

# Online diagnosis of PEMFC by analyzing individual cell voltages

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**Abstract**—Polymer Electrolyte Membrane Fuel Cell (PEMFC) is a promising power source for a wide range of applications. Fault diagnosis, especially online fault diagnosis, is an essential issue to promote the development and widespread use of PEMFC technology. This paper proposes a diagnosis approach for large PEMFC stack. In this approach, flooding fault is concerned; individual cell voltages are chosen as original variables for diagnosis. A dimension reduction method Fisher linear discrimination (FDA) is adopted to extract the features from the cell voltage composed vectors. After that, a classification methodology, Gaussian mixture model (GMM) is applied for fault detection. Flooding experiments were conducted on a 20-cell stack to test the approach. The obtained results showed that data points can be classified to different states of health with a high accuracy. It is also verified that the real-time implementation of the algorithm is feasible.

## I. INTRODUCTION

Increasing environment and resource issues draw the more and more attention. Developing a clean and high efficient power generator is urgent in recent years. Fuel cell, as it has lower emissions of CO<sub>2</sub>, is a promising alternative power generator. In some domains, for instance the transportation applications, PEMFC has been drawing more attention than other types of fuel cell because of its high efficiency, high power density and the ability of operating at low temperatures [1]. However, there are still two barriers: the reliability and durability, which block the wide application of PEMFC.

Fault diagnosis is an efficient solution to overcome these barriers [2]. More particularly, online diagnosis is more effective than offline diagnosis, since it permits an earlier fault detection such that more serious faults can be avoided. Additionally, the diagnosis results can be supported to the control unit, thus help adjusting the control commands.

Since the fuel cell system is a nonlinear one, in which the phenomenon of electrochemistry, thermodynamics, and fluid mechanics are coupled together, reliable diagnosis of fuel cell system is a challenge. Some literatures have proposed several fuel cell diagnostic methods. Physical modeling is an intuitional way to realize the aim of diagnosis [3], however, complicated parameters estimation is needed to get an accurate modeling. In order to overcome the drawbacks of physical model, some "black-box" or "grey-box" models are

applied with the aids of some artificial intelligent methods. In [4], authors proposed neural networks model based procedure to diagnose water management faults. A fuzzy diagnostic model is proposed in [5], which is used to diagnose drying of membrane and accumulation of N<sub>2</sub>/H<sub>2</sub>O in the anode compartment. Some statistical tools were also developed for diagnosis. In [6], a multivariate statistical method is presented, in which faults can be detected by analyzing principal components. In paper [7], authors proposed an approach based on Bayesian networks, which can handle four types of faults in PEMFC system. In addition, paper [8] introduced a signal analysis approach, in which wavelet package translating methodology is used to detect flooding fault. In [9], authors developed a experimental methodology based on the analysis of the Open Circuit Voltage (OCV) in order to detect leakage faults and locate the fault cells inside the stack.

Although these methods can support us some solutions for diagnosis of fuel cell system, there are still matters need to be improved. Most of the methods consider the fuel cell stack as integration. However, the behaviors of cells are different actually [10]. Hence, the otherness of cells should be in consideration. For online diagnosis, the accuracy of fault diagnosis and the implementation cost of the algorithm, which are usually omitted in the literatures, should be evaluated carefully [11].

In this work, we propose an approach for online diagnosis of flooding fault in large PEMFC stack. In the approach, individual cell voltages are analyzed by adopting feature extraction and classification methods. Such that data can be classified to normal class, transition state, and fault state. The performance and the feasibility of the approach for online use are evaluated based on the experimental data of a 20-cell PEMFC stack.

The rest of the paper is organized as follows: In section 2, the PEMFC system and the concerned flooding fault are introduced. The details of experiment platform are presented in section 3. In section 4, the diagnosis approach is expounded, including detailed presentations of methodologies: FDA and GMM. The results of diagnosis are given in the next section, and the feasibility of online implementation is also discussed in this section. Finally, the conclusion and future work are summarized.

## II. PEMFC SYSTEM AND CONCERNED FAULT

### A. PEMFC system

A running PEMFC is usually fed continuously with hydrogen on the anode side and air on the cathode side. With

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the conversion of chemical energy to electric energy, the by-product water is generated meanwhile. To produce a useful voltage or power, many cells have to be connected in series, which is known as a fuel cell stack. In order to make a fuel cell stack operate in an efficient and safe state, three ancillary circuits, other than fuel cell stack, are usually added to the system: hydrogen circuit, air circuit, and cooling circuit. As Fig. 1 shows. In hydrogen circuit and air circuit, the flow rates and pressures of gases can be regulated. temperatures, humidity and pressures. The temperature of fuel cell stack can be regulated by cooling circuit. In addition, a humidify circuit is usually added to the air circuit.

