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Evaluation of Ship Exhaust Gas Measurements based on Dynamic Time Warping

Li Tao, Siyuan Zhang

Shanghai Maritime University, Shanghai, China

Abstract

Ship exhaust emissions have caused serious pollution to the environment. It is an effective method to estimate the sulfur content of marine fuel oil by detecting the concentration of CO2 and SO2 in the exhaust gas of ships. At present, the quality of the data collected by the sniffing method is basically judged by human analysis. In this paper, a dynamic time warping (DTW)-based evaluation method for ship exhaust gas measurement is proposed. Using DTW to obtain the minimum distance value of the measured data, the data quality was evaluated by this value. The study found that when the minimum distance value is less than 30, the data quality is better; when the minimum distance value is greater than 30, the data quality is poor.

Keywords

Ship Sulfur Content Value; Sniffing Method; Ship Exhaust Data Processing; Data Analysis; DTW.

1. Introduction

Ship transportation is an important part of world cargo transportation. In 2017, ship transportation account for more than 80% of global trade volume and more than 70% of global trade volume[1]. Although ship transportation greatly promotes social and economic development, ship emissions also bring great harm to the environment. According to United Nations statistics, CO2 and SO2 emitted by ships accounted for 10% of the world's annual emissions in 2019[2]. Air pollution from ship exhaust emissions can cause heart and lung disease, acidify waters, and affect global ecosystems. Since 70% of ship routes are concentrated within 400 kilometers from the coastline, ship exhaust emissions have become an important source of air pollution in coastal and riverside areas[3].

In order to effectively suppress ship pollution, the International Maritime Organization (IMO) signed the MARPOL Convention in 1973. The Convention includes 6 annexes, which respectively make relevant regulations for different types of ship pollution. From 2006 to 2014, the IMO delineated four international emission control areas, the Baltic Sea, the North Sea, and the North American, American, and Caribbean Seas, and imposed strict restrictions on oil products. China is an important part of the world's maritime transport, and in 2019, China accounted for 7 of the world's top ten ports. In order to reduce pollution caused by ship emissions, the Implementation Plan for Ship Air Pollutant Emission Control Areas implemented on January 1, 2019 stipulates that ships entering domestic emission control areas should use a sulfur content limit of 0.5% (m/m) of marine fuel. From January 1, 2020, seagoing vessels entering inland water control areas should use marine fuel oil with a sulphur content limit of 0.1% (m/m), which is stricter than the previous standard.

With the implementation of corresponding laws and regulations, it is necessary to quickly and effectively detect the sulfur content of ship fuel oil. The most accurate detection method is for maritime law enforcement officers to board the ship to collect fuel samples from ships, use rapid testing equipment to test the samples, and send the samples suspected of exceeding the

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standard to the testing agency for testing to obtain the sulfur content of the ship's fuel oil, but this will cost a lot of money, time and material resources. In addition, it can be detected by optical analysis or sniffing. Optical analysis methods such as differential light absorption spectroscopy[4], lidar[5], and ultraviolet cameras[6] use the local optical properties of the ship plume to estimate the SO2 concentration in the wake. For example, Cao K uses base convolutional neural network and ultraviolet camera images to predict the sulfur content of ship fuel[7]. The sniffing method can estimate the sulfur content by collecting the SO2 concentration and CO2 concentration in the exhaust gas of the ship and the background SO2 concentration and CO2 concentration. For example, J.Beecken proposed to use sniffer technology to measure SO2 of ships[8], such as Zhou proposed a drone equipped with a sniffer device pod to detect the sulfur content of ship exhaust gas[9]. Due to the influence of the environment, operation mode, wind speed and direction and sensor factors, there are differences in the data detected by the drone equipped with the sniffing equipment. For example, Zhou analyzes the bad data in the measurement data, and selects a stable peak interval to estimate the sulfur content[9].And more, hu selects the part with higher data concentration to calculate the sulfur content, but the above measurement methods are all manual data analysis and data analysis. Quality analysis, dynamic time warping(DTW) is a template matching algorithm based on dynamic programming, which locally stretches or compresses the signal according to the similarity of the two signals, so that the two signals are optimally matched, and the similarity of the two signals is compared. It is effectively used in speech recognition[11], biometrics, meteorology and many other fields. For example, Wang uses DTW to calculate the similarity to evaluate the dynamic connectivity between wells[12], and Dong uses DTW to calculate the similarity to achieve fault enhancement[13]. Therefore, this paper proposes an evaluation method of ship exhaust measurement based on dynamic time warping. This method calculates the similarity of data through dynamic time warping algorithm, obtains a minimum distance value, and uses this value to evaluate data quality.

