Analysis of Class Group Distinguishing Based Conceptual Models for Multiple Fault Diagnosis

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Abstract: It is common that multiple fault exists in actual engineering and complex systems. Due to parameters in multiple faults tightly coupled, relationship between the fault mode and known mono-fault features is non-linear. Thus, it is hard to see how distinguish in mapping set for "fault to symptom". In this case, there is no guarantee that traditional diagnosis methods for mono-fault meet the demands. With the requirement, an analysis of the traits of multiple faults is made. A summarization is given to class group distinguishing (CGD) based methods that applied in fault diagnosis. Major defects in the methods that applied in multiple fault diagnosis are analyzed. On that basis, fault modes and symptoms are taken as key points. Conceptual models for multiple fault diagnosis based on CGD are gradually explored. By the models, actual faults can be mapped to one or more known mono-faults via distinguishing analysis, and therefore multiple faults can be diagnosed. There are 4 kinds of flow chart and construction for the models are established. Each of these models presents advantages and disadvantages are separately presented at the end of the chapter.

Key Words: Multiple Fault, Fault Diagnosis, Class Group Distinguishing, Conceptual Models, Cluster, Classification

1 Introduction

As an important part of intelligent fault diagnosis technology, multiple fault diagnosis (MFD, or also can be called Composite Fault Diagnosis) is not only a difficult problem but also a hot direction in current fault diagnosis methods [1]. It is common that multiple fault exists in actual engineering and complex systems.

According to the difference of fault phenomenon and composite methods, the definitions of multiple fault diagnosis by large amounts of current references are mainly in the following 4 categories [2-4].

(1) Different faults are produced in a system at the same time.

(2) Several sequential faults are produced in components of systems.

(3) Multiple class faults, which refer to the faults from the different systems of the same engineering, are produced, such as faults coupling between actuators and observers.

(4) Multiple faults with spatial and temporal characteristics are coupled at the same time.

There is larger difference between different multiple faults, no matter the mechanism or the cause of them. Based on existing diagnosis methods, the basic idea is to process the sampled signals and then to get rid of irrelevant factors such as noise and redundancy in order to highlight the fault information [5]. Furthermore, the sampled signal is converted as diagnostic data sets according to the procedure of “fault detection, data processing, diagnosis inferring”, and then diagnosis is operated [6].

A lot of researches have showed that multiple fault diagnosis is a special class group distinguishing (CGD) problem[7]. The goal of CGD analysis is to gather the objects, which have the similar characteristics, thus some class groups with difference, are formed. The most typical characteristic of class groups is that elements of groups may not be the same, but they are regarded as the same class because of similarity. Therefore, CGD often is applied to solving uncertain problem. The large numbers of current references have proved the validity of CGD method for single fault diagnosis [8].

Composition and coupling of multiple fault symptoms are complex, so the linear relation does not always exist between faults mode and its single fault mode. Therefore, the relationship among all faults system (or faults space), multiple fault subsystem (or fault subspace), mono-faults (or independent subspace), and symptoms is difficult to described via linear function [9]. That is to say, the existing methods for single fault diagnosis cannot be applied to multiple fault diagnosis successfully.

According to above analysis, an overview about fault diagnosis methods based on CGD is showed. Furthermore, the analysis and research on conceptual models are presented for diagnostic data with multiple fault diagnosis.

2 Descriptions about MFD

The model of multiple fault diagnosis is very difficult to establish because of its complex formation mechanism. Compared with single fault, there are more fault symptoms (even “fault masking” phenomenon will appear)[10] in pre-processing data containing multiple fault. Furthermore, there is not a linear relationship between multiple fault data and the single fault data. The symptom of multiple fault is not the same as anyone of single fault, and is also not a simple combination of single fault symptoms[9].