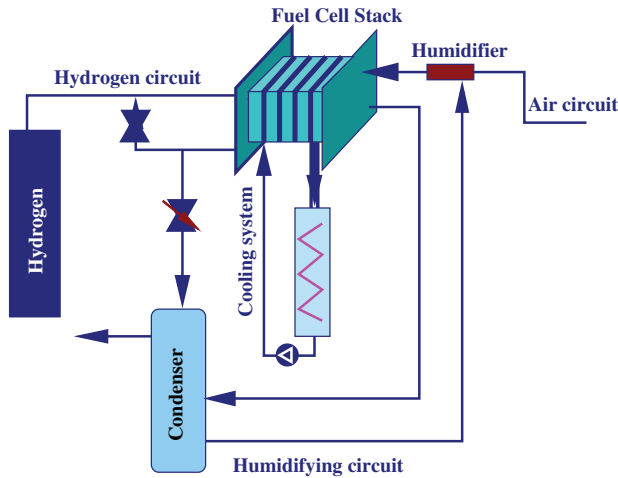


Fig. 1. The schematic of PEMFC system [12]

### B. Presentation of the concerned fault

Kinds of faults may occur in the fuel cell system. The faults may happen inside the fuel cell stack or in the ancillary circuits. The faults of ancillary circuits could lead to the faults of fuel cell stack, so that the faults of fuel cell stack can reflect the faults of ancillary components. Additionally, the fuel cell stack is the heart of the whole system. Consequently, the diagnosis of fuel cell stack is prior and crucial. The paper will focus on one of the most common faults that occur inside the fuel cell stack: "flooding fault".

As Fig. 2 shows, a typical PEMFC consists of bipolar plates (BPs), gas diffusion layers (GDLs), catalyst layers (CLs), and membrane. On both sides of BPs, gas channels are grooved for gas flow. In a proper functioning PEMFC, the membrane should keep a certain water content to make the protons transport through it effectively with low ohmic resistance. Hence, air is humidified before fed into fuel cells (in our system). At the same time, the liquid water is generated in the cathode and expelled from fuel cells with unreacted air. Inside the fuel cell, water transfers among different layers and between anode and cathode [13]. Some factors, such as gas pressures, gas humidities, gas flow rates, stack temperature, and load current, can impact the balance of the water management. The unbalance of water management may cause the presence and accumulation of

liquid water in the gas channels and/or gas porosities of GDLs and CLs, resulting in the flooding fault. Excessive liquid water will block the pathways of reactants, thus make the fuel cell stack degraded. As the water is generated in the cathode side, flooding happens generally in the cathode side.

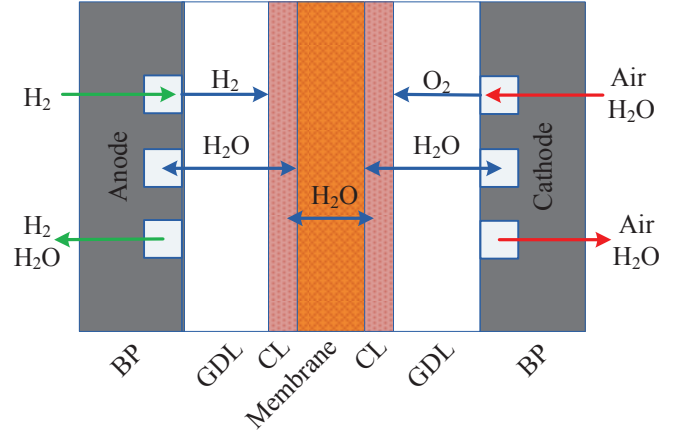


Fig. 2. Schematic picture of water movement inside a PEMFC

## III. EXPERIMENT PLATFORM

A 1 kW PEMFC experiment platform is used to test a 20-cell PEMFC stack. Many physical parameters impacting stack performances can be controlled and measured in order to master the operating conditions as specifically as possible. Stack temperature (measured by a thermocouple placed at the cooling circuit outlet), gas flow rates, fluid hygrometry rates, and load current can be set. Inlet and outlet flow rates ( $D_i$  and  $D_o$ ), pressures ( $P_i$  and  $P_o$ ), stack temperatures ( $T_s$ ), current ( $I$ ), stack voltage ( $v_s$ ) and single cell voltages ( $v_1, v_2, \dots, v_{20}$ ) can be monitored. Table I summarize some parameters of the investigated fuel cell stack. Additional details about the test bench and the test protocol have been previously published in Refs. [14] and [15].

