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Post-processing Technique for Improving the Odor-identification Performance based on E-Nose System

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Abstract

In this paper, we proposed a post-processing technique for improving classification performance of electronic nose (E-Nose) system which may be occurred drift signals from sensor array. An adaptive radial basis function network using stochastic gradient (SG) and singular value decomposition (SVD) is applied to process signals from sensor array. Due to drift from sensor's aging and poisoning problems, the final classification results may be showed bias and fluctuations. The predicted classification results with drift are quantized to determine which identification level each class is on. To mitigate sharp fluctuations moving-averaging (MA) technique is applied to quantized identification results. Finally, quantization and some edge correction process are used to decide levels of the fluctuation-smoothed identification results. The proposed technique has been indicated that E-Nose system was shown correct odor identification results even if drift occurred in sensor array. It has been confirmed throughout the experimental works. The enhancements have produced a very robust odor identification capability which can compensate for decision errors induced from drift effects with sensor array in electronic nose system.

Keywords: Sensor array, Adaptive radial basis function network, Sensors drift, Post-processing technique, Odor identification

1. INTRODUCTION

There is demand for the development of instruments that emulate the senses of humans mimicking the human sense of smell, which is a sophisticated chemosensory system. The electronic nose system is comprised an array of chemical sensors together with associate electronics and pattern recognition techniques [1]. Extremely selective information for discrimination between adsorbed chemicals species can be obtained by analysis of the cross-sensitivities between sensor elements [2]. The electronic nose system sometime showed significant variation of patterns over the long time period even if identical odors were presented. Drift in the signal of the electronic nose system can usually be classified into two categories that includes the short-term drift caused by the memory effects and the long-term drift caused by sensor poisoning and aging [3]. Since all types of drift will after a certain time degrade the initial learned capability of pattern recognition, it causes difficulty with classification of odors after some period of time. A number of possible approaches have been suggested to compensate systematic drift effects such as those caused by aging and poisoning of the sensor materials combined with various circumstances. Adaptive neural networks are currently an active area of research and promise even more sophisticated neural networks that can automatically compensate drift effect [4]. Among them, an adaptive radial basis function (RBF) networks, which had tuned centers and widths using the singular value decomposition (SVD) method or the stochastic gradient (SG) method, had shown good classification performance for the complex and noisy chemical patterns given relatively ill-conditioned clustering centers and widths. The characteristics of adaptive RBF Network based on the SG method to adapt for fine tuning of weights between hidden and output layer based on SVD calculation gave more adaptation capabilities to the RBF network. Also, we could confirmed that an adaptive RBF network could be used for drift compensation of a 32 conducting polymer sensor array over a period of four weeks [5]. In this paper, an identification technique for gas classification from prediction signals of a drifting electronic nose system is presented. For good odor prediction performance, an adaptive Gaussian Radial Basis Function Network (RBFN) using SG and SVD is used to process data from a chemical sensor array. But the method still requires

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better error performance for correct odor identification. The identification technique, through the post-processing of quantization, moving-averaging, another quantization and some edge correction method, has shown correct gas identification results for an electronic nose system with drift. It has been confirmed throughout the experimental works.

2. EXPERIMENTAL

2.1 Radial Basis Function (RBF) Network

The architecture of RBF network has to be simple and consists of input, hidden, and output layers. The basis functions in the hidden layer produce a localized response to the input and typically use hidden layer neurons with Gaussian response functions, in which case the activation levels *Oj* of hidden unit *j* are calculated by

$$O_j = \exp\left(\frac{\|x-c_j\|^2}{2\sigma_j^2}\right) \tag{1}$$

where x is the input vector, c_j is the centers associated with hidden unit j and σ is the width parameters, which represent a measure of the spread of data. The outputs of the hidden units lie between 0 and 1; the closer the input to the center of the Gaussian, the larger the response of the node. The activation level O_j of an output unit is determined by

$$O_j = \sum w_{ji} O_i \tag{2}$$

where w_{ji} is the weight from hidden unit i to output unit j.

The performance of RBF network is highly dependent on the choice of centers and widths in basis function. For a minimum number of nodes, the selected centers should well represent the training data for acceptable classification. Most of the training algorithms for RBF network have been divided into the two stages of processing. Firstly, as a clustering method fuzzy c-means algorithm which we found relatively good is applied to the input patterns in order to determine the centers for hidden layer nodes. After the centers are fixed, the widths are determined in a way that reflects the distribution of the centers and input patterns. Once the centers and widths are fixed, the weights between hidden and output layer are trained by single shot process using SVD. This two-stage method provides some useful solutions in pattern classification problem. However, since the centers and widths are fixed after they are chosen and only the weights are adapted for supervised learning, this method often results in not satisfying performance when input patterns are not particularly clustered.

