ISSN 1392–1207. MECHANIKA. 2015 Volume 21(1): 70–77

Fault detection and diagnosis of belt weigher using improved DBSCAN and Bayesian regularized neural network

ZHU Liang*, HE Fei, TONG Yifei***, LI Dongbo******

**School of Mechanical Engineering, Nanjing University of Science & Technology, Nanjing 210094, China, E-mail: 676205493@qq.com*

***School of Mechanical Engineering, Nanjing University of Science & Technology, Nanjing 210094, China, E-mail: hefei_njust@163.com*

****School of Mechanical Engineering, Nanjing University of Science and Technology, Nanjing 210094, China, E-mail: tyf51129@aliyun.com*

*****School of Mechanical Engineering, Nanjing University of Science and Technology, Nanjing 210094, China, E-mail: lidongbo11@gmail.com*

crossref http://dx.doi.org/10.5755/j01.mech.21.1.8560

1. Introduction

Continuous bulk materials weighing equipment (CBMWE) is measuring equipment for bulk materials trade, widely used in ports, docks, power plant, metallurgy, building materials, electronics, chemical, food, mining, etc. Due to the poor working environment and long time high-load operation, the inaccurate measurement and various faults occur frequently, which cause a great number of economic losses directly. Meanwhile, the fault diagnosis and maintenance also have been plagued by users and manufacturers, because most of the fault diagnosis & maintenance are completed on site by experienced professionals dispatched by the producer, which leads to high costs. Hence, the timely detection, diagnosis and maintenance of the faults are necessary to avoid more economic losses [1]. In order to improve the maintenance quality of equipment and reduce the cost, online fault detection and diagnosis of CBMWE is of great immediate significance. Electronic belt weigher (BW), visual weigher, nuclear scale, etc are the most used CBMWE, whose data has great similarity in that the fault data vary with the flow while the weighing principles are different. Among them, BW is the most widely used CBMWE and has the best performance, so fault detection and diagnosis of CBMWE are studied based on BW in this paper. With the increasing of measurement accuracy, BW has developed from single weighing sensor to multiple ones. Therefore, in this paper, the belt weigher is taken as the research object of fault detection and diagnosis of CBMWE.

Generally speaking, there is a main approach with two steps for online fault detection & diagnosis of BW: the first step is to extract the fault data from the weigher sensors, and the second step is to classify the fault pattern based on the extracted fault data in the previous step [2]. Considering that a belt weigher is the body of real-time variable mass [3], which means that the dosing data including the normal data and fault data vary with the materials flows, it is difficult to extract the fault data directly. But for the belt weigher with multiple weighing units, the dosing data of normal weighing units vary consistently as well as the dosing data of the weighing units with the same fault. So we prefer to apply the clustering algorithm to extracting the dosing data of normal with weighing units as the normal data, owing to the fact that the normal weighing units are in the majority of all the units, and then the fault data can be extract based on the normal data. After that, the machine learning methods are adopted to learn from the fault samples and find out the dynamic features of different faults, so that the dynamic fault data can be classified to the specified fault mode while the fault data vary with the materials flows. In summary, the fault detection & diagnosis can be summarized as an online "clustering & classification" problem in essence.

Clustering is an unsupervised learning algorithm, which has strong robustness for random signal and important application in fault detection and diagnosis. During the detection of fault data, the application of clustering algorithm can reduce the dimension of fault data and keep down the training time of subsequent recognition model. Issam applied kernel k-means into the pre-processing of fault data [4]. Hesam proposed an online fault detection method based on WFCM clustering [5]. However, they both need to specify the number of clusters in advance, and K-means can only discover spherical clusters. Li Yamin introduced affinity propagation clustering algorithm into aeroengine fault diagnosis in emergency [6], which did not need to specify the number of clusters but can't handle noisy data very well. DBSCAN is a kind of density-based clustering algorithm, which can discover clusters of any shape [7, 8], but DBSCAN does not operate well when the density of data space is not uniform [9, 10].