TABLE I  
THE PARAMETERS OF THE INVESTIGATED FUEL CELL STACK

Gas flow field	serpentine
Cell area	100 cm <sup>2</sup>
Cell number	20
Nominal output power	500 W
Nominal operating temperature	50 °C
Operating temperature region	20-65 °C
Operating pressures	1.5 bar
Anode stoichiometry	2
Cathode stoichiometry	4

## IV. THE PROPOSED APPROACH

### A. Selection of variables for diagnosis

Although in our experimental platform, many physical variables can be collected. The collected variables can be written as a set  $\mathcal{T}$

$$\mathcal{T} = \{D_i, D_o, P_i, P_o, T_s, I, v_s, \mathbf{v}_c\} \quad (1)$$

where  $v_c = \{v_1, v_2, \dots, v_{20}\}$ . However, in the condition of keeping high diagnosis accuracy, we try to decrease the number of the sensors so as to improve the reliability and lower the cost in practice. Consequently, just a subset of  $\mathcal{T}$  is selected as the original variables for diagnosis. Individual cell voltages are considered here as the variables for diagnosis for the following reasons:

- 1) The necessity of monitoring individual cell voltage is stressed, since a single cell can induce the malfunction of the stack [16].
- 2) The fuel cell voltages and their variations contain abundant information that can be used to monitor the parameters of the fuel cell model [17]. In other word, the individual cell voltage can be seen as sensors inside the fuel cell stack.
- 3) It is observed that appearance of the liquid water change the flow distributions of the gases, and further make the cell voltage distribution varied [10]. So the distribution and relations among the individual cell voltages contain information for diagnosis.

### B. Description of approach

Pattern classification is an crucial and efficient tool for fault isolation [18]. It can also be applied for fault detection by adding a class of data which represents the normal state [19]. In this work, a parametric classification methodology GMM is adopted. For large fuel cell stack, the number of fuel cell is large. It means the dimension of data for classification will be high. This will make the classification complicated, and the redundancy of high-dimensional data will lower the accuracy of the classification [20]. In order to overcome these problems, before classification, a dimension reduction method FDA is adopted. The procedure is called feature extraction step. As Fig. 3 shows, the diagnosis process is composed by three steps: data acquisition, feature extraction and classification. The feature extraction methodologies FDA and GMM classification are reviewed in the following parts.

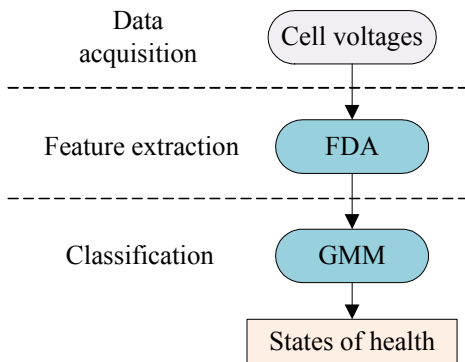


Fig. 3. The flow chart of the proposed diagnosis approach

### C. FDA

FDA is a technique developed for reducing the dimension of the data in the hope of obtaining a more manageable

classification problem. The objective of FDA is to find a mapping vector that makes the data in the same class be projected near to each other while the data in the different classes are separated as far as possible [21] [22].

Given a set of M-dimension objects  $\{\mathbf{x}_1; \mathbf{x}_2; \dots; \mathbf{x}_N\}$ , which belong to  $C$  classes denoted as  $\zeta_1, \zeta_2, \dots, \zeta_C$ , FDA procedure projects each objects to a L-dimension space by M-dimension unit projecting vectors  $\omega_1, \omega_2, \dots, \omega_L$ . Take  $\omega_1$  as example, vector  $\{\mathbf{x}_n\}$  is projected to  $\{y_{n1}\}$

$$y_{n1} = \omega_1^T \mathbf{x}_n \quad (2)$$

In order to seek  $\omega_1$ , within-class variance  $s_w$  is defined in the mapped space

$$s_w = \sum_{i=1}^C \sum_{y_n \in \zeta_i} (y_n - \bar{y}_i)(y_n - \bar{y}_i)^T \quad (3)$$

where  $\bar{y}_i$  is the mean value of data in class  $\omega_i$ :  $\bar{y}_i = \frac{1}{N_i} \sum_{y_n \in \zeta_i} y_n$ .  $N_i$  is the number of data in  $\zeta_i$  which satisfies  $\sum_{i=1}^C N_i = N$ .  $s_w$  represents the variance of the data in the same class.