Based on above analysis, multiple fault can be described by combinations of fault symptoms or single fault. In general, if m symptoms can be acquired from n sampled faults, every fault can be represented by y (where $1<y<m$) symptoms

Assume that $ad(y)$=1 represents y_{th} fault is appeared and

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$ad(y)$=0 represents y_{th} fault is disappeared, each fault can be described to a particular set:

$$fault_l = \{sym_{ly} | ad(y) = 1 \quad l = 1, \ldots, n \quad y = 1, \ldots, m\} \quad (1)$$

where $fault_l$ is fault and sym_{ly} is the symptom of l_{th} fault mapping to y_{th} symptom.

If symptom value is not binarized, Eq.1 can be overwrited as Eq.2:

$$\mathbf{d}_l = [f_{l1} \quad f_{l2} \quad f_{l3} \quad \ldots \quad f_{lm}] \quad (2)$$

where $\mathbf{d}_l$ represents symptom sets of l_{th} fault, f_{ly} represents the actual value of l_{th} fault mapping to y_{th} symptom. Known fault pattern sets $\mathbf{D}$ of fault system can be described by Eq.3.

$$\mathbf{D} = [\mathbf{d}_1 \quad \mathbf{d}_2 \quad \mathbf{d}_3 \quad \ldots \quad \mathbf{d}_n] \quad (3)$$

From the point of fault symptom vector, the multiple fault can not be completely matched with symptom sets of single fault, but it is a collection of multiple single fault from the point of composition [9].

Assume $ap(l)$=1 represents fault l appears at $fault_x$ and $ap(l)$=0 represents fault l disappears at $fault_x$, Eq.4 can be obtained,

$$fault_x = \{fault_l | ap(l) = 1 \quad l = 1, 2, \ldots, n\} \quad (4)$$

where $fault_x$ represents some a multiple fault. Assume there are k single fault and $ar(h)(1 \leq h \leq k \leq n)$ represents the index of single fault, multiple fault can be described by Eq.5.

$$fault_x = \{fault_{ar(h)} | h = 1, 2, \ldots, k\} \quad (5)$$

In general, if multiple fault is regarded as a new fault, its symptom structure is the same as single fault. Combined with Eq.1, multiple fault can be described (shown as Eq.6) by m symptom value vectors.

$$\mathbf{P} = [fp_1 \quad fp_2 \quad fp_3 \quad \ldots \quad fp_m] \quad (6)$$

where fp_y represents some a symptom value and subscript value represents the index of symptom. Overall speaking, multiple fault diagnosis actually is analysis of $\mathbf{P}$.

It is a best analysis method that $\mathbf{P}$ is decoupled into several single fault symptom sets $\mathbf{d}$ which devote to compose $fault_x$. Up till the present moment, there is no solution can completely realize coupled faults separating and faults features extracting due to the complexity of multiple faults coupling types. Therefore, it is invalid to achieve the mapping between multiple faults symptoms and singe fault by means of common linear transformation.

In many diagnostic methods, decoupling and separating are usually done in diagnosis reasoning. Furthermore, as to fault data, it is not decoupled according to different single fault, but recognized by diagnostic methods automatically.

In view of multiple fault diagnosis, there are mainly two kinds of methods, one is based on fault separation [2,11,12] and the other one is CGD[13-15]. They both have their own advantages. For example, the former one considers fault probability while the latter one pays more attention to match with the single fault according to the fault data.

However, a common challenge in actual engineering is that the sample is not enough to learn. Therefore, many solutions, in which completed system model and rich prior knowledge are necessary, are no longer applicable. Furthermore, the challenge also leads to a large difference between actual fault and diagnostic result obtained from learning nonlinear transform method. Overall, the key problem of multiple fault diagnosis is how to identify fault data that contains many single fault features accurately.

3 CGD Methods and Applications in MFD

Multiple fault diagnosis is a process of uncertainty reasoning. Compared with multiple fault samples, single fault samples are relatively abundant. Therefore, multiple fault diagnosis can be considered as a process to match the unknown fault symptoms with the known single fault symptoms (for example, we can design a filter which is sensitive to only one single fault, other faults have no effect on it.) one by one. After this process, all single faults that contribute to multiple faults are discovered. Because of the good performance in single fault diagnosis, CGD is gradually applied to multiple fault diagnosis.

