learning ability of CNN, this algorithm is feasible to learn from the provided noise samples and determine which control filter is more suitable to be used. In this way, it can ensure the users' perceptions of the denoising effect as well as the expected noise reduction results.

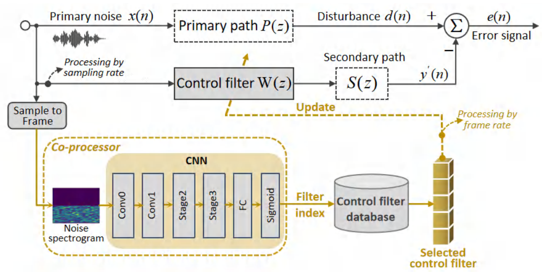


Fig. 1: The architecture of CNN-based SFANC method.

However, most of the currently proposed SFANC methods just focus on one specific dataset [16]. These methods can achieve very good denoising results on the given noise datasets after training. However, due to the complexity of realistic noises, one collected noise dataset is often difficult to include all types of noise, while in practical applications, the noise type that has not been learned may lead to the selection of inappropriate control filters and fail to obtain acceptable noise reduction results [17]–[19]. In order to further improve the generalization capability of SFANC models across diverse noise types, continual learning (CL) is a feasible technique to help SFANC obtain better performance when dealing with complex noise types.

Therefore, a CL-based SFANC method was proposed to improve the long-term generalization ability of the algorithm.

As CL technique allows the model to continually learn and handle new unknown data, the model can achieve multi-task sequential training. Moreover, instead of retraining the entire model on all previous datasets, the CL-based algorithm allows for updating the existing model with only a small amount of data containing the new noise type. To solve the problem of catastrophic forgetting, exact replay method was utilized in this algorithm to ensure satisfactory results when dealing with old noise types that have been learned. In this way, the proposed method is more beneficial to adapt to complex real-world noise scenarios, with an advantage in practical applications by continuing to learn when encountering new types of noise and obtaining relatively good denoising results later.

The subsequent sections of this paper are organized as follows. Firstly, the basic theory of CL is introduced in Section 2, explaining the reason of forgetting and importance of the exact replay method. Next, the details of experiments on the CL-based SFANC with exact replay method are provided in Section 3, where the main findings and existing challenges are also discussed. Eventually, the whole paper is concluded in Section 4.

II. Continual Learning Based SFANC with Exact Replay Method

With the development of deep neural networks, such models have become particularly popular in recent years and have been widely applied in various fields. As humans have the ability to constantly learn and expand knowledge from past experience, we hope that the designed model has the similar ability to generalize knowledge [20]. In other words, not only is the designed model expected to apply the previously learned knowledge to new environment, but also it can remember what has learned before. To achieve the goal of learning multiple tasks and applying the learned knowledge to multiple environments, the continual learning (CL) technique is what we need. CL is defined as a process of constant development based on increasingly complicated environment and behaviors, which could develop more complex skills on what has already learned [21]. It is able to sequentially learn from multiple tasks with a consecutive discovery of new knowledge [22]. CL is also called lifelong learning, incremental learning and sequential learning, with no strict distinction between these terms [20].

However, most of the deep learning models are trained on static and identically distributed datasets, causing the problem that the trained model cannot adapt or expand its behavior over time or across different tasks [23]–[26]. Therefore, these models are unable to adapt to varying circumstances and learn from sequential experience [27]. When they are exposed to new tasks or new data, these models may forget previously learned knowledge and obtain poor performance on previous tasks. Such a phenomenon is called catastrophic forgetting [28], where the parameters of the network learned before are partially or even completely overwritten when learning from new datasets during the process of training. This will lead to a significant degradation in the performance of the