The between-class variance  $s_b$  which represents the variance between data in different classes is defined as

$$s_b = \sum_{i=1}^C N_i (\bar{y}_i - \bar{y})(\bar{y}_i - \bar{y})^T \quad (4)$$

where  $\bar{y}$  is the mean value of total data:  $\bar{y} = \frac{1}{N} \sum_{n=1}^N y_n$ .

We hope to construct a scalar which has the quality that it is large when the between-class covariance is large and within-class covariance is small. One such scalar is given as

$$J(\mathbf{w}) = s_w^{-1} s_b \quad (5)$$

Substitute  $\{y_n\}$  with  $\{\mathbf{w}^T \mathbf{x}_n\}$ , (5) can be converted to

$$J(\omega_1) = \frac{\omega_1^T \mathbf{S}_b \omega_1}{\omega_1^T \mathbf{S}_w \omega_1} \quad (6)$$

where  $\mathbf{S}_b$  named within class scatter matrix is defined as

$$\mathbf{S}_w = \sum_{i=1}^C \sum_{\mathbf{x}_n \in \zeta_i} (\mathbf{x}_n - \bar{\mathbf{x}}_i)(\mathbf{x}_n - \bar{\mathbf{x}}_i)^T \quad (7)$$

$\bar{\mathbf{x}}_i$  is mean vector in class  $\zeta_i$ :  $\bar{\mathbf{x}}_i = \frac{1}{N_i} \sum_{\mathbf{x}_n \in \zeta_i} \mathbf{x}_n$ .  $\mathbf{S}_b$  named between class scatter matrix is defined as

$$\mathbf{S}_b = \sum_{i=1}^C N_i (\bar{\mathbf{x}}_i - \bar{\mathbf{x}})(\bar{\mathbf{x}}_i - \bar{\mathbf{x}})^T \quad (8)$$

where  $\bar{\mathbf{x}}$  is the mean vector of total data:  $\bar{\mathbf{x}} = \frac{1}{N} \sum_{n=1}^N \mathbf{x}_n$ . Both  $\mathbf{S}_w$  and  $\mathbf{S}_b$  are symmetric and positive semidefinite. Usually,  $\mathbf{S}_w$  is nonsingular while  $\mathbf{S}_b$  is singular.

Differentiating (6) with respect to  $\omega_1$ , it is easy to prove that the optimal solution of  $\omega_1$  is equal to eigenvector of  $\mathbf{S}_w^{-1} \mathbf{S}_b$  that corresponds to the largest eigenvalue. Consequently, it can be inferred that the mapping vectors  $\omega_1, \omega_2, \dots, \omega_L$  are equal to the eigenvectors of  $\mathbf{S}_w^{-1} \mathbf{S}_b$  that correspond to the first  $L$  largest eigenvalues.

Since  $\mathbf{S}_b$  is the sum of  $C$  matrixes of rank one or less, only  $C - 1$  of these are independent,  $\mathbf{S}_b$  is of rank  $C - 1$  or less. Thus, no more than  $C - 1$  of the eigenvalues are nonzero. The desired mapping vectors correspond to these nonzero eigenvalues. Hence, the maximum of feature space dimension  $L$  we can get is  $C - 1$  [21].

#### D. GMM

GMM is a parametric classification methodology based on Bayes decision theory [23]. Bayes' formula is given

$$p(\zeta_i|\mathbf{x}_n) = \frac{p(\mathbf{x}_n|\zeta_i)p(\zeta_i)}{p(\mathbf{x}_n)} \quad (9)$$

where  $p(\zeta_i|\mathbf{x}_n)$ ,  $p(\mathbf{x}_n|\zeta_i)$ , and  $p(\zeta_i)$  are respectively named as posterior, class-conditional probability, and prior probability. To decide which class a data point  $\mathbf{x}_n$  belongs to, we should compare the posterior  $p(\zeta_i|\mathbf{x}_n)$ . It is resolved that  $\mathbf{x}_n$  belongs to the class with the largest posterior. In other words, we just need to compare  $p(\mathbf{x}_n|\zeta_i)p(\zeta_i)$  with different  $i$ . The prior probability  $p(\zeta_i)$  is usually thought to be the frequency weight of data belongs to  $\zeta_i$ , so the main object is to estimate the class-conditional probability density  $p(\mathbf{x}_n|\zeta_i)$ .