As for fault pattern recognition, fault diagnosis is cosnsidered as the problem of multi-classification after the fault data is detected online. Various approaches developed for this purpose can be mainly divided into two categories. The first is mathematical model-based, like multinomial logistic regression [11] and Bayesian networks [12]. The second is related to the artificial intelligence, like fuzzy classifier [13], artificial neural networks (ANN) [14], SVM [15] and ELM [16]. Recently, more and more attentions have been paid to the development of artificial intelligence. Most of artificial intelligence approaches are based on ANN which have great capabilities in modeling nonlinear systems. Bo et al. presented an approach for motor rolling bearing fault diagnosis using neural networks and time/ frequency-domain bearing vibration analysis [17]. They applied the bearing vibration frequency features and time-domain characteristics into a neural network to recognize the fault patterns. Mahdieh and Farhad proposed a hybrid neural network for soft fault diagnosis of the circuit under test, which avoided the local optimum by using genetic algorithm and can obtain the accurate optimal solution quickly owing to the rapid convergence of back propagation algorithm [18]. S.S. Tayarani presented a dynamic neural network for fault diagnosis of a dual spool aircraft jet engine, which used an IIR (infinite impulse response) filter to generate dynamics between the input and output of a neuron and consequently of the entire network [19]. Xiaoyue et al. introduced probability neural network as the classifier of fault diagnosis [20]. However, they are only based on empirical risk minimization principle, and the experiment data of CBMWE or BW is relatively difficult to collect. Therefore, this paper tries to make the classifier simple enough with the regularization theory.

In this paper, we propose an improved DBSCAN, and build a fault diagnosis machine of BW by combining the improved DBSCAN with ANN. The remainder of this paper is organized as follows. In Section 2, a framework of the BW's online fault detection & diagnosis is proposed. In Section 3, an improved DBSCAN is proposed and applied into the fault detection online. Section 4 introduces the Bayesian regularization neural network (BRNN) as a novel approach into the fault diagnosis of BW. In Section 5 the experiment of BW's online fault detection and diagnosis using the improved DBSCAN and BRNN is conduct to validate the effectiveness of the model proposed in this paper, and Section 6 summarizes some conclusions.

2. Fault detection and diagnosis of BW based on clustering and classification

As mentioned in the introduction, in order to achieve the intelligent fault detection and diagnosis of BW, a scheme is proposed that extract the normal data and detect the fault data using clustering algorithm at the same time, and then identify the fault pattern by the classification of the detected fault data, as shown in Fig. 1.

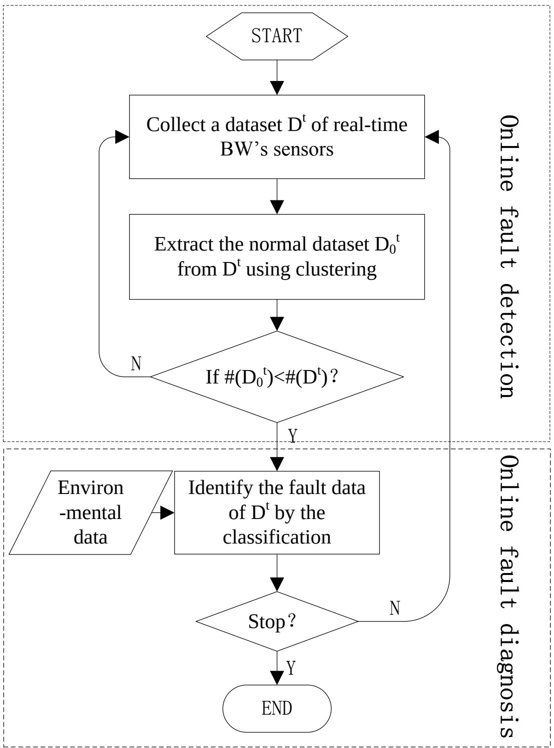

Fig. 1 Process of online fault detection & diagnosis

In the practical situation, the fault data points are fewer relative to the normal points, so the following assumption can be made:

Suppose $D^t=\left\{x_1^t,x_2^t,\ldots x_m^t\right\}$ is the sample dataset of m weighing sensors containing the normal dataset $D_0^t=\left\{x_{01}^t,x_{02}^t,\ldots x_{0m_0}^t\right\}$ and k (unknown) kinds of fault $\left\{D_1^t,D_2^t,\ldots D_k^t\right\},D_i^t=\left\{x_{i1}^t,x_{i2}^t,\ldots x_{im_i}^t\right\},i=1,\ldots,k \quad \sum_{i=0}^{k} m_i=m$ at time t. And then according to the fact we can assume that the number of data points in D_0^t is larger than any one in D_i^t, namely $\#\left(D_0^t\right)>\max_i\left(\#\left(D_i^t\right)\right)$.