2.2 Radial Basis Function – Stochastic Gradient (RBF-SG) Algorithm

In this section, an adaptation method to select optimum centers and widths for RBF network is presented. Also, the weights between hidden and output layer can be also tuned during the adaptation routine for widths and centers. For given set of input patterns measured using a thirty-two element sensor array, the fuzzy c-means algorithm with random initial conditions is carried out to find locations of clusters' centers which are then fed into the hidden layer units of RBF network. The Euclidean distance between the input patterns and the clusters' center is evaluated, then a Gaussian basis function with initial widths is applied. The weights between hidden and output units are trained by a single shot process using the Singular Value Decomposition (SVD) method, because RBF network is applied as a supervised learning algorithm for odors classification. For the tuning of centers and widths, weights were initially selected by a fuzzy c-means algorithm. Patterns distributions and weights are also initialized by SVD in the very first learning stage, the SG method being adapted to finely tune centers and widths as described in as follows: [4].

$$\Delta c_j^n = c_j^{(n+1)} - c_j^n = -\mu_c \frac{\partial e_n^2}{\partial c_j^{(n)}}$$

$$= \mu_c e_n \omega_j^{(n)} \exp\left(\frac{-\|x_n - c_j^{(n)}\|^2}{(\sigma_j^n)^2}\right) \frac{(x_n - c_j^{(n)})}{(\sigma_j^n)^2} \tag{3}$$

$$\Delta \sigma_j^{(n)} = \sigma_j^{(n+1)} - \sigma_j^n = -\mu_s \frac{\partial e_n^2}{\partial \sigma_j^n}$$

$$= \mu_c e_n \omega_j^n \exp\left(\frac{-\|x_n - c_j^{(n)}\|^2}{(\sigma_j^n)^2}\right) \frac{\|x_n - c_j^{(n)}\|^2}{(\sigma_j^n)^2} \tag{4}$$

Where μ_s and μ_c are adaptation coefficients for widths σ_j , and centers c_j, respectively, and they control the speed of adaptation. The weights between the hidden and output layer are also tuned by SVD calculation in the same iteration together with centers and widths

2.3 Post-Processing Technique

Because of drift from sensor aging and poisoning problems, the prediction outputs from RBF (without SG) or RBF-SG algorithm

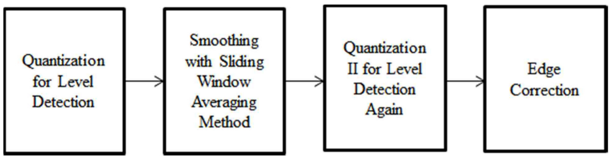

Fig. 1. Post-processing Technique.

still show bias and fluctuations. Judging odors from the prediction signal from those algorithms gives rise to still not acceptable number of identification errors. An improved identification method for odor decision can be made by post-processing the prediction signals of a drifting odor sensing system. As depicted in Fig. 1, the prediction signal having bias and fluctuations are quantized first to determine what decision level each prediction output sample is on.

The output of the first quantization stage shows on which level the samples are but many decision errors occur due to fluctuations from noise and bias from sensor drift. In our experiments with data measured over period of 4 weeks, the drift does not exceed one-step distance and RBF-SG algorithm has shown fluctuations within one or two-step distance. Still we can't tell which level samples with sharp edges are on. Now we need to smooth those sharp fluctuations. To mitigate sharp fluctuations sliding window Moving-Averaging method is applied to the quantized outputs. Then sharp fluctuations are smoothed below half step. Level decision to this output is needed again, using quantization process II. From this quantization process II, some errors are detected within 1 or 2 samples around edges. We can find solutions for edge correction using the prediction data again. Using edges of quantization II output as the central points, we search rising edges of the prediction data within + - 2 samples around the central point. If any rising edge is detected in the prediction data around the central point of quantization II output, the detected edge becomes the right one. If not, the central points are the correct edges.

3. RESULTS AND DISCUSSIONS

For testing the performance of the classifier based on adaptive RBF network on drifting data, we used an electronic nose system that has an array of conducting polymer sensors mounted on ceramic substrate with associate electronic developed by Prof. Krishna Persaud at University of Manchester, U.K. [6]. A conducting polymer sensor array consisting of 32 sensors was used to collect patterns from solvent vapors measured over period

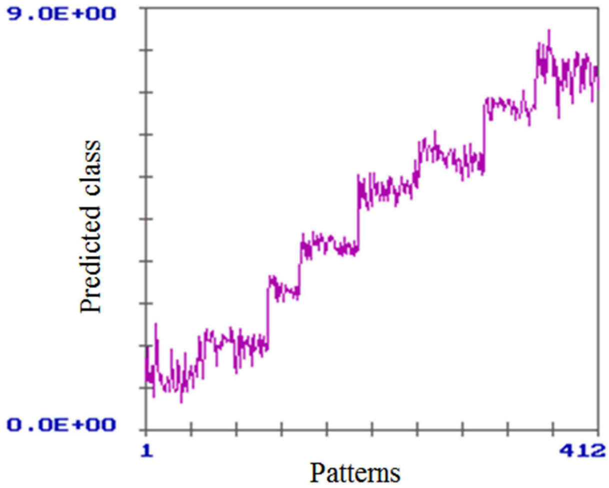

Fig. 2(a). Prediction results of RBF-SG for 3-4 weeks data.