GMM is a efficient probability distribution model to express the class-conditional probability  $p(\mathbf{x}_n|\zeta_i)$ . In GMM, class-conditional probability density is represented as a weighted sum of Gaussian component densities.

A Gaussian mixture model is a weighted sum of  $R$  component Gaussian densities as the following equation,

$$p(\mathbf{x}_n|\lambda) = \sum_{i=1}^R p(c_i)p(\mathbf{x}_n|c_i, \lambda) \quad (10)$$

where  $p(c_i)$ ,  $i = 1, \dots, R$  are the mixture weights, which satisfies  $\sum_{i=1}^R p(c_i) = 1$ ,  $p(\mathbf{x}_n|c_i, \lambda)$  are the component Gaussian densities. Each component density is a M-variate Gaussian function of the form,

$$p(\mathbf{x}_n|c_i, \lambda) = \frac{1}{(2\pi)^{M/2}|\Sigma_i|^{1/2}} \exp\left\{-\frac{1}{2}(\mathbf{x}_n - \boldsymbol{\mu}_i)^T \Sigma_i^{-1}(\mathbf{x}_n - \boldsymbol{\mu}_i)\right\} \quad (11)$$

with mean vector  $\boldsymbol{\mu}_i$  and covariance matrix  $\Sigma_i$ . Parameters  $\boldsymbol{\mu}_i$ ,  $\Sigma_i$  and  $p(c_i)$  are collectively represented by the notation  $\lambda$ ,

$$\lambda = \{p(c_i), \boldsymbol{\mu}_i, \Sigma_i\} \quad i = 1, \dots, R. \quad (12)$$

Before the model training process, the Gaussian component number  $R$  is usually settled according to the complexity of the data distribution. In the training process, GMM parameter collection  $\lambda$  needs to be estimated from training data. Expectation-Maximization (EM) algorithm is a commonly used method. By iterations,  $\lambda$  can be estimated. The details about EM algorithm can be found in [24].

#### E. Online implementations of the methodologies

In consideration of the online implementation for FDA, memory space is needed to save  $L \times M$  float numbers for mapping vectors  $\boldsymbol{\omega}_1, \boldsymbol{\omega}_2, \dots, \boldsymbol{\omega}_L$ . To calculate the features,  $L \times M$  times of multiplication operations and  $L \times (M -$

1) times of addition operations are needed to be proceeded for a FDA procedure. Concerning the online implementation for GMM, the parameters of models, including parameter set  $\lambda$  and prior probability need to be saved. Memory for saving  $CR \binom{M+1}{2} \binom{M+2}{2} + C$  float numbers are required. The  $CR(M^2 + M + 1) + C$  times of multiplication operations and  $CR$  times of exponent arithmetic operations need to be carried out for a procedure. It will be shown in the next section that the implementations of the methodologies can be easily realized.

## V. RESULTS AND DISCUSSION

### A. Experiment introduction

In order to verify our proposed approach, the flooding experiments were carried out. The temperature of stack was decreased from 50 °C to 35 °C in order to favor water condensation, while the other experiment conditions were kept in nominal values. To certify the repeatability approach, several independent flooding experiments were carried out. In these experiments, the flooding was induced from normal operating conditions. At the end of each test, the load was firstly disconnected from the stack while the air was kept for a length of time. In addition, when we restarted a new experiment, the air circuit was started before adding the load. During the periods, the liquid water inside the fuel cell was cleared away, which certified that there was no flooding occurred at the beginning of each experiment.