As described in Section 1, a belt weigher is the body of real-variable mass, so that there are increase and discharge of materials on any weighing unit at any time, which means D^t varies with the time and $D_i^{t_1}$ is different from $D_i^{t_2}$ for any I = 0,1,2,...k if $t_1\neq t_2$ [3]. However, the difference among $D_i^t=\left\{x_{i1}^t,x_{i2}^t,\ldots x_{im_i}^t\right\}$ is infinitesimally small while the Euclidean distance between $x_i^t\in D_i^t$ and $x_j^t\in D_j^t$ for any i, j = 0, 1, ... , k is still very large. Therefore, the fault detection can be realized by extracting the D_0^t and determining whether $\#\left(D_0^t\right)<\#\left(D^t\right)$ with the assumption that $\#\left(D_0^t\right)>\max_i\left(\#\left(D_i^t\right)\right)$, as well as the extraction of fault data. After that, the fault diagnosis can be completed by classifying the fault pattern with fault data with the machine learning methods.

3. Online fault detection based on improved DBSCAN

3.1. DBSCAN

The key idea of DBSCAN is that for each point of a cluster the neighborhood of a given radius has to contain at least a minimum number of points, i.e. the density in the neighborhood has to exceed some threshold. The shape of a neighborhood is determined by the distance function for two points p and q, denoted by *dist(p,q)*.

Definition 1. The *Eps-neighborhood* of a point p, denoted by $N_{Eps}(p)$, is defined by $N_{Eps}(p)=\left\{q\in D\mid dist(p,q)\leq Eps\right\}$.

Definition 2. An object p is directly density-reachable from an object q wrt. *Eps* and *MinPts* in the set of objects D if

(1) $p\in N_{Eps}(q)$ is the *Eps*-neighborhood of q),

(2) $|N_{Eps(q)}|\geq MinPts$.

Definition 3. A point p is *density-reachable* from a point q wrt. *Eps* and *MinPts* if there is a chain of points $p_1,\ldots,p_n$, $p_1=q$, $p_n=p$ such that p_{i+1} is directly density-reachable from p_i.

Definition 4**.** An object p is density-connected to an object q wrt. *Eps* and *MinPts* in the set of objects D if there is an object $o\in D$ such that both p and q are density-reachable from o wrt. *Eps* and *MinPts* in D.

Definition 5 Let D be a database of points. A cluster C wrt. *Eps* and *MinPts* is a non-empty subset of D satisfying the following conditions:

(1) $\forall$ p, q: if $p \in C$ and q is density-reachable from p wrt. *Eps* and *MinPts*, then $q \in C$. (Maximality).
(2) $\forall$ p, $q \in$ C: p is density-connected to q wrt. *Eps* and *MinPts*. (Connectivity).

Definition 6. Let $C_1,\ldots, C_k$ be the clusters of the database D wrt. parameters Eps_i and $MinPts_i$, $i = 1,\ldots,k$. Then the noise is the set of points in the database D not belonging to any cluster C_i, i.e. noise = $\{p \in D | \forall\ i : p \notin C_i\}$ [7].

An object is core object if it satisfies condition (2) of Definition 2, and a border object is such an object that is not a core object itself but is density-reachable from another core object.

On the basis of the above definition, steps of DBSCAN algorithm are as follows:

Step1. In the given dataset $D=\{x_1, x_2,\ldots, x_N\}$, select an unprocessed data point x_t randomly;

Step 2. If the selected data point x_t is a core object, and then the data points, which are density-reachable from x_t, form a cluster; else the selected data point x_t is a border object, and then jump out of the loop, looking for the next point.

Step 3. Repeat Step1 and 2, until all the points in the dataset D are processed.

3.2. Online fault detection of BW based on the improved DBSCAN

Based on the above assumption in Section 2, this paper proposes to achieve the online fault detection by applying the online clustering to separating the normal data points D_0^t from the fault data points $\left\{D_1^t,\ldots D_k^t\right\}$. Generally, there are two ways of the separation by online clustering: one is to extract the normal data points from the background; the other one is to cluster the dataset D^t into $\left\{C_1, C_2, \ldots, C_k,\right\}$ by applying clustering algorithm without specifying the class number in advance, and then get the normal dataset $D_0^t = \underset{i}{argmax}\left(\#\left(D_i^t\right)\right)$. In practice, the latter way is picked up as the scheme of fault detection owing to its better reliability, which is depicted in Fig. 2.

