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PAPER

A Federated Model Update Method for Intelligent Gas Sensor Replacement

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SUMMARY Due to the limited lifespan of Micro-Electro-Mechanical Systems (MEMS), their components need to be replaced regularly. For intelligent devices such as electronic noses, updating an intelligent gas sensor system requires establishing a new classifier model for the newly inserted gas sensor probes because of the poor consistency between the signals collected by the new and original systems. The traditional method involves retraining the new model by collecting adequate data of the gas sensor array under strict laboratory conditions, which is time-consuming and resource-intensive. To simplify and expedite this process, a federated learning method called FedGSSU is proposed for gas sensor system updating. Two datasets were used to verify the effectiveness of the proposed framework. The experimental results show that FedGSSU can effectively utilize the original classifier model to obtain a new classifier model while only replacing the gas sensor array. The consistency between the new gas sensor system and the original one reaches up to 90.17%, and the test accuracy is increased by 4 percentage points compared to the traditional method. While replacing sensors with FedGSSU will reduce recognition accuracy slightly, it is more acceptable in scenarios where high accuracy is not required than re-calibrating sensors and re-training the classifier.

key words: *Gas sensor, sensor replacement, model update, classifier model.*

1. Introduction

The monitoring and detection of volatile organic compounds (VOCs) have become increasingly important in recent years, with researchers dedicating more attention to this field [1]. One common method for air quality monitoring is through the use of a simple system architecture that employs an independent gas sensor array. This system drives electronics and utilizes appropriate pattern recognition algorithms to identify different types of gases [2-5].

In real-time environmental monitoring applications, micro-electro-mechanical systems (MEMS) with gas sensors offer numerous advantages over traditional detection methods [6]. These include their small size, high sensitivity, fast response time, and ease of integration into arrays. MEMS integrate various gas sensors onto a single piece of silicon, utilizing different gas sensors to mitigate the cross-effect of sensitivity among gases. This allows for the accurate recognition of different gases [7-10].

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In practice, however, sensors are not capable of maintaining optimal performance over an extended period [11,12]. During prolonged usage, unforeseen changes such as poisoning or aging may occur within the sensor, limiting its lifespan and necessitating replacement [13,14]. Furthermore, even sensors of the same type can exhibit varying nanostructures in their sensitive films, resulting in disparate output signals when exposed to the same gas environment [15,16]. Consequently, after replacing a gas sensor array, the original gas recognition classifier model may no longer accurately identify the target gas [17]. Thus, it becomes necessary to recalibrate the classifier model for the new sensor array.

The conventional approach to constructing a sensor classifier model involves exposing the sensor array to various concentrations of gases in distinct environments, collecting signal samples, and utilizing these data points to create a training dataset for the classification system [18]. The objective of this training process is to develop a gas recognition system capable of automatically identifying the concentration of each gas component. However, due to the intricate nature of the sensor array training process and the substantial volume of data required, traditional methods struggle to achieve automation [19]. As a result, this method necessitates the involvement of professionals in a laboratory setting and is not feasible for end-users to execute independently. Consequently, the upkeep costs and complexity associated with sensor systems are significantly high [20].

Federated Learning (FL) is a cutting-edge technique that enables multiple devices to collaboratively learn a robust model [21,22]. In recent years, numerous FL frameworks have been successfully applied to address practical challenges in diverse fields such as intelligent marketing and intelligent diagnosis [23]. Inspired by the FL algorithm, this paper proposes FedGSSU, an innovative approach that streamlines and accelerates the development of an effective new classifier model without necessitating experimental measurements. Taking advantage of the strong computing capabilities of intelligent gas recognition equipment, FedGSSU refines the parameters of the new classifier model using an overdetermined equation. Through iterative

optimization, the optimal model of the new classifier is ultimately obtained.

The structure of this paper is organized as follows: The subsequent section elucidates FL and the methodology based on overdetermined equations for parameter adjustment. Subsequently, the framework and core algorithm are presented in the third section, followed by experimental results, discussions, and concluding remarks.