CGD contains classification analysis and clustering analysis. Classification analysis is a process of allocating the unknown input mode to different classes and its classification rules is made artificially. Clustering analysis is a process of concentrating similar samples and separating dissimilar samples. There are some differences between them. Classification is a supervised process and large samples are needed. Clustering is an unsupervised and heuristic search process.

CGD rules usually are needed in classification analysis before CGD is used for fault diagnosis. To achieve a performance of distinguishing different fault modes, an unknown sample is allocated into some known fault modes. Based on the influence parameters of system and certain rules, fault objects are divided into several independent groups. This is a clustering analysis process, which can determine whether unknown fault belongs to the groups or not. Both of these two analysis methods lead to a similar result that similar samples should in the same group and dissimilar samples should in different groups.

For example, through Learning Vector Quantization and Self-organizing Mapping (SOM-LVQ) fault classification method, multiple fault diagnosis can be realized by putting the multiple faults in the same groups [16]. By means of Principal Component Analysis (PCA), fault data can be projected to principal component space which is made of normal samples, leading it to be distinguished by Support Vector Machine (SVM) [12,17]. Fisher discriminant method was applied to the mixed fault classification of transformer vibration signal, and the energy can spread to other components to realize multiple fault identification and distinction [18]. Based on combination of artificial neural networks, fault diagnosis can be operated from the point of pattern recognition [19]. The solution composed by wavelet transformation and fuzzy theory can acquire fault feature vector efficiently, and then fault pattern classification is operated based on fuzzy logistic reasoning [15,20,21]. Data mining can be used to classify the sample data and each class represents a fault pattern. Because this pattern classification (or pattern matching process) multiple fault diagnosis can be realized [22]. Multi-class problem can be converted to 2-class problem via multiple fault classifier based on the optimal binary tree. And the converted 2-class samples can be used to construct an optimal classifier for this decision node [23]. When several single faults appear at the same time, the output of fuzzy neural network is the fuzzy membership degree of each fault. This method can also realize the efficient classification for boundary fuzzy data [24].

Besides, there are also large amount of solutions applied to multiple fault diagnosis, such as Self-organized Neural Network [4,25], Kernel Fuzzy Clustering diagnosis[26], hierarchical clustering [27], multi-kernel support vector machine[28], optimized support vector machine[29] and radius basis function[30].

As these methods shown, all kinds of traditional and latest CGD method can be used to deal with multiple fault diagnosis.

However, a defect common to all these methods is that the classification or clustering analysis is used only in one process of the diagnostic procedure. So in multiple fault diagnosis, complete diagnostic models are lacked for many improved solutions that originally applied only to single fault diagnosis.

4 CGD based Models for MFD

In general, the multiple fault diagnosis model can be considered as a black box while its input is an unknown fault and its output is a combination of single faults that make up this fault pattern. If there are n single faults in this fault system, 2^n-n-1 multiple faults may exist. As shown in Fig.1, diagnostic result **R** describes whether **d** is existed or not. If written formation of collection, **R** should be a subset of known fault mode set **D**. Now, the diagnosis of **P** can be achieved by some methods of uncertain problem solving.

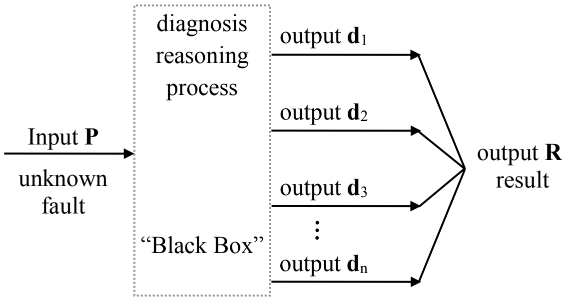

Fig. 1: An ideal way of thinking for MFD

4.1 Fault Diagnosis Based on CGD

Fault diagnosis problem can generally be described as "identifying unknown fault under the condition of some known fault features".