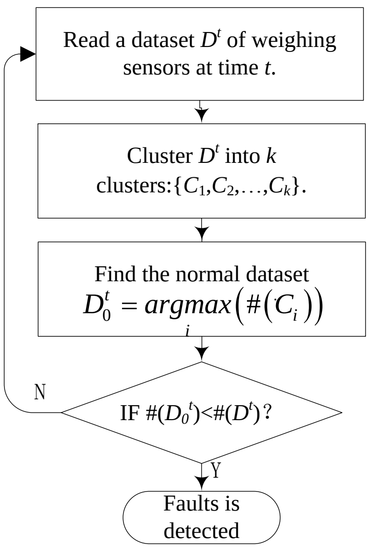

Fig. 2 Process of online fault detection

In order to detect the fault online, firstly, the clustering algorithm is presented to divide the sample data of BW into different clusters as soon as the dataset D^t is sampled, and then the normal dataset is found out by $D_0^t = \underset{i}{argmax}\left(\#\left(D_i^t\right)\right)$, and finally whether $\#(D_0^t)<\#(D^t)$ is judged.

However, the density of the dataset of weighing sensors varies while the BW operates in different flows, which can lead to great changes in the distribution of distance function, so the original DBSCAN doesn't have a good robustness in different flows. In order to improve the robustness, the improved DBSCAN is presented by replacing the distance function $dist\left(x, x_t\right) = \left\| x - x_t \right\|^2$ with the similarity function in the DBSCAN:

$$\left.\begin{aligned} r\left(x_t, x\right) &= \sqrt{\sum_{i=1}^{m} s\left(x_t\left(i\right), x\left(i\right)\right)^2}, \\ s\left(x_t\left(i\right), x\left(i\right)\right) &= \begin{cases} 0, & x_t\left(i\right) = x\left(i\right) = 0 \\ \dfrac{\left|x_t\left(i\right) - x\left(i\right)\right|}{max\left(\left|x_t\left(i\right)\right|, \left|x\left(i\right)\right|\right)}, & \text{else.} \end{cases} \end{aligned}\right\} \tag{1}$$

The similarity function is in essence an adaptive normalization, so the improved DBSCAN is able to avoid the impact of different flows.

4. Online fault diagnosis based on BRNN

4.1. BRNN

ANN is one of the most widely used methods in fault diagnosis, especially the back propagation neural network (BPNN). BPNN is a supervised algorithm which is typically trained by minimizing the loss function with the gradient descent method. Given the samples $\{(x_1,y_1),\ldots,(x_n,y_n)\}$, $x_i \in \mathbb{R}^m$, the loss function based on ERM is as follows:

$$L\left(\boldsymbol{w}\right) = \frac{1}{2n}\sum_{p=1}^{n}\left(t_p - y_p\right)^T\left(t_p - y_p\right), \tag{2}$$

where t_p is the expecting output.

However, the neural network, which is trained by adopting Eq. (2) as the loss function, tends to overfit when the train samples are not enough. Therefore, in consideration of that the fault diagnosis data of BW is very difficult to sample, BRNN is developed into the fault diagnosis of BW and the loss function is:

$$\left.\begin{aligned} &L\left(\boldsymbol{w}\right) = \alpha E_D + \beta E_W; \\ &E_D = \left(\frac{1}{2n}\sum_{p=1}^{n}\left\|t_p - y_p\right\|^2\right); E_W = \left\|\boldsymbol{w}\right\|^2, \end{aligned}\right\} \tag{3}$$

where E_D is the empirical risk, E_W is the regularization term, and α, β are objective function parameters [21]. With the Bayesian regularization, the potential for overfitting of network can be greatly reduced. In BRNN the weights are considered as random variables with Gaussian distribution and thus their density function can be updated as:

$$P\left(\boldsymbol{w} \mid D,\alpha,\beta,M\right)=\frac{P\left(D \mid \boldsymbol{w},\beta,M\right)P\left(\boldsymbol{w} \mid \alpha,M\right)}{P\left(D \mid \alpha,\beta,M\right)}, \quad (4)$$

