Time-domain global similarity method for automatic data cleaning for multi-channel measurement systems in magnetic confinement fusion devices

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Abstract

To guarantee the availability and reliability of data source in Magnetic Confinement Fusion (MCF) devices, incorrect diagnostic data, which cannot reflect real physical properties of measured objects, should be sorted out before further analysis and study. Traditional data sorting cannot meet the growing demand of MCF research because of the low-efficiency, time-delay, and lack of objective criteria. In this paper, a Time-Domain Global Similarity (TDGS) method based on machine learning technologies is proposed for the automatic data cleaning of MCF devices. Traditional data sorting aims to the classification of original diagnostic data sequences, which are different in both length and evolution properties under various discharge parameters. Hence the classification criteria are affected by many discharge parameters and vary shot by shot. The focus of TDGS method is turned to the physical similarity between data sequences from different channels, which are more essential and independent of discharge parameters. The complexity arisen from real discharge parameters during data cleaning is avoided in the TDGS method by transforming the general data sorting problem into a binary classification problem about the physical similarity between data sequences. As a demonstration of its application to multi-channel measurement systems, the TDGS method is applied to the EAST POlarimeter-INterferomeTer (POINT) system. The optimized performance of the method evaluated by 24-fold cross-validation has reached $0.9871 \pm 0.0385.$

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I. INTRODUCTION

With the development of Magnetic Confinement Fusion (MCF) science and diagnostic techniques, massive diagnostic data are increasingly generated. Original diagnostic data could be unreliable due to various interference sources and complex measuring conditions in MCF devices, such as mechanical vibration, electromagnetic interference, signal saturation, and hardware failures. To guarantee the availability and reliability of data source, incorrect diagnostic data, dubbed dirty data, which cannot reflect real physical properties of measured objects, should be sorted out before further analysis and study. The identification of incorrect data can be regarded as a typical classification problem, i.e., how to properly divide the original data set into two groups, correct and incorrect one. Since experimental setups and discharge processes are diverse, measured quantities from different shots, diagnostic systems, and devices evolve in totally different ways. Incorrect diagnostic results also vary due to their uncertain causes. Therefore, it is difficult to define general and clear criteria for data cleaning. Traditionally, dirty data are searched and removed manually with the assistant of computer programs, mainly according to some simple rules, common experiences, and sometimes personal intuitions. These data cleaning programs and rules only apply to certain specific data and usually performs poorly. Explosively increasing fusion data cannot be satisfactorily cleaned in time. Real-time processing and feed-back control require much faster data cleaning methods, which can remove dirty data in a short time, say millisecond. On the other hand, subjective factors in manual data cleaning processes lead to inconsistent results. To meet the demand of fusion energy research, the speed, efficiency, and accuracy of fusion data cleaning should be improved imperatively. Automatic data cleaning methods based on machine learning is a strong candidate for breaking through the bottleneck of massive data application in fusion research.

In recent years, as computing ability and storage capacity grow rapidly, Artificial Intelligence (AI) and machine learning have been widely applied to a variety of scientific research fields, such as image processing, biology, and astronomy[1–3], showing great advantages of extracting new patterns and principles from complicated big data set. In MCF research, machine learning has been applied in disruption prediction [4–9], plasma equilibrium parameters extraction [10], data retrieval [11], L-H transition time estimation [12], charge exchange spectra analysis [13], neoclassical transport database construction [14], turbulent transport construction [15], electron temperature profile reconstruction [16], and energy confinement scaling [17]. These pioneering works have pushed the fusion energy research forward in many aspects respectively. Wider, larger scale, and systematic application of machine learning in fusion science will trigger radical changes. Effective data cleaning also becomes the essential prerequisite for the application of AI, data mining, and big data techniques in fusion research. Machine learning in turn offers powerful tools for diagnostic data cleaning. Precise data cleaning can be achieved by using objective classification model trained by original data using supervised machine learning methods. The application speed of well trained model will be easily optimized to meet the requirement of real-time feedback control. With the support of supercomputer, massive fusion data can be processed effectively to relieve the data processing pressures of researchers. The robustness and universality of classification models lays a foundation for the large-scale applications of machine learning in fusion science.