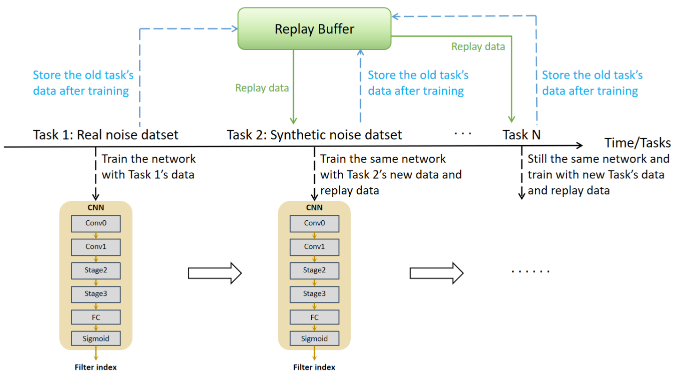


Fig. 2: The block diagram of continual learning with exact replay method.

model on previously learned tasks, which is also one of the main challenges to achieve CL through multi-task sequential training.

Therefore, in order to realize CL in deep neural networks, the problem of forgetting should be considered. Exact replay is one of the simplest and most effective methods that can be applied in CL. The main idea of this method is to directly store the original training data of previous tasks in the replay buffer. The stored data will then be partially replayed when training new tasks to mitigate the impact of catastrophic forgetting. As the original data that used for previous tasks is stored and reused, it is called exact replay method.

In this paper, the proposed algorithm combines CL technique with exact replay method and the SFANC algorithm to achieve the goal that the model could be trained by several noise datasets under different circumstances and obtain satisfactory noise reduction performance on old tasks. The whole training process using CL and the exact replay method is shown in Fig. 2. As the exact replay method requires additional replay buffer to store the previously learned data instead of modifying the network architecture or adding additional constraints to the loss function, the CNN architecture is the same as the one in Fig. 1. After training of each task, the used training data for this task is stored in the replay buffer, which will be used as the replay data for training of the task. In addition, not all the old data will be used during training. Instead, each training batch will randomly sample some old data from replay buffer to replace some of the new task's training data. The proportion of replay data depends on the parameter setting. Therefore, the actual training data of all tasks except for the first task will contain both the previously learned old data and the new task's data.

In this way, the CL-based SFANC with exact replay method could achieve multi-task sequential training, which helps adapt to complex noise distribution in realistic applications and select the most suitable pre-trained noise control filter based on the incoming noise type. Moreover, as the exact replay method is utilized, the model is able to remember the previously learned noise types when training new datasets, which can effectively alleviate the problem of forgetting caused by CL and multi-task sequential training.

III. Experiments and Discussions

To evaluate the noise reduction performance of the CL based SFANC with exact replay method on different noise datasets as well as its mitigation effect on the problem of catastrophic forgetting, 4 simple experiments were designed and implemented for verification. For simplicity, only 2 tasks were used for the multi-task sequential training, which are enough to show the phenomenon of catastrophic forgetting. One task uses the real noise dataset and another uses synthetic noise dataset. Therefore, the complete training process in the experiment contains two stages, Task 1 and Task 2, which correspond to the two different datasets respectively. The training sequence of the two noise datasets was exchanged as well to present that different noise features and training sequence will affect the final model performance. In addition, depending on whether the exact replay method is adopted, experiments were also conducted separately to demonstrate the effect on mitigating the problem of forgetting. Finally, the four experiments will be compared in pairs according to the training sequence and whether to use the exact replay method.

The exact replay method was implemented by randomly sampling a portion of the stored old data from previous tasks and replacing the new task's training data. In our experiments, the importance of the new task was set to be 0.5, meaning that, half of the original task 2 training data would be substituted with replay data during the training of task 2.

The performance of the model under different experimental conditions is summarized in Table 1. In addition, the "Original Task 1 Accuracy" in Table 1 represents the performance on the task 1 testing set after the first stage of training, which will be degraded due to the problem of forgetting. At that time, the data of task 2 had not been used for training yet. Therefore, there is no accuracy of task 2 after the first stage of training. Besides, the "None" stands for taking no measures to prevent the model from forgetting old knowledge. In other words, "None" stands for without replay method.