where D represents the data set, M is the particular neural network model used, and $\boldsymbol{w}$ is the vector of network weights [22]. With the assumption that the noise in the training set data is Gaussian, the probability density function for the weights can be determined. And then the optimal regularization parameters α and β are obtained at the minimum point $\boldsymbol{w}^{MP}$ which can be acquired by minimizing the objective function $L(\boldsymbol{w})$ using the Levenberg-Marquardt algorithm:

$$\begin{cases} \alpha^{MP}=\dfrac{\gamma}{2E_W\left(\boldsymbol{w}^{MP}\right)}, \\ \beta^{MP}=\dfrac{n-\gamma}{2E_D\left(\boldsymbol{w}^{MP}\right)}, \\ \gamma=N-2\alpha^{MP}tr\left(\boldsymbol{H}^{MP}\right)^{-1}, \end{cases} \quad (5)$$

where γ is the effective number of well-measured parameters, and $\boldsymbol{H}$ is the Hessian matrix of $L(\boldsymbol{w})$ which is computed with the Gauss-Newton approximation: $\boldsymbol{H}=\nabla^2 L(\boldsymbol{w})\approx 2\beta\boldsymbol{J}^T\boldsymbol{J}+2\alpha\boldsymbol{I}_N$ ($\boldsymbol{J}$ is the Jacobian matrix of $L(\mathbf{w})$, and N is the total number of parameters in the network) [23], [21].

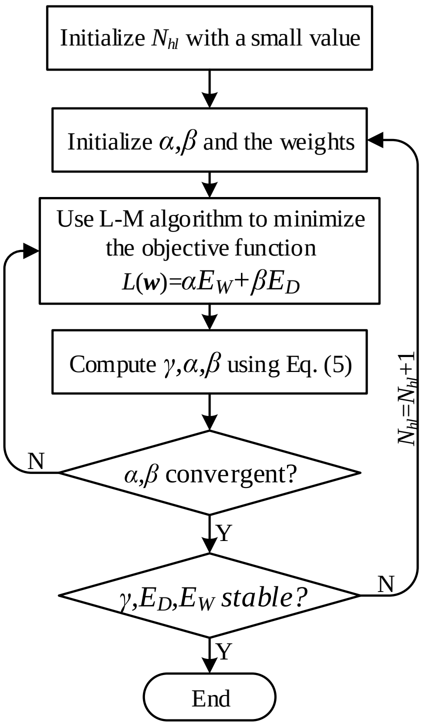

Fig. 3 The training process of BRNN

The training process of BRNN shown in Fig. 3 is similar to the EM algorithm (Expectation Maximization algorithm). After the initialization, the training is conducted through repeating that solve Eq. (5) after the L-M minimization of Eq. (3) until γ, E_D and E_W of the networks keep basically stable or remain unchanged after each training. The number of hidden layer neurons N_{hl} can be determined based on γ, E_D and E_W in the training. A small value of N_{hl} is assigned in the initialization, and then the value of N_{hl} increases until the end of training.

4.2. Fault diagnosis based on BRNN

In this paper, a three layered feedforward BRNN including one input layer, one hidden layer, and one output layer is developed as a classifier to identify the given binary fault pattern of BW. The tangent sigmoid function $tanh(x)$ is chosen as the activation function of the hidden layer, and the linear function is chosen for the output layer [24].

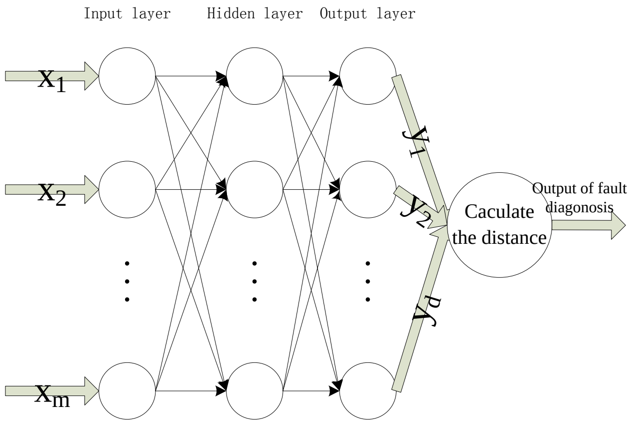

Fig. 4 Schematic diagram of fault diagnosis

Fault diagnosis is a classification problem in essence, while the feedforward network is designed for the regression problem. Thus, the fault patterns need to be encoded as binary data before building the diagnosis model, and then the classification will be accomplished by finding the nearest fault pattern of the binary output. The detailed process of fault diagnosis is shown as follows (Fig. 4):

Step 1. Encode the fault patterns as binary data, and train the feedforward network as Fig. 3 depicts;

Step 2. Apply the trained network to predicting the binary output of the given test data;

Step 3. Calculate the distance between the predicted binary output and all fault patterns, and then find out the closest fault pattern to the binary output.