In this paper, a new data cleaning method based on the Time-Domain Global Similarity (TDGS) among data sequences defined by typical machine learning technologies is proposed. The general-purposed TDGS method can be used to automatically sort dirty diagnostic data from MUlti-channel Measurement (MUM) systems in MCF experiments. Most diagnostic systems of MCF devices are MUM systems, which measure the time evolution of plasma parameters from different locations or directions with multiple independent measuring channels, such as common interferometer systems [18], polarimeter systems [19–23], electron cyclotron emission imaging systems [24], etc. Time sequences of diagnostic data from different channels of the MUM system reflect related yet distinct aspects of the same observed object. Therefore these diagnostic data are physically associated. We define this relation as physical similarity. The physical similarity just exists between correct data sequences from different channels of the MUM system. The dirty data, which are caused by a variety of interference sources, are physically dissimilar from correct data sequences or each other. To overcome the difficulty of direct classification, the TDGS method sorts the dirty data by classifying the physical similarity between diagnostic data sequences from different channels under the same discharge. Traditional data sorting aims to the classification of original diagnostic data sequences, which are different in both length and evolution properties under various discharge parameters. Hence the classification criteria are affected by many discharge parameters and vary shot by shot. The focus of TDGS method turns to the physical similarity between data sequences from different channels, which are more essential and independent of discharge parameters. Then the complexity arisen from real discharge parameters during data cleaning is avoided in TDGS method by transforming the general data sorting problem into a binary classification problem about the physical similarity between data sequences.

In TDGS method, the sample set is generated by the direct sum of two original diagnostic data sequences from two different channels of a MUM system in the same discharge. By combining two data sequences from different channels of an N-channel MUM system as one sample, C_N^2 samples can be generated for one discharge, and $P\ast C_N^2$ samples can be generated for P discharges. Each sample is tagged by several indices which indicates the corresponding physical similarity between two sequences. These indices span a high dimensional index-space, in which these samples can be classified into two groups, physical similar samples and physical dissimilar ones. A physical similar sample is constituted by two correct data sequences. If a sample is classified to be physical dissimilar, its constituents contain at least one dirty data sequence. According to this rule, the dirty diagnostic data can be properly identified by physical similarity. In many MUM systems of MCF devices, the physical similarity between diagnostic data exists in time domain rather than frequency domain. And the dissimilarity between dirty data, or dirty and clean data, is in global scale for most of the time, instead of local and small scale, see Fig. 1. TDGS method employs different definitions of distance between two time-series signals as tag indices of a sample, measuring this global time-domain similarity. To guarantee precise classification, different kinds of distance functions are adopted to map signals from a high-dimensional space

of original data sequences into a lower-dimensional feature space. Because in different discharges the length of diagnostic data sequences changes, original data sequences should be normalized in distance functions to guarantee length independence. Then samples generated from different discharges can be joined together as a unified sample set, used as the training set or the test set. To demonstrate the performance of TDGS method, it is tested by the data cleaning of POlarimetry-INTerferometry (POINT) system on EAST Tokamak. The performance in this paper refers to the accuracy rate of classification results about physical similarity. In this example, Support Vector Machine (SVM) is adopted as the classification algorithm, which has advantage in solving nonlinear, high-dimensional problems [25–28]. The k-fold cross-validation is used as model assessment method because it can provide an effectively unbiased error estimate. In k-fold cross-validation method, all samples contribute to both training and validation, and each sample is used for validation only once [29]. For practical purpose of data cleaning for MCF devices, the samples of a validation set are selected to be generated by the data from one discharge, rather than randomly from the whole set. Evaluated by 24-fold cross-validation, the accuracy rate of TDGS method in cleaning the dirty density data of POINT system can reach 0.9871 ± 0.0385 , which meets the application requirements of POINT system. By applying TDGS method to the data cleaning of POINT system, the reliability and availability of data source from POINT system are evidently enhanced quickly and conveniently.