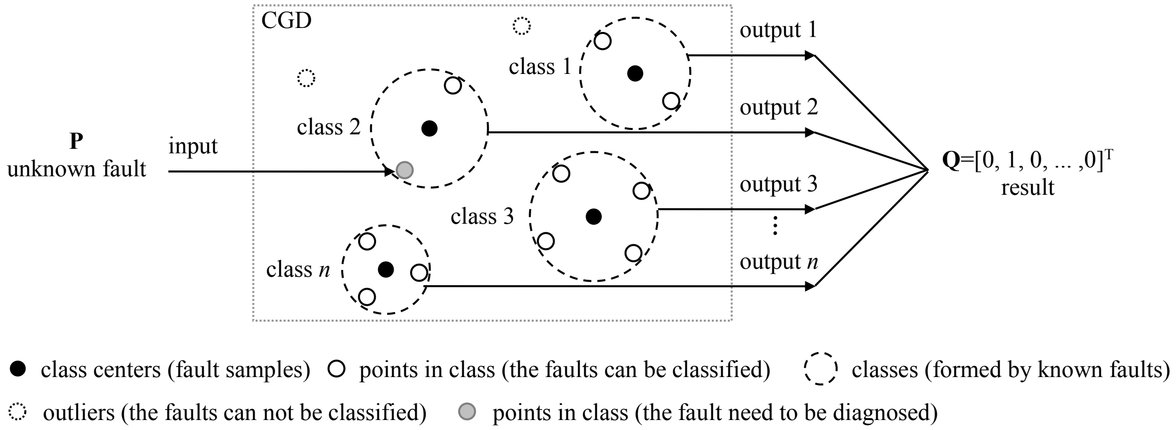

Fig. 2: Ways of thinking for fault diagnosis based on CGD

As shown in Fig.2, for fault diagnosis based on CGD unknown fault **P** is the input to classification or clustering model and then is compared with known fault samples to make it fall into a class that is corresponding to a fault mode. At this time, the boundary of class group is clear and independent each other. From the point of output vector **Q** ("0" describes non-fault and "1" described fault), a strict competition mechanism that which one the unknown fault is in all known faults is showed in CGD process.

Of course, there must be some unknown faults to be outliers (They cannot be divided into any a class), leading to an uncertain diagnostic result. In this diagnostic process, uniqueness and exclusiveness (the number of "1" cannot be greater than 1 in **Q**) of diagnostic result can be guaranteed. Based on this idea, it is possible that CGD is applied in single fault diagnosis. However, traditional methods based on CGD are not applied, because output vector **Q** of multiple fault diagnosis may have a lot of "1"(one point can not be divided into multiple classes at the same time).

4.2 MFD Based on Crossing Class Group

Based on the idea of Sec.4.1, class group can be crossing when classification. For a fault mode containing more single faults, if unknown fault can go to the crossing area, the fault corresponding crossing class is diagnostic result. This is a logical idea (especially performed in collection sets) but obviously, common CGD algorithm can not do uncertain logic reasoning. Furthermore, there is not a mature class boundary determination algorithm that can guarantee to produce crossing among multiple class groups.

4.3 MFD Based on Feature Decomposition and CGD

The unknown fault can be processed via designing decoupling device because **P** may contains multiple faults. Each known single fault $\mathbf{d}_l$ is decomposed to obtain fault symptom vector $\mathbf{p}_l'$ and then removes unrelated parts in it. Lastly, $\mathbf{p}_l'$ is classified.

Where n fault symptoms $\mathbf{p}_l'$, which is available from input **P** decomposing, is determined whether it is in some a class or not via CGD. Furthermore, a $n\times n$ matrix $\mathbf{\Theta}$ is acquired, where raw (assume index is j, $j\in[1,n]$) shows classification result of $\mathbf{p}_l'$ and column (assume index is i, $i\in[1,n]$) shows i_{th} known fault. The ideal diagnostic result is that "1" of j_{th} raw only appears in j_{th} column (namely i=j).