5. Case study

In this section, a case study is conducted on the test of 3# array belt weigher (ABW) in the BW test center of Nanjing Sanai Industrial Automation Co. Ltd. 3# ABW can recycle the materials. The real-time data are collected by ARM7 and transmitted through RS485 bus to the upper PC which receives the data by using MATLAB serial communication. In order to yield the best results, both the training data and real-time data are normalized within the range [0,1] by the “mapminmax” function. The improved DBSCAN and BRNN are realized with MATLAB system software system. All the programs are implemented by the hardware of Core i3-2.35G CPU, memory 6G and hard disk 500G.

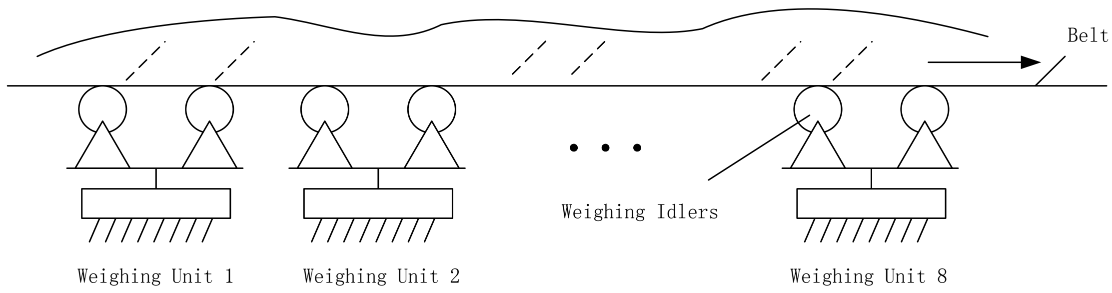

Fig. 5 Schematic diagram of ABW

As shown in Fig. 5, 3# ABW, which takes 42 seconds (2.21 m/s) to run a cycle, includes 8 weighing units which are far enough away from the loading point to avoid the interference caused by the impact of the load, especially the sudden large materials [25].

5.1. Fault pattern of ABW

The sampling frequency of each weighing unit is 10 Hz. The data at each time is composed of the real-time data from 8 weighing unit and several parameters of BW. Six kinds of common fault, which are listed and coded in Table 1, are simulated in 3# ABW and each weighing unit has the similar fault patterns. Because there are at most three weighing unit areas existing fault at the same time in actual operation, each group in the experiment only makes at most 4 weighing unit areas simulate fault. Moreover, different groups are conducted at the flows of no-load, 200 t/h, 500 t/h and 800 t/h to validate the effectiveness and feasibility of the fault detection & diagnosis model. The total amount of materials through the BW at each flow is 50 t. The major parameters of 3# ABW are listed in Table 2:

Table 1

Fault patterns of ABW

Fault Pattern	Fault Code
Normal	[0,0,0]
Wear on the surface of sensors	[0,0,1]
The stuck weighing frame	[0,1,0]
Looseness on weighing frame	[0,1,1]
Poor sensor connection	[1,0,0]
The stuck idler	[1,0,1]
Looseness on sensors	[1,1,0]

Table 2

Parameters of 3# ABW

Width of belt, mm	Idler spacing, mm	Thickness of belt, mm	Groove angle of idler
1000	1200	12	30°

5.2. Experiment of online fault detection based on improved DBSCAN

The experiment of online fault detection is conducted by comparing the accuracy and instantaneity of various clustering algorithms. DBSCAN, improved DBSCAN and fuzzy hierarchical clustering (FHC) are applied to the online clustering analysis of the real-time data from 8 weighing unit with noise when BW operates at the flow of no-load, 200, 500 and 800 t/h respectively.