The rest parts of this paper are organized as follows. In Sec. II, the theory and procedure of TDGS method for automatic diagnostic data cleaning of MUM systems are introduced. In Sec. III, as an example, TDGS method is applied to dirty data sorting of POINT system. In Sec. IV, the assessment of TDGS method is studied in detail. In Sec. V, the prospects of applying TDGS method to data cleaning in more MUM systems of MCF devices are discussed. Moreover, the further optimization of TDGS method is also proposed.

II. TIME-DOMAIN GLOBAL SIMILARITY METHOD

TDGS method aims to automatically sort out the incorrect diagnostic data of the MUM system. By transforming the direct data sequence classification problem into a binary classification problem about the physical similarity between diagnostic data sequences, TDGS method eliminates the complexity arisen from discharge parameters during data cleaning. In this section, the theory and procedure of training TDGS model for data cleaning of MUM systems are explained in details, including data preprocessing, sample set generation, model training, and application.

Preprocessing procedures of TDGS method contains digital filtering and normalization. For many MUM systems in MCF devices, the physical similarity between channels exists in global time scale. Different filter methods can be used to remove the small time scale fluctuations in original data. Here we choose the median filter method, which is performed by letting a window move over the points of the sequence and replacing the value at the center of the window by the median of the original values within the window [30], as digital filtering technique to eliminate the small-scale information. The original sequence S_{mj} is transformed to S'_{mj} by median filter of window size n, namely

$$S'_{mj} = \text{Median}Filter(S_{mj}, n), \qquad (1)$$

where S_{mj} denotes the original time series signal measured by the *jth* channel of the MUM system under the *mth* discharge. By adaptively choosing the window size *n* of median filter, we efficiently remove high-frequency details, which matters little to the global profile of data sequences.

The ranges of diagnostic data sequences from various channels, discharge parameters, and diagnostic systems are different. To remove the dependence of physical similarity on absolute values, TDGS method normalizes all original data sequences to the same scale with Z-score transformation. The sequence S'_{mj} is transformed to S''_{mj} under Z-score transformation as

$$S_{mj}^{\prime\prime} = \frac{S_{mj}^{\prime} - E(S_{mj}^{\prime})}{D(S_{mj}^{\prime})},$$
(2)

where $E(S'_{mj})$ and $D(S'_{mj})$ denote the average value and standard deviation of the sequence S'_{mj} respectively. After data preprocessing, the distinction of length and magnitude of data sequences can be eliminated, which favors to the generation of a unified sample set.

The second step of TDGS method is to define the sample Sp_{ij}^m , sample label $Label_{ij}^m$, and sample feature l_{ijk}^m using the preprocessed data. By combining any pair of data sequences from different channels of the MUM system under the same discharge, the sample set in TDGS method is defined as