2. Related Work

2.1 Federated Learning

The aim of FL is to develop a resilient model through the collaboration of multiple devices. Federated Averaging (FedAvg), a synchronous distributed optimization algorithm, is arguably the most renowned FL algorithm [24]. It encompasses local updates and global aggregation, with the learning process outlined in Eq. 1.

$$\mathrm{w}_t^i \triangleq \begin{cases} \mathrm{w}_{t-1}^i - \eta \nabla F^i(\mathrm{w}_{t-1}^i) & \text{if } t \bmod n \neq 0 \\ \sum_{i \in N} \frac{|D^i|}{|D|} \left[\mathrm{w}_{t-1}^i - \eta \nabla F^i\left(\mathrm{w}_{t-1}^i\right)\right] & \text{if } t \bmod n = 0 \end{cases} \quad (1)$$

Each node (*node*^{i}) utilizes stochastic gradient descent (SGD) with a learning rate η to iteratively refine its local model w^i, repeating this process every n epochs. Subsequently, a parameter server aggregates all w^i to generate a comprehensive global model w, which is then disseminated back to each node for the subsequent iteration.

However, FedAvg faces scalability issues and performs poorly when dealing with non-independent and identically distributed (Non-IID) data. To address these challenges, Li et al. [25] proposed a decentralized pipelined SGD framework (Pipe-SGD) for distributed deep net training. This framework enhances FedAvg by eliminating the parameter server and replacing global aggregation with global inter-node-model transfer. In Pipe-SGD, the learning process involves synchronizing a new model w^i with the previously learned model w^{i-1}, and transferring the model from the original *node*$^{i-1}$ to the new *node*^{i} in this FL process.

2.2 Solving Overdetermined Equations

Generally, there is no definitive solution to overdetermined equations, necessitating an approximate solution in most cases. A linear equation can be defined as follows:

$$Ax = b \quad (2)$$

where $A \in R^{m \times n}$, $x \in R^n$ and $b \in R^m$. If $m > n$, then it is called an overdetermined equation and is commonly solved with the least square method. That is, the following problem is solved:

$$\min \|Ax - b\|_2^2 \quad (3)$$

When the coefficient matrix of Eq. 2 is full rank, Eq. 3 has a unique solution. Numerous results have been obtained in the study of Eq. 2. The more conventional approach involves solving the linear equations using the same method as Eq. 4 [26].

$$A^T Ax = A^T b \quad (4)$$

3. The Proposed FedGSSU Method

3.1 Overview of the Method

The gas sensor system designed in this paper, with the required analog and digital circuitry, as shown in Fig.1, comprises two independent sets of sensor array sockets connected to the signal processing module. Normally, one socket is occupied by the sensor array while the other remains empty. If the original sensor array is nearing the end of its useful life, a new sensor array is inserted into the empty socket without altering the original one. During the federated cycle in the FedGSSU, the gas sensor system undergoes model learning and parameter updating. The original classifier model of the gas sensor array serves as the basis for this process. Simultaneously, both the original and new sensor arrays are exposed to the same gas environment to train a new classifier model, as depicted in Fig.2. Finally, after completing the updating process, the original sensor array is unplugged from its socket.

3.2 Algorithm Description

In this paper, the parameters of the model from the original gas sensor system are optimized to make it more suitable for the new sensor array. This is achieved by solving several overdetermined equations at the end of the original sensors' lifespan. To obtain datasets for training and testing, both the original and new sensor arrays are placed in the same gas environment. Multiple overdetermined equations are constructed layer by layer between the dataset from the new sensor array and the output vector of each layer of the original classifier model using the dataset from the original sensor array. By solving these equations, an optimized classifier model is obtained that can be used with the new sensor array.

The first step in this process is to collect datasets from both the original and new sensor arrays simultaneously. The

parameters of the new model are then adjusted to achieve optimization, with a focus on adjusting the parameters of each layer. The layer parameters of the original classifier model are extracted and used to calculate the output vector of each layer of neurons using the dataset from the original sensor array. The output of each layer of the original model is then combined with the input vector of the same position layer of the new model to build equations layer by layer. The solutions to these equations become the parameters for the new layer. This optimization process allows the classifier model to better adapt to unknown data within the same task field. The main contribution of this paper is that through FedGSSU, a new classifier model can be obtained from the original classifier model by replacing only the gas sensor array, without having to replace the entire gas identification system.