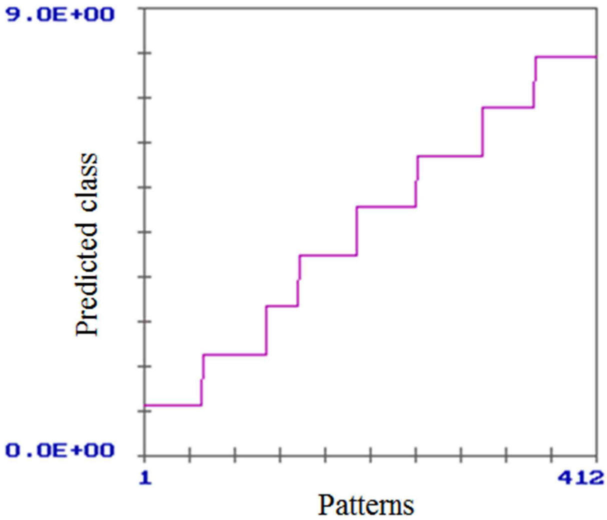

Fig. 2(b). Target data.

of 4 weeks. For network training, eight centers for each class were chosen from a total of 520 patterns in weeks 1 and 2 data sets. The trained system was then tested against 412 patterns of solvents from weeks 3 and 4 data sets. After having trained the RBF network using weeks 1 and 2 data sets obtained from 1% acetonitrile (ac1), 10% acetonitrile (ac10), 1% acetone (ae), 1% butanone (bu), 10% methanol (me), 1% propanol (pr1), 10% propanol(pr10), and water (wa) , the adaptive RBF network with SG tuning method for centers and widths was applied to the previously unseen data from weeks 3 and 4 to evaluate odor prediction under drift effects. Fig. 2(a) shows the predicted output of the network. The weights of RBF-SG algorithm are also updated using the SVD method in the training session. Though this result indicates that the adaptive RBF network using SG works well in the prediction of the previously unseen patterns over

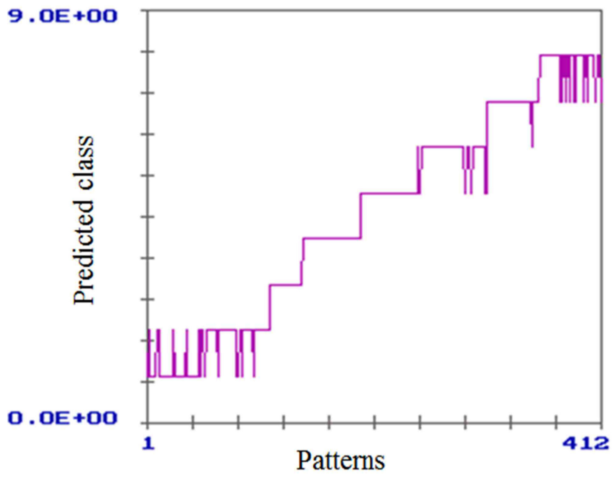

Fig. 2(c). Decision results without proposed method (8% error).

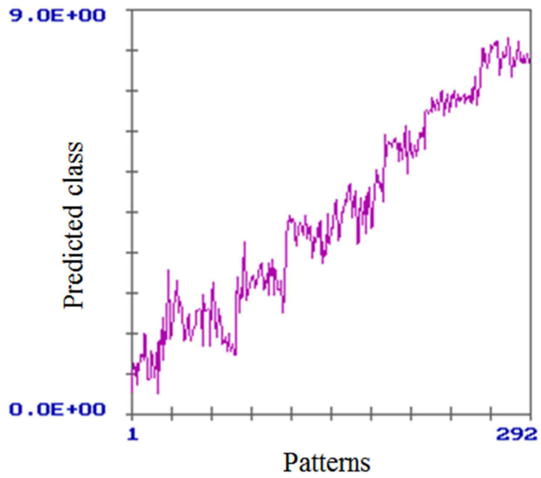

Fig. 3(a). Prediction results of RBF (not using SG).