$$Sp_{ij}^m = S_{mi}^{\prime\prime} \oplus S_{mj}^{\prime\prime}, \tag{3}$$

where the sample Sp_{ij}^m is the combination of preprocessed data sequence S''_{mi} from the *i*th channel and S''_{mj} from the *j*th channel of the MUM system under the *mth* discharge. The sample label $Label_{ij}^m$ assigned to the sample Sp_{ij}^m is used to judge the corresponding physical similarity between the preprocessed data S''_{mi} and S''_{mj} . The physical similarity is labeled according to the correctness of data sequences. If the data sequences from channel i and channel j under shot m are correct, the label $Label^m_{ij}$ is tagged as +1, which means these two sequences are physical similar with each other. If the data sequences from channel i and channel j under shot m contain at least one incorrect data sequence, the label $Label^m_{ij}$ is tagged as -1, which means these two sequences are physical disting as -1, which means these two sequences are physical disting as -1, which means these two sequences are physical disting as -1, which means these two sequences are physical disting as -1, which means these two sequences are physical disting as -1, which means these two sequences are physical disting as -1, which means these two sequences are physical disting as -1, which means these two sequences are physical disting as -1, which means these two sequences are physical disting as -1, which means these two sequences are physical disting as -1, which means these two sequences are physical disting as -1, which means these two sequences are physical disting as -1, which means these two sequences are physical disting as -1, which means these two sequences are physical disting as -1, which means these two sequences are physical disting as -1, which means these two sequences are physical disting as -1, which means these two sequences are physical disting as -1, which means these two sequences are physical disting as -1, which means these two sequences are physical disting as -1, which means the preprocessed data of an N-channel MUM system under P discharges, $P * C_N^2 = \frac{P * N(N-1)}{2}$ samples can be generated.

In many MUM systems of MCF devices, there exists physical similarity between diagnostic data sequences in time domain. Considering that the dimension of the sample is too large for input, say a million, reducing the dimension by selecting a set of principal features is necessary to avoid the curse of dimension and relieve the heavy calculation burden. TDGS method employs multiple distance functions between data sequences as sample features, i.e.,

$$l_{ijk}^m = D_k(\boldsymbol{S''_{mi}}, \boldsymbol{S''_{mj}}), \qquad (4)$$

where D_k is the *kth* distance function employed in TDGS method, and sample feature l_{ijk}^m denotes the *kth* sample feature extracted from the sample Sp_{ij}^m . The definitions of all the distance functions D_k are listed in Table. I. A variety of distance functions, such as Euclidean Distance, Chebyshev Distance, and Correlation distance, are selected for measuring the physical similarity in various aspects. The contribution of Chebyshev Distance is remarkable in the classification of the sudden change at some point in the data sequence. The first-order and second-order differential of Euclidean Distance are more important in the case when the variation tendency of incorrect data sequences is obviously different from the correct ones. Some distance functions are affected by lengths of data sequences. For example, the Euclidean Distance would be larger if lengths of input signals are longer. The lengths of data sequences would be longer if the time durations of corresponding discharges are longer or the sampling rates are higher. But the sample features should not be affected by the time duration of discharges or the sampling rates of signals. So those distance functions which are affected by lengths of corresponding data sequences are normalized by the length T of data sequences. Then samples from different discharges with various time durations and sampling rates can be normalized to the same standard for similarity.

Table I. Mathematical definitions of distance functions as 11 features of a sample adopted in TDGS method. T is the length of the input data sequence.

Feature id	$D_k(oldsymbol{S_1},oldsymbol{S_2}))$
1	$rac{\ oldsymbol{S_1-S_2}\ _2}{T}$
2	$\frac{\ \boldsymbol{S_1}{-}\boldsymbol{S_2}\ _1}{T}$
3	$\ oldsymbol{S_1}-oldsymbol{S_2}\ _\infty$
4	$\frac{\mathbf{S}_1{}^T\mathbf{S}_2}{\ \mathbf{S}_1\ _2\ \mathbf{S}_2\ _2}$
5	$\frac{E((\mathbf{S}_1 - E(\mathbf{S}_1))(\mathbf{S}_2 - E(\mathbf{S}_2)))}{\sqrt{D(\mathbf{S}_1)}\sqrt{D(\mathbf{S}_2)}}$
6	$1 - D_5(\mathbf{S_1}, \mathbf{S_2})$
7	$\ d \left(\mathbf{S}_1 - \mathbf{S}_2 \right) / dt \ _2 / \mathbf{T}$
8	$\ d \left(\mathbf{S}_1 - \mathbf{S}_2 \right) / dt \ _1 / \mathbf{T}$
9	$\ d^2 \left(\mathbf{S}_1 - \mathbf{S}_2 \right) / dt^2 \ _2 / \mathbf{T}$
10	$\ d^2 \left(\mathbf{S}_1 - \mathbf{S}_2 \right) / dt^2 \ _1 / \mathbf{T}$
11	$(\sum_{k=1}^{10} D_k(\mathbf{S_1}, \mathbf{S}_2)^2)^{0.5}$