The entire process involves changing only the model parameters of the network, without altering the network structure. The specific method is as follows:

Step 1: The model A for the classifier is known, its inputs $\mathrm{X}^A = \{x_1^A, x_2^A, \cdots, x_n^A\}$ are obtained from the original sensor array, and its outputs are $\mathrm{Y}^A = f_A(\mathrm{X}^A) = \{y_1^A, y_2^A, \cdots, y_n^A\}$, where n is the number of feature vectors. The model B of which the network structure is exactly the same as A is unknow, and its inputs $\mathrm{X}^B = \{x_1^B, x_2^B, \cdots, x_n^B\}$ are obtained from the new sensor array. The outputs of the classifier with the model B are expected to be equal to Y^A. The model B cannot be trained by dataset D which are formed by X^B and Y^A, because Y^A does not contain all labels under the condition of no laboratory measurements. Starting from the first layer of each model, the output of each layer of Model B will approximate the output of the antipodal layer of Model A.

Step 2: The parameters of model B will be adjusted. In the federated period, the parameters of the original classifier model A, namely, the weight matrix $Weight$ and the bias matrix $Bias$, are extracted. The original sensor array acquires the feature vector of the dataset as the input vector X. The hidden layer output is calculated as $H = f^1(Weight_1^T \cdot X + Bias_1)$, and the output layer output is $O = f^2(H^T \cdot Weight_2 + Bias_2)$. For the i-th input sample in the dataset Q_t measured by the newly placed sensors, the bias term is expressed as W_0^i, $X_0^i = 1$. Then, the overdetermined equations can be established:

$$Weight_1^T \cdot X + Bias_1 = W_1^T \cdot X^i \tag{5}$$

In this way, the weight vector W_1 of the first layer (including the bias term) can be obtained. Similarly, the weight vector W_2 of the second layer (including the bias term) can be obtained. The solution vector obtained by this method is the least squares solution, which will not fine-tune the parameters by combining all the layers together.

Step 3: The weight parameter obtained in the previous step is constructed to obtain the final classifier B.

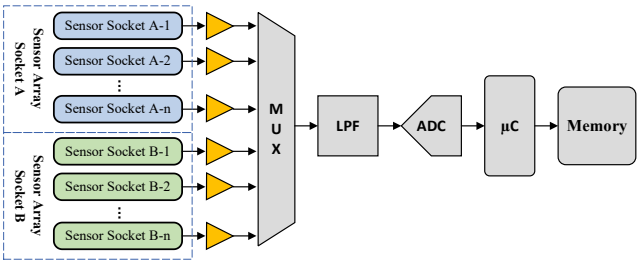

Fig. 1 Sensor arrays with interface electronics blocks, which include the amplifiers, multiplexer (MUX), low-pass filter (LPF), analog to digital converter (ADC), microcontroller (µC) and memory.

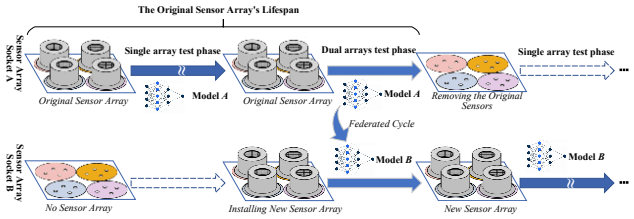

Fig. 2 Overview of the FedGSSU Method.

4. Experiment and Analysis

Three separate experiments were conducted utilizing three distinct datasets to validate the proposed methodology. The subsequent experiments serve a dual purpose:

- The aim of the study is to ascertain whether a viable classifier model can be developed through FedGSSU.
- Another objective is to establish guidelines for determining the federated cycle and the coexistence environment of two distinct sets of gas sensors.