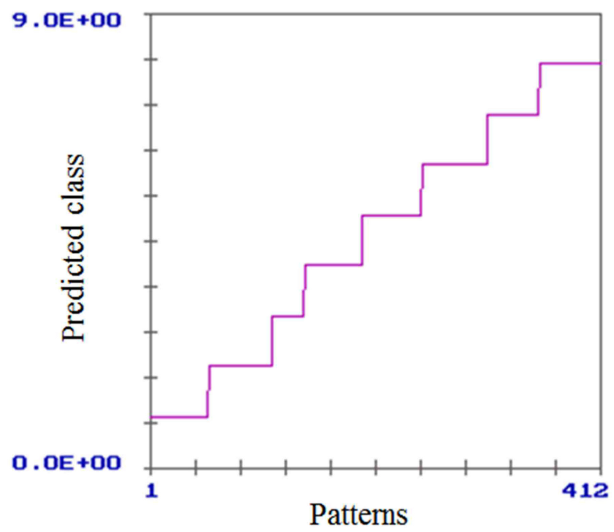

Fig. 2(d). Decision results with proposed method (0% error).

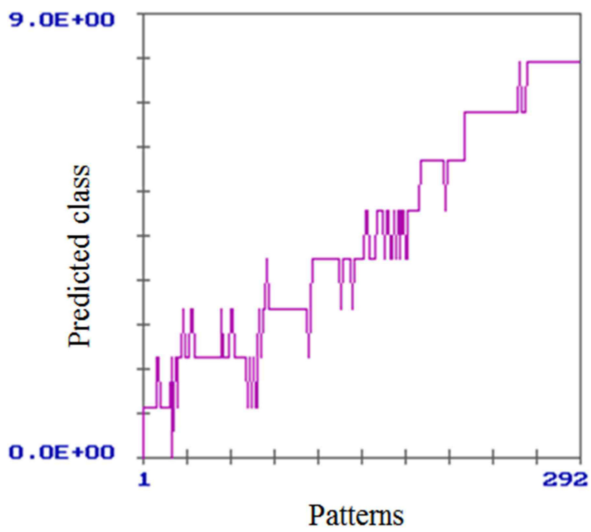

Fig. 3(b). Decision results without proposed technique (18% error).

a period of 4 weeks, it has still noticeable decision errors. The error performance was compared when we use the proposed identification post processing method vs. when not use it.

The prediction output of RBF-SG and the identification results from the proposed post processing method are shown in Fig. 2 (c) and (d) respectively. We acquired the error performance improvement from 8% to 0%.

Perfect identification performance was resulted in. In Fig. 3 (a), the prediction output of RBF without using SG and the results from the proposed post processing method are presented. It has shown 18% vs. 11% of error for RBF without using SG, which are illustrated in Figs. 3 (b) and (c). This implies that using this simple post processing method even to not finely tuned RBF classifiers, considerable error performance improvement can be acquired.

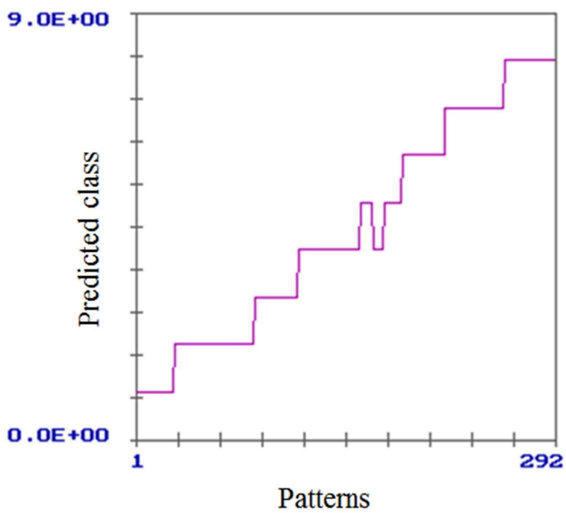

Fig. 3(c). The identification results using the proposed technique (11% error).

4. CONCLUSIONS

This paper presents a post processing techniques to improve identification error performance in the adaptive RBF network under conditions of data sets that show some drift. With the use of the SG method for tuning of centers and widths including weights calculation by SVD, we confirmed that the adaptive RBF network has good odor prediction performance after some period of time, even if the sensors suffered from drift. But the decision performances from RBF or RBF-SG algorithm still need more improvement. The proposed techniques for identification performance improvement that consists in quantization, smoothing, quantization again and edge correction processes shows that even to not finely tuned RBF classifiers, considerable error performance improvement can be acquired. In RBF-SG case, we acquired Perfect identification performance.

The enhancements have produced a very robust odor classifier which can compensate for decision errors induced from drift effect with sensor array in electronic nose system.

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