After magnitude normalization and time normalization, the scale of data sequences is unified. Then samples from different discharges can be fairly treated in the sample set (X, Y), defined by its components

$$\begin{cases} \boldsymbol{X} = \left\{ \bigoplus_{k} l_{ijk}^{m} \right\}_{i,j,m}, \\ \boldsymbol{Y} = \left\{ \boldsymbol{Label}_{ij}^{m} \right\}_{i,j,m}. \end{cases}$$
(5)

In the training procedures of TDGS method, many classification algorithms can be used. Here we use Support Vector Machine (SVM) to train classifiers for the physical similarity between data sequences. In SVM, input samples are mapped to a high-dimensional feature space. A good classification is achieved by constructing a linear separating hyperplane in this feature space with the maximal margin to the nearest samples of any class [25–27]. Mathematically, the SVM seeks the solution of the following optimization problem

$$\begin{cases} \min_{\mathbf{W}, b, \xi} \frac{1}{2} \mathbf{W}^T \mathbf{W} + C \sum_{i=1}^{l} \xi_i, \\ subject \ to \ \mathbf{Y}_i (\mathbf{W}^T \phi(\mathbf{X}_i) + b) \ge 1 - \xi_i, \\ \xi_i \ge 0, \end{cases}$$
(6)

where \boldsymbol{W} is the normal vector of the targeted separating hyperplane, C is the penalty parameter of the error term. And $K(\mathbf{X}_i, \mathbf{X}_j) = \phi(\mathbf{X}_i)^T \phi(\mathbf{X}_j)$ is defined as the kernel function. Proper selection of kernel function for different classification problems can optimize the performance by mapping samples to appropriate high-dimensional feature space. Sequential minimal optimization (SMO) is adopted as a common iterative method for solving this quadratic programming (QP) problem [28].

After classification of the physical similarity, dirty diagnostic data of MUM systems can be identified according to the tagged similarity relations between data sequences. On the one hand, by scanning through all samples tagged with similarity, the data which are similar to each other under the same discharge can be marked as correct data. On the other hand, by scanning through all samples tagged with dissimilarity, the data which are dissimilar from all the other diagnostic data sequences under the same discharge can be tagged as incorrect data. Calculation burden and inconsistent error accumulation of data cleaning depends on the judgment rules given the physical similarity classification has been finished. There are still some optimization schemes for improving the performance of data cleaning at this stage. The rule adopted in this paper is an absolute judging rule. Next step, we would adopt a non-absolute judging rule. For example, the sequence which is dissimilar from 90% of the other sequences can be tagged as incorrect data. Then the degree parameter introduced by the judging rule can change the mapping relations between performance of TDGS method about physical similarity and correctness of data sequences. In some cases, proper setting of the degree parameter would improve the data cleaning performance of TDGS method.

III. APPLICATIONS OF TDGS METHOD ON DENSITY DATA CLEANING FOR POLARIMETRY-INTERFEROMETRY SYS-TEM

In this section, TDGS method is used to clean the density data of POINT system as an application example. By applying TDGS method to sort out the incorrect density data automatically, the reliability and availability of diagnostic data measured by POINT system can be improved, which is beneficial for the study and application of POINT data, for example, maintaining steadystate plasma.