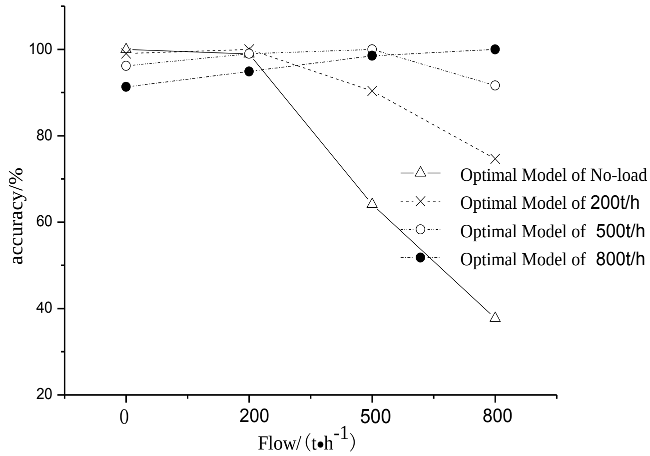

Fig. 6 Clustering effect chart of DBSCAN

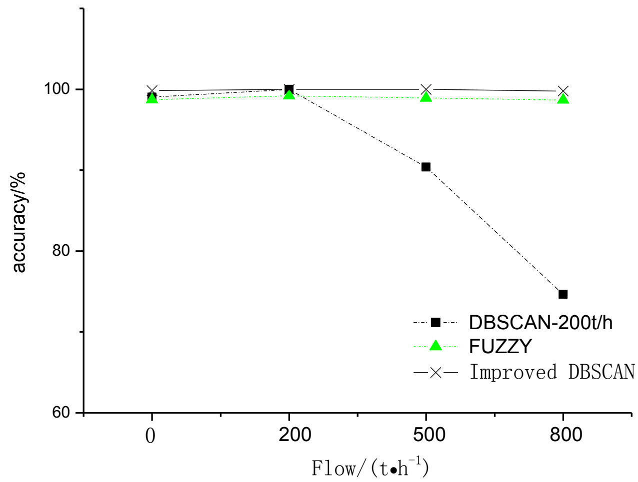

Fig. 7 The accuracy of clustering algorithms

Fig. 6 illustrates the bad robustness of DBSCAN for different flows. In order to realize the fault detection of different flows, four optimal models based on the DBSCAN can be acquired through learning the data of four flows respectively. However, all the optimal four models cannot handle the data of all flows well. In other words, the fault detection model based on DBSCAN is unable to be adjusted with one *Eps* and one *MinPts* to handle all the data of different flows well. Thus, it is necessary to improve DBSCAN by replacing the distance function $dist(p,q)$ with the similarity function $r(p,q)$.

As shown in Fig. 7, both the accuracy of FHC and improved DBSCAN is very high and has no significant changes at different flows, namely much better robustness than DBSCAN. That's because both the FHC and improved DBSCAN calculate the similarity of any two points instead of the distance, and as described above the calculation process of the similarity is in essence an adaptive normalization. Moreover, the improved DBSCAN has a bit higher accuracy than FHC owing to its good noise processing capability [26].

In addition to the accuracy and robustness, Table 3 details the instantaneity of FHC and improved DBSCAN, and it can be easily concluded that the improved DBSCAN consumes less time and is more suitable for online fault detection than FHC. That's because the average run time complexity of DBSCAN is O(*n*log n*) [7] while the one of FHC is $O(n^2)$ [27]. All the average accuracy and test time is obtained with respect to all the 6 different fault patterns listed Table 1.

Table 3

Comparison of clustering algorithms

Clustering algorithms	Average accuracy, %	Average time of each group/us
FHC	96.4	5.637
Improved DBSCAN	99.7	2.113

5.3. Experiment of online fault diagnosis

In order to evaluate the performance of our proposed fault diagnosis scheme, 4 sets of training data are generated corresponding to 4 flows of no-load, 200, 500 and 800 t/h, and each set contains 250 sample data. The fault diagnosis model is trained as proposed in Section 3.2 with the training data. Table 4 summarizes the results for training different BRNN of three layers. Notice that γ, E_W and E_D keep basically stable for all models with $N_{hl} \geq 8$, so the number of hidden layer neurons is set to 8.