Various physical variables, denoted as  $\mathcal{T}$  in (1), were sampled in the flooding process. The sampling period is 150 ms, which can guarantee the bandwidth of flooding dynamics. Specifically, the cell voltages are analyzed. The cell voltages in one experiment can be presented as a matrix

$$\mathcal{V} = \{\mathbf{v}_1; \mathbf{v}_2; \dots; \mathbf{v}_N\} \quad (13)$$

where the  $n^{th}$  row vector  $\mathbf{v}_n$  is composed by individual cell voltages

$$\mathbf{v}_n = \{v_n^1, v_n^2, \dots, v_n^{20}\} \quad (14)$$

where numbers 1, 2, ..., 20, are index numbers of fuel cells, whose locations are from air inlet side to air outlet side.  $n$  is the sequential number of the sample, the total sample number is  $N = 6400$ . This matrix will be used to train the FDA and GMM models.

### B. Results

Since FDA and GMM are both supervised methodologies, data for training must be labeled before training procedure. In the flooding course, it is considered that the liquid water accumulates as time. Consequently, the samples are roughly but reasonably labeled that the 1<sup>th</sup> to the 2500<sup>th</sup> samples are in normal state, the 2501<sup>th</sup> to the 3500<sup>th</sup> samples are in transition state, the 3501<sup>th</sup> to 6400<sup>th</sup> samples are in fault state.

The wave forms of cell voltages in a flooding process are as Fig. 4. It can be seen that cell voltages all overall decrease in the flooding process (although both momentary increases and decreases exist); however the magnitudes and

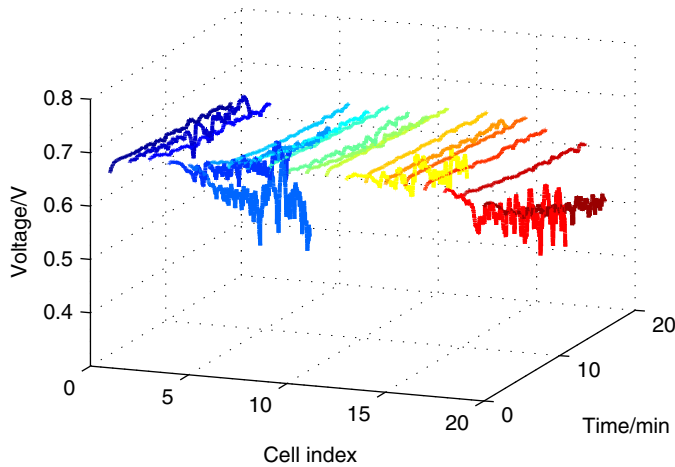


Fig. 4. Cell voltages in flooding process

speeds of the voltage drops are various. Several cells degrade more severely than others. The probable reason for this phenomenon is that, the distributions of liquid water in the stack is nonuniform. By comparing the different experiment results, it is found that the degraded extents of a concerned fuel cell are varied with experiments. In order to slack the impact of the spacial randomness of the flooding occurring, the elements of vectors  $\{v_n\}$  are sorted firstly in ascending orders.

After this treatment, the FDA is employed to handle the matrix  $\mathcal{V}$ . By using FDA, the original 20-dimension vectors  $\{v_n\}$  are projected to a 2-dimension feature space. The two features are plotted as Fig. 5. It can be observed that

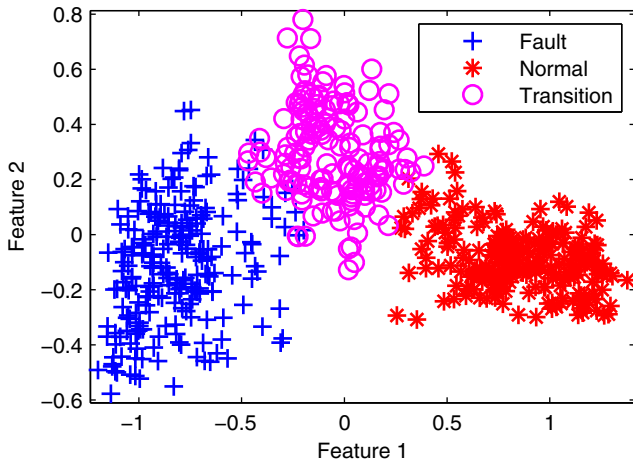


Fig. 5. Features extracted by FDA procedure

data points within each class are gathered, while data points between classes are scattered simultaneously. Just a small overlap occurs between transition class and fault class.

After feature extraction, GMM classification is proceeded

in the 2-dimension feature space. Since data points within each class are concentratedly distributed, the number of Gaussian components  $R$  is set as 1. Parameter collection  $\lambda$  of each class are estimated by EM algorithm.