POINT is a typical 11-channel MUM system, which measures line-average electron density of EAST tokamak at different vertical locations with independent measuring channels. [21–23]. Original density data of POINT system contains dirty data sequences caused by mechanical vibration, electromagnetic interference, collinear error, or hardware failures [23]. Original density sequences of POINT system under three discharges with different parameters, i.e., shot 62287, 56180, and 58888, are plotted in Fig. 1. By comparing any two time evolutions of density from different shots, it can be observed that the evolutions of density sequences under various discharges are totally different from each other. Meanwhile, the incorrect density sequences evolve differently even under the same discharge, see the three incorrect data sequences marked with red boxes in shot 58888. It is difficult to find direct, general, and clear criteria for sorting out the incorrect density sequences even only for the three shots shown in Fig. 1. By further observation, the correct density data of different channels under the same charge are globally similar to each other. For example, all evolutions of density from channel 1 to channel 10 in shot 62287 can be recognized to have three stages, i.e., the climbing stage from 0 s to 1.5 s, the plateau stage from 1.5 s to 7 s, and the declining stage from 7 s to 7.3 s. Correct data sequences from different channels of POINT system reflect plasma properties with independent measurement channels at different locations. There exits time-domain global similarity in correct density signals of POINT system. This similarity originates from the associated relation between plasma properties at

different locations. Based on this physical similarity, TDGS method can be efficient to sort out the incorrect density data of POINT system.

Data preprocessing of this application contains digital filtering and normalization. There exits local differences between correct time-series density sequences under the same charge. For example, the data sequences from channel 1 to channel 10 in shot 62287 evolve differently at the start moment of the declining stage, see Fig. 1. Removing these small-scale fluctuations by median filter can improve the classification performance for physical similarity. Meanwhile, the ranges and lengths of time-series density sequences under various discharges are different. To guarantee the scale independence on absolute values, original density sequences should be normalized to the same magnitude scale with Z-score transformation. To guarantee the length independence, feature 1, 2, 7, 8, 9, 10, see Table I, should be normalized with the length of sequences. Considering that the sampling rate of POINT system is unchanged during the selected 24 shots, we adopt the acquisition time of corresponding discharges directly as the indices for length normalization. After scale normalization and length normalization, the effect of absolute value and length of sequences can be eliminated. Then a unified sample set can be generated from the preprocessed data.

In conventional operations of POINT system, the ratio of incorrect density data is much less than the ratio of correct ones. When samples of one class are much more than the other class, most classifiers are biased towards the major class and lead to very poor classification rates on minor class. To improve the classification accuracy on cleaning of density data for POINT system, we balance the training database by undersampling the majority class, i.e., the Figure 1. Original time-series density sequences from different channels of EAST POlarimeter-INterferomeTer (POINT) system are plotted in three typical discharges (shot 62287, 56180, 58888). The channel id of corresponding sequences is labeled. The incorrect sequences are marked with red boxes.



correct density data. To reveal the performance of the classification model in general sense, different types of incorrect density data of POINT system are collected in the training set as far as possible. In this application, density data measured by 11 channels of POINT system under 24 discharges are chosen to generate the sample set. Considering that each sample of TDGS method is produced by combining two diagnostic data sequences from different channels under the same discharge, $24*C_{11}^2 = 1320$ samples can be generated for this 11-channel MUM system. To demonstrate the distribution structure of data set, the ratios of bad channels and dissimilar samples for each single discharge are separately shown in Fig. 2. Here the ratio of bad channels denotes the proportion of incorrect diagnostic data sequences to total diagnostic data sequences. And the ratio of dissimilar samples denotes the proportion of samples tagged

with dissimilarity to total samples. According to the definition of physical similarity in TDGS method, two types of samples are tagged with dissimilarity in this application. Type A is consist of a correct density data sequence and an incorrect one under the same discharge. Type B is consist of two incorrect density data sequences from different channels under the same discharge. For example, the ratio of bad channels of POINT system for shot 58888 is 3/11, see Fig. 1. Corresponding numbers of dissimilar samples of Type A and Type B are $C_8^1 * C_3^1 = 24$ and $C_3^2 = 3$ respectively. Hence the ratio of dissimilar samples in shot 58888 is $(C_8^1 * C_3^1 + C_3^2)/C_{11}^2 = 27/55$. The ratio of total similar samples to total dissimilar samples in the sample set is about 1.9. Different classes are almost balanced in the training set, which is good for obtaining a better prediction performance using TDGS method.