4.1 Experiment 1

(1) Dataset Description

The dataset contains time series data from 16 chemical sensors exposed to different concentrations of a gas mixture. The mixture consists of two pairs of gases: methane and ethylene, as well as carbon monoxide and ethylene. Each pair was measured 16 times consecutively, and the sensor array was operated continuously for 12 hours without interruption. The operating voltage of the sensors was maintained at approximately 5V throughout the experiment. Each measurement involved collecting 16 sensor array signals continuously, and the concentration level was randomly varied [27]. In this study, data samples of methane, carbon monoxide, and ethylene were selected after

processing the experimental dataset.

After the gas measurements were completed, 8 features were extracted from the time series data collected by each specific sensor. These features included two different types:

The maximum resistance changes in the sensor during the steady change of the gas concentration, that is, the difference between the maximum value, and the baseline value [25]:

$$\Delta R = \max_m r[m] - \min_m r[m] \quad (6)$$

The rate of change in ΔR is:

$$\|\Delta R\| = \frac{\max_m r[m] - \min_m r[m]}{\max_m r[m]} \quad (7)$$

where $r[m]$ represents the time series of the sensor resistance and m is the discrete index of time.

The set of dynamic characteristics of the sensor that reflect the increase in the sensor response or the decay of the transient portion, that is, the exponential moving average (ema_α), under controlled conditions throughout the measurement process.

$$y[m] = (1-\alpha)y[m-1] + \alpha(r[m] - r[m-1]) \quad (8)$$

where α ($\alpha \in [0,1]$) is the smoothing coefficient and the initial state is $y[0] = 0$. ΔR and $\|\Delta R\|$ are the characteristics of the steady-state response signal of the gas sensors. When α = 0.1, 0.01, 0.001, the maximum and minimum values of $ema_\alpha(r[m])$ are the characteristics of the transient response signal. Therefore, the sensor array obtains the $128 \times (8 \times 16)$-dimensional feature vectors to form each test [29].

The aim of this experiment is to eliminate the impact of drift. To achieve this, we have set an interval of 6 hours between each dataset and divided the data into two subsets, as illustrated in Table 1 and 2.

Table 1 Details of the dataset. Each row corresponds to the number of three samples collected during a period of one batch.

Batch ID	Number of samples		
	Methane	CO	Ethylene
Batch 1	30	30	30
Batch 2	40	30	30

Table 2 Dataset details. The number of data samples per batch and the time intervals.

Batch ID	Number of samples	Time interval
Batch 1	90	6 h
Batch 2	100	6 h

(2) Experiment

The table presents a total of two datasets, which are categorized as original and new datasets in this experiment. The purpose of using batch1 as the coexistence period for both sets of sensors is to clearly observe the performance of the newly developed classifier. To simulate a real-world scenario with fewer gas analytes, only one gas analyte was selected for the dataset. Subsequently, the new classifier model was optimized based on the methodology proposed in this paper.

A comparison of consistency was made between the original classifier model and the new classifier model. This involved comparing the labels obtained from the new model with the predicted labels from the original model under different test data and batches to observe the effect. The experimental results revealed that the unoptimized new model had an average consistency of 65.78% when compared to the original model. However, after optimization, the consistency of the new model relative to the original model improved significantly, with an average consistency of 90.165%. These results are presented in Table 3.

Table 3 Performance of the classifiers.

Batch ID	Consistency (in %) for batches 1 and 2.	
	Unoptimized new model	Optimized new model
Batch 1	65.56	93.33
Batch 2	66.00	87.00
Batch 3	65.78	90.17

Table 4 Comparison of accuracy of several methods.

Performance of models under the federated batch (%)		
Traditional method	TCA	FedGSSU
93.00	81.00	97.00

(3) Discussion

Table 3 illustrates that the proposed method successfully migrates and obtains a new classifier model, with optimized performance after tuning. From a model consistency perspective, the new classifier demonstrates the ability to learn the original model structure. The classifier, which adjusts parameters layer by layer, exhibits a consistency of over 90% when compared to the original model. This paper also compares three methods for obtaining the new classifier model after replacement: the traditional method which trains the first batch of data from the new sensor array in a standard environment, the classic transfer learning method (TCA) [30], and the method proposed in this paper, which fully utilizes residual classification information from the original sensor array. Table 4 presents the test accuracy of the three methods under federated batches, indicating that the model obtained through the proposed method performs better when there is no significant drift in the sensor array.