After the parameter estimation process, class-conditional probability density of each class is obtained. The prior probability of each class is set as the frequency weight of data within the class. By multiply class-conditional probability densities with prior probabilities, we can get the posterior of each class. The posteriors of the three classes are plotted as Fig. 6.

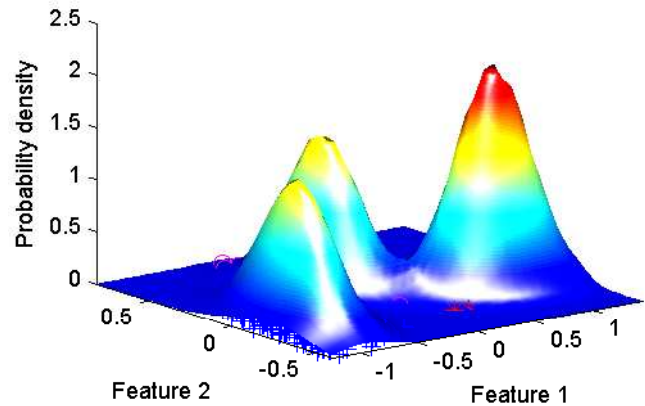


Fig. 6. The posteriors of three classes

By comparing the posteriors of different classes, the two-dimension feature space can be divided to 3 zones, which represents respectively normal state, transition state, and fault state. The three zones and boundaries between them are shown as Fig. 7.

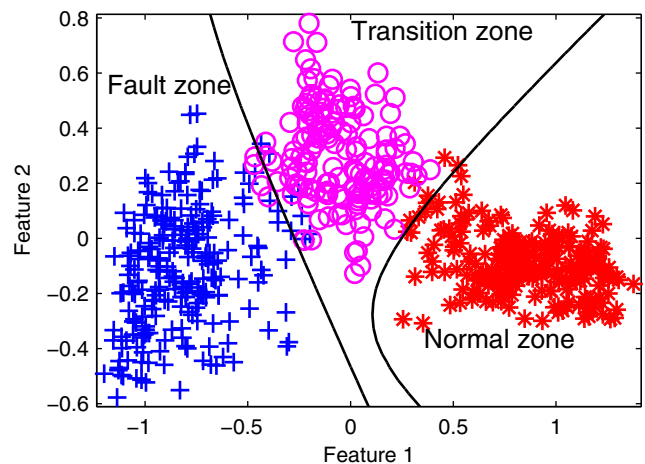


Fig. 7. Partition of three zones in feature space

### C. Discussion

To evaluate the performance of proposed approach for online application, two aspects are considered: diagnosis accuracy and feasibility of the real-time implementation.

- 1) In order to evaluate how accurately it will perform in practice, a popular cross-validation methodology which named K-fold cross-validation is used. In K-fold cross-validation, the total data is randomly divided into  $K$  subsets. Of the  $K$  subsets,  $K - 1$  are chosen as training data and rest one subset is used to test the classifier. The error rate, which is defined as proportion of samples that are wrongly classified, is calculated. The training and test process is then repeated  $K$  times. The averaged error rate is then obtained to evaluate the classifier. Here, the number of folds  $K$  is set to be 10, after several tests, the average error rates are always less than 3%.
- 2) According to section 3, to implement our approach, we need to save 736 float number, less than 1.5 k of 16 bit memory are needed. For one diagnosis procedure, 64 times multiplication operations, 38 times addition operations and 3 exponent arithmetic operations. These operations should be done in a sampling period 150 ms. The required memory and computation speed can be satisfied by a common DSP (Digital Signal Processor).
- 3) Lack of physical significance and difficult to sample data that covers the whole fault zones are two drawbacks of the approach. Therefore, the proposed approach needs to be compared with other diagnosis methods in all directions.

### VI. CONCLUSION

In this paper, a diagnosis approach of large PEMFC stack is proposed. The approach is based on analysis of individual cell voltages in flooding process. By adopting feature extraction methodology FDA combined with GMM classification, data points can be classified into three states of health: normal state, transition state, fault state. The error rates of the diagnosis results are low and the software cost of the algorithm can be satisfied easily by a common DSP. It is therefore a suitable approach for online diagnosis.

Two aspects are under study to improve the performance of our approach: first, since the labeling process of the training data is arbitrary in the paper, a more convincing labeling method is being studied with the help of a fluidic model. Second, the approach can be extended to multi faults diagnosis by adding new classes to the training data, such extension is also in process of studying in our laboratory.

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