Figure 2. In the sample set generated from density data of POINT system, the ratios of bad channels and dissimilar samples are plotted for each shot.



Different classification models with various parameter settings can be adopted

in TDGS method. By testing the performance of candidate models, most suitable classifier with optimized parameters will be selected for real applications. In this case, SVM is chosen as the classification algorithm. SMO is adopted as the iterative method. Key parameters, including the window size of median filter, kernel functions of SVM, and penalty factor are optimized by model selection. By comparing the performance of candidate models, most suitable classifier with optimized parameters will be selected. Proper window size of median filter can eliminate the small-scale information while preserving the feature of physical similarity for plasma density. Appropriate penalty factor helps to avoid overfitting. Linear, Polynomial, and Gaussian radial basis (RBF) kernel functions are applied in this problem, see Table. II. Linear kernel is the simplest kernel function among them, with least adjustable parameters. RBF kernel has an additional parameter γ , while the Polynomial kernel has more adjustable parameters, including the slope α , the constant term r, and the polynomial order d. To reduce the calculation amount during the parameter optimization of Polynomial kernel, the value of polynomial order d is restricted to 3 and 4. By selecting a kernel function and corresponding kernel parameters, the classification can be handled in a proper high-dimensional feature space. Following these operation procedures, the optimized classification model for density data cleaning of POINT system can be achieved by TDGS method.

IV. ASSESSMENT OF TDGS METHOD

In this section, model selection and assessment of TDGS method are introduced. Corresponding assessment results of applying TDGS method to density data cleaning for POINT system are exhibited, which demonstrates the advan-

Kernel function	Mathematical form
Linear	$\mathbf{X}_{i}^{T}\mathbf{X}_{j}$
Polynomial	$(\alpha \mathbf{X}_i^T \mathbf{X}_j + r)^d, \alpha > 0$
Radial basis function (RBF)	$\exp(-\gamma \parallel \mathbf{X}_i - \mathbf{X}_j \parallel^2), \gamma > 0$

Table II. Kernel functions chosen for optimization in the application of TDGS method on density data cleaning for POINT system. Here α , r, d, and γ are corresponding kernel parameters.

tage of applying TDGS method to MUM systems in MCF devices.

To provide an effectively unbiased error estimate, k-fold cross-validation is adopted as the assessment method for TDGS method. In k-fold crossvalidation, the sample set is evenly divided into k groups. One group is chosen as the validation set, and the rest k-1 groups constitute the training set. Then, the assessment process is repeated k times by assigning each group as the validation set once [31]. In the data cleaning for MCF devices during experimental period, the test sample set is generated from the same discharge. To assessment the performance of TDGS method for practical application, we govern that the samples in each group are generated from the same discharge. For the sample set generated from density data under 24 discharges, the model assessment method of POINT system turns out to be 24-fold cross-validation. In each test of the 24-fold cross-validation, the classification accuracies with different kernel functions are shown in Fig. 3. The classification accuracy in most tests behaves as good as 100%, which demonstrates that the optimized models with linear, 3^{rd} -order polynomial, 4^{rd} -order polynomial, and gaussian radial basis kernel functions can all accurately sort out incorrect density data of POINT system caused by common error sources.

For different kernel functions, the classification performances evaluated by

Figure 3. In each test of 24-fold cross-validation, the classification accuracy of applying TDGS method to the sorting of density data measured by POINT system with various kernel functions is plotted. Here the legend 'linear' denotes linear kernel; 'polynomial (3)' denotes 3^{rd} -order polynomial kernel; 'polynomial (4)' denotes 4^{rd} -order polynomial kernel; 'rbf' denotes gaussian radial basis kernel function, and the scaling factor (sigma) equals 1.