As shown in Fig.3, the columns existing "1" are composition of diagnostic result. Above-mentioned method has a simple process in CGD. It is generally equal to single fault diagnosis method based on CGD applied in n group of unknown fault vector $\mathbf{p}_l'$. Its output vector (assumed $\boldsymbol{\theta}_l$) contains at most one "1" and $\boldsymbol{\Theta}$ is a combination of n $\boldsymbol{\theta}$. Besides, this method exists a process of decomposing, in which amount unrelated with known fault $\mathbf{d}_l$ need to be removed. In ideal conditions, if $\mathbf{P}$ contains $\mathbf{d}_l$, $\mathbf{p}_l'$ acquired from decomposition is equal to $\mathbf{d}_l$. On the contrary, $\mathbf{p}_l'$ will be equal to a n-dimensional raw vector (namely $\mathbf{d}_0$). If CGD is operated at this time, $\mathbf{p}_l'$ will be a outlier.

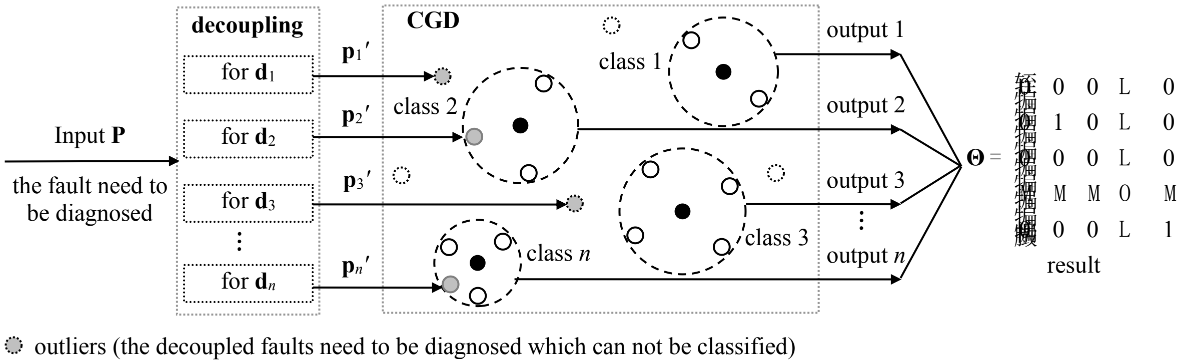

Fig. 3: A way for MFD based on CGD and feature decomposition

In actual systems, couplings among symptoms are complex and non-linear. It is very difficult to decouple unknown fault based on known fault. Therefore, this method is reasonable but its decomposition operator is so difficult to get that it is not applied.

The above methods are all regarding known fault samples as rules of CGD. However, from the point of diagnosis process, both of them are realized multiple fault diagnosis used CGD of single fault, which exists hard to avoid problems.

4.4 MFD Based on CGD Using the Fault Need to be Diagnosed as Class Center

The fault need to be diagnosed is regarded as the rules of CGD as shown in Fig.4. All known fault samples are classified as input($\mathbf{d}_l$) and then each known fault is determined whether it is gone to a class of taking unknown fault ($\mathbf{P}$) as class center(assumed as x). If it is gone into a class, it is a part of diagnostic result. After all known fault pass the experiment via iterating the input, a complete diagnostic result is output $\boldsymbol{\Xi}$.