TABLE I: The performance under different experimental conditions

Training Sequence	Real to Synthetic Noise		Synthetic to Real Noise	
Methods	None	Exact Replay	None	Exact Replay
Original Task 1 Accuracy (%)	94.35	94.35	98.93	98.93
Final Task 1 Accuracy (%)	29.10	94.15	76.64	99.36
Final Task 2 Accuracy (%)	99.21	99.21	93.60	93.95

From Table 1, it can be found that in such multi-task sequential training experiments, if no additional methods were adopted to prevent forgetting, the models tend to exhibit a degradation in performance on old tasks when training new task. In detail, when the model was first trained on real noise, the final performance shows degradation in accuracy on the old task (real noise), decreasing from 0.9435 to 0.2910, which indicates the significant forgetting. Similarly, after exchanging the training sequence, the model's accuracy on the old task (synthetic noise) decreases from 0.9893 to 0.7664, which also demonstrates forgetting. If the exact replay method was employed, the accuracy of both training sequences on the old task has remained at a satisfactory level. More comparisons and analyses can be found in the following sections.

The Adam was utilized as optimizer during the two stages of training, where the initial learning rate was set to be 0.01. In both tasks, the learning rate was scheduled to decay by a factor of 0.1 every 10 epochs. The initial learning rate for Task 1 was set to 0.01, whereas a smaller initial learning rate of 0.005 was applied to Task 2 in order to protect the learned weights of Task 1 from being significantly modified, helping to preserve the previously learned knowledge. As the experiments were multi-task sequential training on the same model, the optimizer's internal states would be retained to ensure the continuity of the optimization process. Moreover, the l_2 regularization was also employed to constrain the weights and prevent overfitting during training. The weight decay was set to be 1e-4. In addition, the batch size was 128. Each task or each stage was set to train 40 epochs, so the total number of training epochs for the whole experiment was 80. The performance during the continual learning on different tasks were also provided, which can be found in Fig. 3 to Fig. 6.

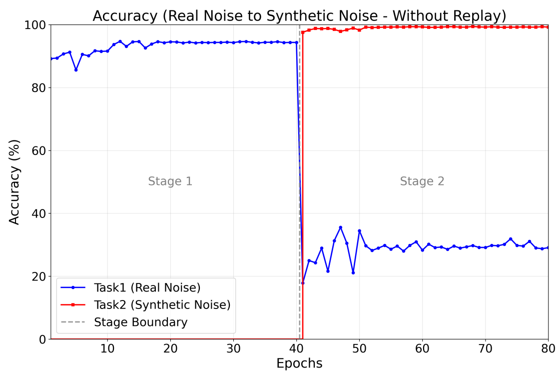


Fig. 3: The performance during CL, where the model transitions from Task 1 (Real Noise) to Task 2 (Synthetic Noise) without replay.

A. Comparison of Different Training Sequences

As illustrated in Fig. 3 and Fig. 4, when the exact replay method was not employed to mitigate the forgetting problem, the model's performance on the old task (Task 1) degrades during the training of new data (Task 2), regardless of whether the model was first trained on real noise or synthetic noise. Particularly, when trained initially on real noise, the model exhibits significant forgetting of previously learned knowledge. A possible explanation for this phenomenon is that the model initially adapts to complex noise features, which may conflict with subsequently learned simpler features, resulting in the overwriting of certain parameters and consequently worse performance. In contrast, when the model wad first trained

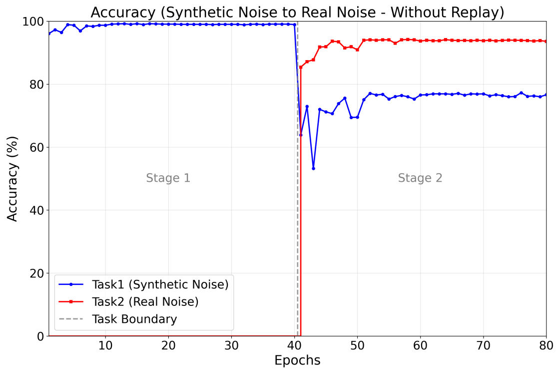


Fig. 4: The performance during CL, where the model transitions from Task 1 (Synthetic Noise) to Task 2 (Real Noise) without replay.