Table 4

Training results of fault diagnosis model

N_{hl}	E_W	E_D	γ	N
2	15.9	0.0924	10.8	15
4	15	0.0888	11.7	27
6	15.7	0.088	12.7	39
8	15	0.104	12.3	51
10	15	0.105	12.3	63

After training the fault diagnosis model, the fault diagnosis model is also tested with the real-time data from 8 weighing unit and several parameters of BW when BW operates at the flow of no-load, 200, 500 and 800 t/h respectively. During the test, the fault diagnosis model identifies the fault pattern as soon as the fault detection of the real-time data is completed. Finally, the results of the proposed fault diagnosis model based on BRNN are compared with those of BPNN, RBF and GRNN, as shown in Table 5.

The average accuracy is also obtained with respect to all the 6 different fault patterns as well as the average test time. According to the comparison, the fault diagnosis model based on BRNN spends less time owing to the less hidden layer neurons while the model based on RBF or GRNN contains 56 hidden layer neurons. Also, the model based on BRNN has the best performance, because BRNN has a much better generalization than the others when the training samples of BW are relatively few. Besides, during the experiments of BW, the study finds that the accuracy of model based on BPNN or RBF is very sensitive to the normalization, but the accuracy of model based on BRNN is not.

Table 5

Comparison of different classifiers

Classifiers	Average accuracy, %	Average test time of a dataset/us
BRNN	93.13	29.32
BPNN	83.05	37.84
RBF	86.85	34.77
GRNN	90.28	26.94

6. Conclusions

In this paper, in order to cope with the uneven density data caused by different materials flows or the increase and discharge of materials of the same flow on any weighing unit at any time, we have proposed an improved DBSCAN by replacing the distance function with the similarity function, and apply the improved DBSCAN to the online fault detection of BW. After that, BRNN is introduced into the online fault diagnosis of BW, which is able to classify the fault data detected by the improved DBSCAN into different fault patterns. Finally, as a demonstrated example, the online fault detection and diagnosis experiments of ABW using improved DBSCAN and Bayesian Regularized Neural Network is conducted. The results summarized in Fig. 7 and Table 3 indicate that the fault detection model of BW based on improved DBSCAN has excellent real-time performance and great robustness for handling the uneven density data. The results summarized in Table 4 and 5 show that the fault diagnosis model of BW using Bayesian regularized neural network has not only a more excellent generalization but also better ability to recognize the fault pattern of BW than the other algorithm such as RBF, BPNN, GRNN. Furthermore, the presented research is a novel approach in the bulk material trade and should be very useful to the fault detection or diagnosis of continuous bulk materials weighing equipment.

Acknowledgements

This work was financially supported by Innovation Fund for Small Technology-based Firms of China (13C26213202062), National Natural Science Foundation of China (51105157) and "excellence plans-zijin star" Foundation of Nanjing University of Science. The support are gratefully acknowledged. The authors would also thank Dr. Zhu Haihua, Dong Ying, Wang Weimin and Zhang Wei for their recommendation.

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ZHU Liang, HE Fei, TONG Yifei, LI Dongbo

FAULT DETECTION AND DIAGNOSIS OF BELT WEIGHER USING IMPROVED DBSCAN AND BAYESIAN REGULARIZED NEURAL NETWORK

S u m m a r y

Various faults occurred in the continuous bulk materials weighing equipment (CBMWE) usually lead to more economic loss and waste of human resources inevitably. A new approach based on the improved DBSCAN (Density-Based Spatial Clustering of Applications with Noise) clustering and Bayesian regularization neural network (BRNN) is proposed for online fault detection and diagnosis of CBMWE--electronic belt weigher (BW). Firstly, in view of the fault data varying with the materials flows or the increase and discharge of materials of the same flow on any weighing unit at any time, an improved DBSCAN clustering algorithm is developed to realize the online fault detection by extracting the fault data with the clustering analysis of the real-time data. Secondly, BRNN is proposed as a classifier to identify the fault pattern with the extracted fault data. Both the models of online fault detection and diagnosis are realized using MATLAB. Finally, the test result shows that the proposed online fault detection and diagnosis model is able to cope with the online fault detection and diagnosis of BW and also yields great diagnostic accuracy. In general, this approach for online fault detection and diagnosis of BW has a great significance to bulk weighing equipment.

Keywords: DBSCAN; Bayesian regularization; neural network; belt weigher; online fault detection and diagnosis.

Received November 04, 2014
Accepted February 02, 2015