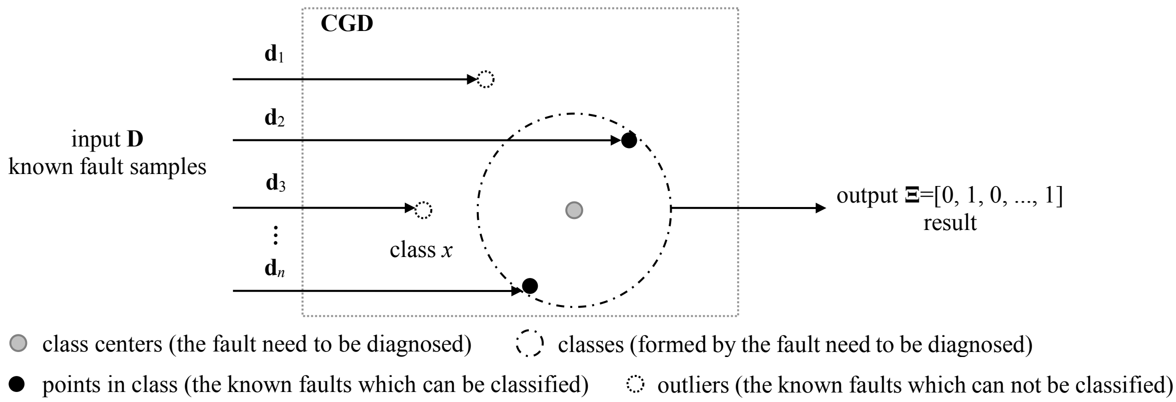

Fig.4: A way for MFD based on CGD (take the fault need to be diagnosed as the class center)

This method can turn faults (similar to their own) into groups, which avoids the difficulties of front several methods. However, due to fault composition is not clear in advance, the coupling of multiple faults is likely to lead to an incomplete result(unknown fault sets are not similar to any known fault or are similar to an unrelated fault).

4.5 MFD Based on CGD Using the Fault Need to be Diagnosed and Known Fault Samples as Class Centers

As mentioned above, multiple fault diagnosis is made of many different single faults and thus forms a special domain of influence. Based on the formation process of class or cluster in CGD, this domain should be more attractive to its composing single fault. However, for a specific single fault, it is difficult to guarantee the similarity between the single fault and unknown fault because the latter may have some symptom data of other fault modes.

A disadvantage of this method is that class group x may contain other faults that made of $\mathbf{P}$ except $\mathbf{d}_l$. Based on the principle that the maximum similarity is in one class, the classification by this method can be viewed as the result of diagnosis result.

On the other hand, the composing fault of $\mathbf{P}$ may not be in the class x. That is a possible outcome due to the uncertainty of multiple faults. When two different faults cannot form two independent class groups respectively, there is enough evidence to justify the big similarity between the composing faults. In addition, this does not violate the principle of "The similarity is minimal outside the class". At this time the classification algorithm need to be adjusted to make the class group fall under class x.

In the CGD process, there is only one certain class group whose class center is the unknown fault. The determination of class boundaries (the range of influence) is under the influence of many uncertain factors. An instructive rule cannot be given by common classification analysis methods.

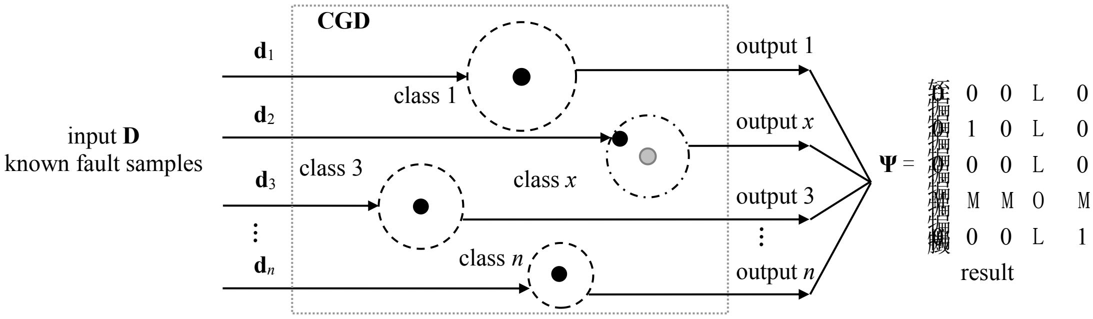

Fig.5: A way for MFD based on CGD (take the fault need to be diagnosed and known fault samples as class centers)

As shown in Fig.5, the diagnosis mechanism is improved by using the stated ideas. This mechanism combines the advantages of all the previous mechanisms. The core thought of the new mechanism is still to match the unknown fault with the known single fault ($\mathbf{d}_l$) one by one. What makes it different is that, in CGD process, other known faults can form independent class groups respectively. It is hope that this unsupervised learning process can distinguish the class groups.