24-fold cross-validation and corresponding model parameters are listed in Table. III. The performance of linear kernel function is outstandingly more accurate and stable than other kernel functions. On the other hand, linear kernel function has less kernel parameters to be optimized and faster training speed [27]. Therefore, the linear kernel function is a good choice for data cleaning in this problem. With optimized parameters, i.e., linear kernel function with penalty factor equals 8, and window size of median filter equals 1000, the performance of TDGS method evaluated by 24-fold cross-validation in cleaning density data of POINT system has reached 0.9871 ± 0.0385 . The average predication time of linear model for a new discharge is about 0.6752 ms. Moreover, the recall rate and false alarm of linear model for dissimilar samples are 0.9792 and 0.0294 respectively. Here the recall rate of dissimilar samples means the ratio of correctly predicted dissimilar samples to all dissimilar samples. The false alarm of dissimilar samples means the ratio of similar samples that are incorrectly predicted as dissimilar to all samples that are predicted as dissimilar. To evaluate this data cleaning model with a large set of discharges, we have picked out density data of POINT system under other 167 shots as test set. The performance of the optimized linear model in cleaning this new dataset has reached 0.9518 ± 0.0810 . These data demonstrate that the optimized linear model can be used as the final data cleaning model for real density data analysis of POINT system reliably.

Table III. For various kernel functions, the optimized classification performances evaluated by 24fold cross-validation and corresponding model parameters in applying TDGS method to the density data cleaning of POINT system.

Kernel functions	Performance	Penalty factor	Window size of median filter
Linear	$0.9871 {\pm} 0.0385$	8	1000
Polynomial(3)	$0.9712 {\pm} 0.0741$	1	800
Polynomial(4)	$0.9288 {\pm} 0.1178$	5	2000
Rbf	$0.9652 {\pm} 0.0597$	1	1900

In linear SVM, the contributions of each features can be ranked according to the absolute value of weight vector \boldsymbol{W} . The larger $|W_i|$ is, the more important role is played by the *ith* feature in the linear model [32]. The absolute values of weight vectors in the final classification model are shown in Fig. 4. It can be observed that each feature has evident contribution in this model, and the contribution of feature 3, i.e., the Chebyshev Distance $||\boldsymbol{S_1} - \boldsymbol{S_2}||_{\infty}$, is the biggest.



Figure 4. The absolute value of weight factors in the optimized linear classification model for the density data cleaning of POINT system.

v. SUMMARY

In this paper, machine learning is applied to the automatic data cleaning of MCF devices for the first time. Correct diagnostic data sequences from different channels of MUM systems, which reflect related yet distinct aspects of the same observed object, are physical similar with each other. Based on this physical similarity, we propose a general-purposed TDGS method to sort out the dirty diagnostic data of MUM systems in MCF devices. The optimized performance of TDGS method evaluated by 24-fold cross-validation in sorting the density data of POINT system has reached 0.9871±0.0385. In the future, we will apply TDGS method to clean the POINT data and other MUM systems in MCF devices. In large-scale applications of TDGS method, predication speed and robustness should be further considered as assessment indicators for model selection. Meanwhile, the algorithm for data cleaning based on physical similarity between data sequences should be further optimized to achieve less calculation amount and error accumulation. Moreover, the physical similarity in frequency-domain can also be utilized in some data cleaning problem of MUM systems.

ACKNOWLEDGMENTS

This research is supported by Key Research Program of Frontier Sciences CAS (QYZDB-SSW-SYS004), National Natural Science Foundation of China (NSFC-11575185,11575186), National Magnetic Confinement Fusion Energy Research Project (2015GB111003,2014GB124005), JSPS-NRF-NSFC A3 Foresight Program (NSFC-11261140328),and the GeoAlgorithmic Plasma Simulator (GAPS) Project.

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