4.2 Experiment 2

(1) Dataset Description

To validate the effectiveness of the new classifier model, this experiment employs the test dataset published by The University of California, Irvine. The sensor array utilized comprises 16 gas sensors, with four types of sensors and four sensors of each type. Six gases are tested, including acetaldehyde, ammonia, ethylene, acetone, toluene, and ethanol, with gas concentrations ranging from 5 ppmv to 1000 ppmv. The resulting dataset encompasses 13,910 recordings of 16 chemical sensors spanning over 36 months. The dataset contains six gas analytes at varying concentrations, aiming to distinguish between the six analytes regardless of their concentrations.

The data collected over a period of 36 months is divided into ten batches of datasets to fulfill the training requirements of the classifier. The data processing method employed in this experiment is precisely identical to that utilized in the initial experiment, and further details regarding the dataset are provided in [11].

(2) Experiment

In order to facilitate the observation of the classification effect of the newly obtained classifier after model migration, we opted not to use the end of the original sensor array's lifespan as the coexistence cycle for the old and new sensors. Instead, we chose the 16th month as the coexistence period for both sets of sensors to simulate practical applications. After a certain period of time has passed since the original sensor array was put into use, a new sensor array is introduced to learn the classification labels.

However, when the sensor is exposed to an analyte, its response is significantly different from when it is exposed to clean air (not exposed to the analyte) [27]. By analyzing the sensor array, a more suitable classifier model can be obtained for a specific classification task. In actual air monitoring applications, the concentration of gaseous analytes is usually low. To verify the validity of the new classifier after model migration in cases with fewer gas analytes, only one analyte from the data collected in the 16th month (Batch 5) is selected as the dataset. During this period, the new dataset learns the classification labels and completes the model migration. The classifier model is then optimized according to the method proposed in this paper.

Five settings are considered to better validate the method. The dataset is divided into two parts: the original dataset (Old Batch) and the new dataset (New Batch). To better present the recognition performance of the classifier, the toluene sample was removed from the entire dataset.

- **Setting 1**: A classifier was trained using data from the original sensors for the first two months (Old Batch 1) as the original classifier model. The subsequent batches were used as test sets.
- **Setting 2**: A new classifier model was trained using data from the new sensors for the first two months (New Batch 1), and subsequent batches were used as test sets.
- **Setting 3**: The model from Setting 1 was utilized to directly test the data of New Batches 5-10.
- **Setting 4**: A classifier was trained using the labels from Old Batch 5 tested in Setting 1 and the input set from New Batch 5. Subsequent batches were used as test sets.
- **Setting 5**: The method proposed in this paper is utilized to optimize the classifier model in Setting 4.

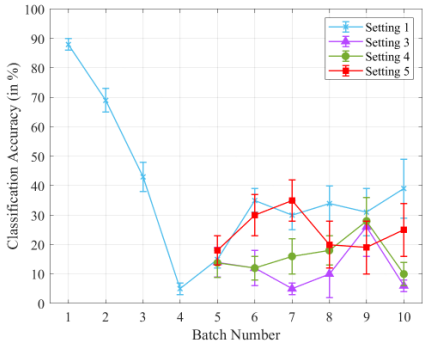

Fig. 3 The performance of the classifiers obtained from Setting 1 (×), Setting 3 (△), Setting 4 (○), and Setting 5 (□) is depicted in the graph. The red continuous line represents the results achieved using Setting 5 (□), which is the proposed method in this paper.

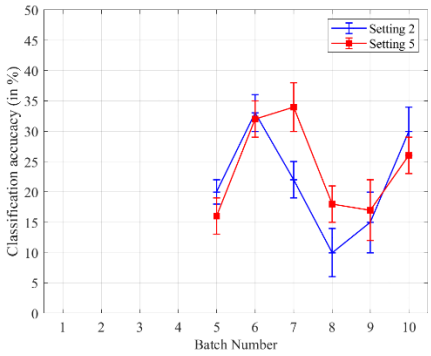

Fig. 4 The classifier performance comparison between the traditional method (Setting 2 (+)) and the proposed method in this paper (Setting 5 (□)) is shown in the graph.