As there are existing distinctions among different known faults, when the unknown fault contains a certain fault which is not the class center of the class group, the unknown fault should be the one that has the biggest similarity with the known fault.

4.6 MFD Based on CGD Using the Decoupled Faults Need to be Diagnosed and Known Fault samples as Class Centers

If the certain fault $\mathbf{d}_l$ is the component of unknown fault **P**, but outside of the class. That is possible because **P** contains too much other fault symptom, thus reduce the similarity between **P** and $\mathbf{d}_l$. Given this, the method stated in 4.3 can be used to change the input.

Fig.6 shows that this method combines the advantages of all the previous method and guarantees the difference among the input vectors. Possible faults are used in CGD process and the uncertainty that some single faults may be put in the same class remains. However, the difficult problem of decoupling is inevitable.

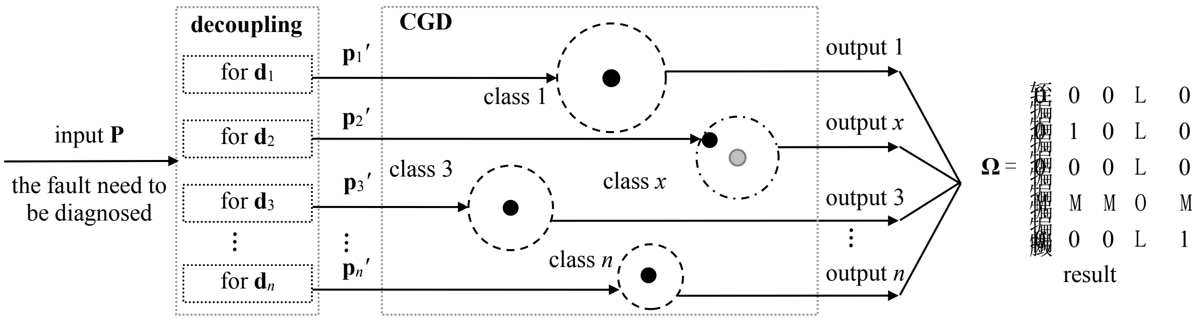

Fig.6: A way for MFD based on CGD (take the decoupled faults need to be diagnosed and known fault samples as class centers)

4.7 Summary

Overall speaking, proposed conceptual models can meet the needs of multiple fault diagnosis in principle via gradually exploration of "fault-symptom" based on CGD. However, some problems need to be taken into account when the conceptual model is converted to actual algorithm.

(1) All the known mono-faults need to be formed independent groups. However, the processes would be affected by diversity of fault systems.

(2) In the case of uncertain fault mechanism, how can class center and boundary determined.

(3) In the case of nonlinear fault symptom coupling, how can fault feature sets decoupled.

(4) Time complexity of above methods has not yet been considered.

5 Conclusions

A analysis of definition for multiple faults is made in this paper. The current problem of multiple fault diagnosis and its existing methods are also analyzed. Relationships between multiple fault diagnosis and single fault diagnosis are proposed. Based on those, CGD applied in fault diagnosis and multiple fault diagnosis is analyzed. Furthermore, multiple fault diagnosis conceptual models based on CGD are explored.

In the above proposed ideas, the method based on "Multiple Fault Diagnosis Based on Crossing Class Group" is difficult to be applied because of crossing class. However, the idea can be used in the method of using relationship between collections discriminant. The rest of the four diagnostic conceptual model can search for similar known fault and remove not enough similar fault via applying CGD, which conforms to the fundamental principles(detect, identify, distinguish and judge) of fault diagnosis. If the specific algorithm can be researched, it is expected to be transformed into actual method and put into application.

Of course, these models also exist concrete problems to be solved, and their effectiveness has not been verified. Avoid its disadvantages and used into practical applications will be the focus content of further researches.

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