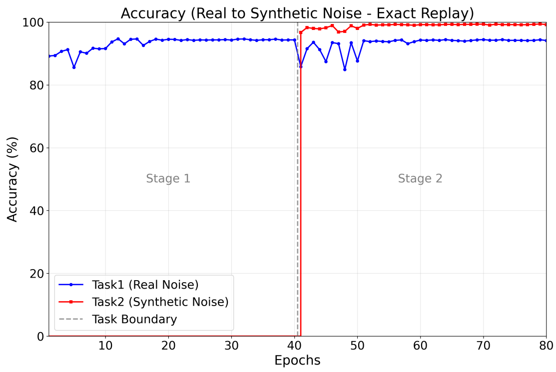


Fig. 5: The performance during CL, where the model transitions from Task 1 (Real Noise) to Task 2 (Synthetic Noise) with exact replay.

on synthetic noise, although some degree of forgetting still occurs, the model can progressively extend from simple noise features to more complex ones, ultimately demonstrating less forgetting.

From Fig. 5 and Fig. 6, it can be observed that when the exact replay method was employed, the model achieves satisfactory accuracy on both tasks regardless of the training sequence.

B. Comparison of Different Training Methods

By comparing Fig. 3 and Fig. 5, Fig. 4 and Fig. 6, we can observe that under identical training sequence, the model using exact replay method maintains similar final accuracy on the old task to its stage 1 performance, which presents the significant effect on mitigating catastrophic forgetting in CL. Furthermore, the experimental results also reveal that models trained under different sequences achieve approximate accuracy on respective tasks after applying exact replay method. This validates the effectiveness of the exact replay method.

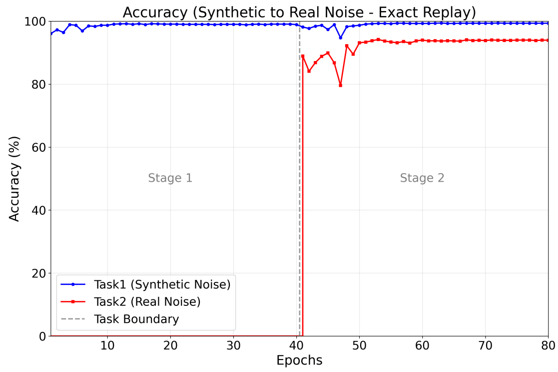


Fig. 6: The performance during CL, where the model transitions from Task 1 (Synthetic Noise) to Task 2 (Real Noise) with exact replay.

C. Noise Cancellation

In this section, the SFANC algorithm was also applied based on the trained models to cancel the two types of noise (real noise and synthetic noise), corresponding to two noise datasets during CL training. The noise reduction results of different SFANC algorithms were shown from Fig. 7 to Fig. 9. In particularly, these noises do not belong to any of the training datasets used before.

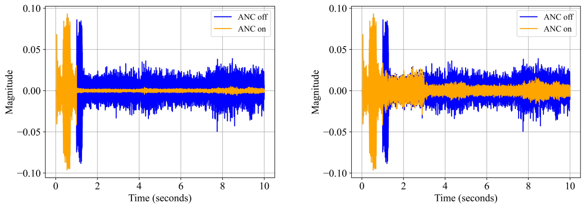
In addition, it is necessary to consider the noise cancellation effect of high-frequency noise and low-frequency noise respectively for synthetic noise. Therefore, two kinds of noise with different noise components are tested individually, which were low-frequency noise from 251 Hz to 980 Hz and high-frequency noise from 1173 Hz to 1624 Hz. As real noise may contain various noise components, it is not necessary to do so. Thus, the noise cancellation results for real noise are shown in Fig. 7, while Fig. 8 and Fig. 9 are the results for low-frequency synthetic noise and high-frequency synthetic noise respectively.

It can be observed form Fig. 7 to Fig. 9 that all the models using CL technique with exact replay method exhibit significantly superior performance to the ones without CL. Moreover, Fig. 8 and Fig.9 also present that the proposed algorithm has satisfactory noise reduction effect for low-frequency noise. Finally, the experimental results also indicate the necessity of CL with exact replay method when conducting multi-task sequential training.