(3) Discussion

The classifier trained in Setting 1 is considered the original classifier model as it cannot be known in advance during the experiment. As observed from the trend curve, there is a decline in sensor recognition performance after drifting. In Setting 3, the original classifier model is directly applied to the response data of the new sensor array, resulting in relatively poor classification performance. On the other hand, Settings 4 and 5 are based on the proposed model

migration method. The original classifier model is first migrated to the new sensor array, and then optimized by adjusting the parameters to obtain the final classifier model.

As shown in Fig.3, the recognition rate of the classifier generally decreases over time due to the drift in sensor performance within the selected dataset. This phenomenon is caused by the aging of the sensor structure, which inevitably affects their test results over time [27]. However, it can be observed that the classifier model under Setting 4 still maintains a certain level of recognition rate, indicating that the proposed method in this paper is capable of efficiently migrating the original classifier model to a new sensor array.

Furthermore, after parameter adjustment, the optimized model demonstrated a better recognition rate than the unoptimized model, and its performance was close to that of the original classifier model. This suggests that layer-by-layer adjustment can effectively optimize the performance of the classifier.

The data recognition rate of the 9th batch was notably high, considering the impact of the gas concentration of the test set on the performance of the classifier in this experiment.

The classifier trained in Setting 2 represents the novel classifier model, utilizing the same methodology as that employed in Setting 1. This configuration aims to assess the recognition performance of the newly proposed method's classifier model and compare it with a traditionally trained classifier model in the same gaseous environment. The experimental outcomes are illustrated in Fig.4.

4.3 Experiment 3

(1) The experimental setup

Through the first two experiments, we verify the effectiveness of FedGSSU algorithm using public data. We then developed a hardware system (Fig.5) to further validate the FedGSSU algorithm through a year of measurements, as well as the deviations from the original data as the number of sensor replacements increased.

The sensor system has two sets of sensor array sockets, each containing eight sockets. In this experiment, 8 sensors, TGS2600, TGS2602, TGS2610 and TGS2620 (2 of each) produced by Figaro Inc, were selected for each array. All the sensors are installed in a quartz tube, one end of which is connected to a computer-controlled continuous gas supply system and the other end to the exhaust system.

The analytes under analysis (i.e., 300±100 ppmv acetone, 150±50 ppmv ethylene and 300±100 ppmv ethanol) are added to this background in random order. The total flow rate across the sensing chamber is set to 200 ml/min and kept constant for the whole measurement process.

To generate the dataset, we followed a measurement procedure consisting of the following steps. First, the desired concentration of the odorant was injected by the continuous flow system into the quartz tube for 100s. Then, the quartz tube was cleaned with dry air for 300s before the concentration phase of a new measurement. Finally, the measurement process herein described was replicated for subsequent measurements.

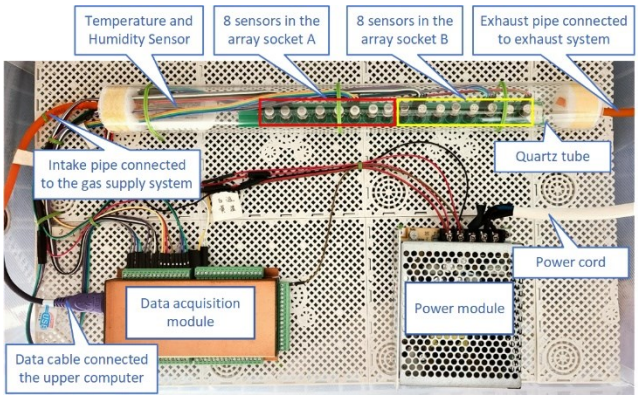

Fig. 5 Experimental setup used for data acquisition.

(2) Experiment

The dataset was collected over a period of 12 months using three sets of sensors. The first set was installed in the array socket A and was used from the 1st to 7th month, and then removed. The second set was installed in the array socket B and was used from the 4th to 12th month. The third set was installed in the array socket A and was used from the 8th to 12th month. The exact distribution of the number of measurements per month is shown in Table 5.