D. Discussions

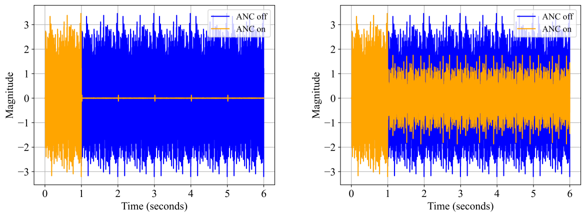
In this section, additional details of the proposed algorithm will be analyzed and summarized. Through previous comparisons and analysis, it has been demonstrated that the training sequence from simple features to complex ones contributes to the effectiveness of CL training. Moreover, the exact replay method was proven to be able to effectively address the catastrophic forgetting problem in CL.

However, the exact replay method has also some challenges. In detail, the experiments conducted in this paper only con-



(a) SFANC with CL (b) SFANC without CL

Fig. 7: Error signals of different SFANC algorithms for real noise.



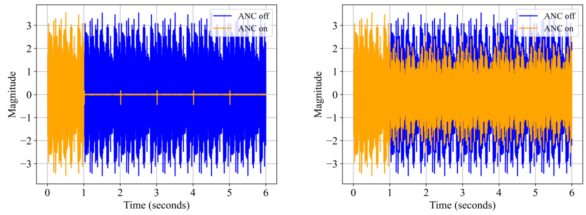
(a) SFANC with CL (b) SFANC without CL

Fig. 8: Error signals of different SFANC algorithms for synthetic noise from 251 Hz to 980 Hz.

tained two tasks, corresponding to two distinct noise datasets. Since the exact replay method stores all previously learned old data, in our experiments, it only required to save the training data from Task 1 into the replay buffer. The real noise dataset and the synthetic noise dataset used in this paper consist of 13,000 and 14,000 samples, occupying 3.92 GB and 875 MB of memory respectively. Additionally, only the first second of the real noise data was utilized. The replay buffer sizes in the experiments were then 101.66 MB and 109.48 MB, which are significantly smaller than the original training datasets. This is because the replay buffer does not need to store all sample information but only retains the feature representations that are processed and fed into the network.

However, in practical applications, as the number of tasks increases and real world training data becomes more extensive and complex, the additional memory required by the replay buffer grows substantially, which is one of its key limitations. Another challenge arises from the importance assigned to new tasks in the experiments, which was set to 0.5 in our experiments. It means that each training batch consisted of half new task samples and half randomly sampled replay buffer samples, which introduces a new problem that not all the new task data can be fully utilized for training within a single epoch. Therefore, to ensure comprehensive learning of new task data distributions, the exact replay method may require more epochs to guarantee uniform sample usage. Nevertheless, the risk that a minority of samples might be underutilized still remains, which is an inherent drawback of this method.

Therefore, even though the exact replay method achieves highly effective mitigation of catastrophic forgetting in CL, its real world applicability still has several constraints. Future work could be explored to find alternative strategies to further



(a) SFANC with CL (b) SFANC without CL

Fig. 9: Error signals of different SFANC algorithms for synthetic noise from 1173 Hz to 1624 Hz.

mitigate the problem of forgetting, enabling trained models to achieve stronger generalization capabilities in more complicated practical scenarios.

IV. Conclusions

In order to better adapt to the complex and dynamic noise scenarios, the continual learning (CL) technique could be applied to SFANC to perform multi-task sequential training, helping SFANC algorithm to select more appropriate control filters when confronted with novel noise types. In this paper, a CL-based SFANC with exact replay method was introduced. Instead of retraining the entire network on all past datasets, the proposed algorithm allows for incrementally updating the existing model with limited new data containing new noise types, thereby enhancing its adaptability to complex noise distributions. The experiments demonstrate that the proposed algorithm can effectively mitigate the problem of forgetting in CL and achieve satisfactory noise reduction results on both old tasks and new tasks. In addition, the training sequence from simple noise features to complex ones was also verified to be better. Moreover, the challenges of exact replay method, including the replay buffer size and its inherent risk during training, were also discussed. In the future, more effort could be made to explore other alternative approaches to mitigate forgetting and achieve stronger generalization capabilities in complex scenarios.

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