Table 5 Dataset details. Each column corresponds to samples collected during a period of one month for three gases.

Analytes	Monthly Number of Examples											
	1	2	3	4	5	6	7	8	9	10	11	12
Acetone	40	154	9	80	23	34	67	51	19	60	100	102
Ethylene	74	11	79	15	24	68	85	68	80	52	56	27
Ethanol	66	15	93	85	133	78	27	61	81	69	24	51

The first set of the sensors is considered the original sensor array. The original gas classification model is trained with its dataset in the 1st month. This model was used to identify the dataset from the first set from the 2nd to 7th month. The classification accuracies are shown by the blue curve (+) in Figure 6.

Assume that in the 4th month we are going to replace the first set of sensors with the second set. Through FedGSSU, the second classifier model is obtained from the original

classifier model using the datasets from the first and second sets at the 4th month. The second model was used to identify the dataset from the second set from the 4th to 12th month. The classification accuracies are shown by the red curve (○) in Figure 6.

It is also assumed that in the 8th month we are going to replace the second set of sensors with the third set. Through FedGSSU, the third classifier model is obtained from the second classifier model using the datasets from the second and third sets at the 8th month. The third model was used to identify the dataset from the second set from the 4th to 12th month. The classification accuracies are shown by the green curve (△) in Figure 6.

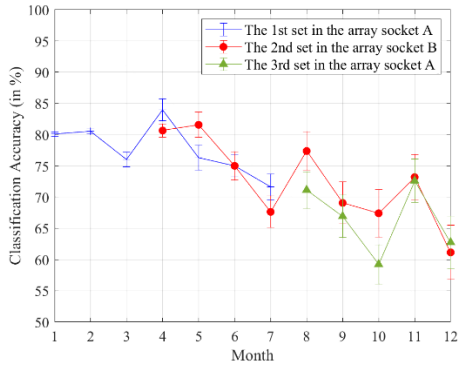

Fig. 6 The classification performance of the original sensor array and that after two sensor replacements.

(3) Discussion

Figure 6 shows the gas recognition performance using the original sensor array and two replacements. It can be found that all the classification accuracies of the three sets of sensors decrease with time. This is mainly caused by the time drift of the sensors. Using the original, second and third sets of sensors, the average accuracy is 77.65%, 72.57% and 66.53, respectively. Overall accuracies decrease by 5.08% and 6.04%, respectively. This is not only due to the replacement of sensors and models, but also due to the time drift of the sensors.

Over the same time period, such as from the 4th to 7th month, the average accuracies using the original and second set of sensors is 76.72% and 76.22%. The accuracy rate remains basically the same after the first sensor replacement. From the 8th to 12th month, the average accuracy using the second and third sets of sensors was 69.64% and 66.53%. After the second sensor replacement, the accuracy decreases by 3.11%. This decrease is mainly due to errors introduced by the FedGSSU algorithm when updating the model.

5. Conclusion

This paper investigates the performance of a newly developed classifier model, which is derived from the original model. The approach involves transferring the original model to additional sensors with limited time and cost constraints. The classifier's performance is optimized by fine-tuning its parameters layer by layer. Three distinct datasets were chosen to validate our methodology. The first dataset spans 36 months, while the second covers a period of 12 hours, mimicking real-world sensor applications and short-term drift-free operation, respectively. The third dataset, which spans 12 months, is collected by us to measure the decline in accuracy after multiple sensor replacements.

The experimental findings demonstrate the following: a) Migration learning can yield a novel classifier model by merely replacing the gas sensor array. b) Even with a reduced model transition time, an effective classification model can still be achieved. c) The new gas sensor array must coexist with the original one for a certain duration to obtain the classifier model. d) Although replacing the sensor will reduce the gas recognition accuracy, considering the actual life of the sensors are 1.5 to 2 years, replacing the sensor once can extend the life of the gas recognition system by at least 1.5 years. In application scenarios where high accuracy is not required, this decrease in accuracy is acceptable.

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