2. Related Theory

2.1. Section Headings

The main thing of the DTW algorithm is to solve the frame matching matrix and the accumulated distance of the two time series. The frame matching matrix stores the distance between any two points in the two time series, and then uses the dynamic warping algorithm to solve the minimum cumulative distance when the two time series are matched, that is, the minimum dynamic warping distance, so as to judge the time series Similarity [41]. The larger the dynamic warping distance, the worse the similarity between the two time series. The specific algorithm is described as follows:

Suppose there are two time series,A and B, a test sequence of length N and a reference sequence of length M, respectively, $A=\{A_1,A_2,\ldots A_N\}$, $B=\{B_1,B_2,\ldots B_M\}$ .The distance between any two corresponding frames in two time series is represented by $d(A_n,B_m)$, where n and m represent the subscripts ($1\le n\le N, 1\le m\le M$) of any frame in sequences A and B. The Euclidean distance is calculated as the judgment index of the similarity between the nth frame of the A sequence and the mth frame of the B sequence, that is, for two n-dimensional vector sums with the same length, $a=\{a_1,a_2,\ldots a_n\}$, $b=\{b_1,b_2,\ldots b_n\}$ .The total distance of the corresponding frames is $d(a,b)=\sum_{i=1}^{n}(a_i-b_i)^2$.

The frame matching matrix of the A sequence and the B sequence is represented by a grid diagram, and the grid numbers of the abscissa and the ordinate are the length N of the A sequence and the length M of the B sequence, respectively. And the horizontal and vertical

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coordinates are marked from the grid interval in the lower left corner, and the marked value is 1, 2, ... to the sequence length. Then it is necessary to find the regular path of the two sequences in the grid graph, there are many different path possibilities.

Points with similar changing trends in two time series are corresponded by dynamic programming algorithm, and the correspondence is called regular path. As shown in the figure, define W as the regular path of time series T and Q, and the kth element in W is defined as wk=(i,j)k,W={w1,w2,w3,…,wk,…,wK }, where K is the compensation for paths of different lengths. The constraints from the kth budget to the k+1th element include boundary, continuity, and monotonicity.

Boundary: each path ends from w1(1,1) to wk(n,m), that is, from the first matching point to the last matching point.

Continuity: The current element can only be aligned with the points around itself, and a point will not be skipped, that is, the k element wk(I,j) in the regular path, the next element WK+1(a,b), satisfies $a-i \le 1$ and $b-j \le$, which indicates that the regular path contains all the elements in the time series, and each point in the matrix is traversed once.

Monotonicity: The kth element wk(i,j) in the regular path, the next element k+1 element Wk(a,b), where $a-i \ge 0$ and $b-j \ge 0$.

According to these constraints, it can be concluded that if the path passes through the point (i, j), then the next passing point can only be (i+1,j) or (i,j+1) or (i+1,j+1), so the value range of K is [max(n,m),n+m-1].

There are multiple paths that can satisfy these constraints, but DTW finds the optimal regular path that minimizes the accumulated distance along the path, and the minimum accumulated distance is D(i,j). Define DTW(T,Q) as the optimal regular path in time series T and Q. It is considered that the smaller the value of DTW(T, Q), the greater the similarity of time series curves. And call this value Minvalue.

$$\begin{aligned} DTW(T,Q) &= \min\{\sqrt{\sum_{k=1}^{K} w_k} / K \\ &= D(i,j) \\ &= d\left(t_i,q_j\right)+min\left[D\left(i+1,j\right),D\left(i+1,j+1\right),D\left(i,j+1\right)\right] \end{aligned} \tag{1}$$

2.2. Data Smoothing

Data smoothing can effectively remove unwanted noise or behavior from the data. Usually data smoothing methods include Mean Average, Exponential Mean Average and SG filtering. This paper mainly uses the moving average method, also known as the moving average method.

Assuming that the observed value is noisy, and the mean of the noise is 0 and the variance is σ2, the relationship between the observed value and the actual value is as follows:

$$Gt = \frac{\sum_{i=1}^{n}(Yt-i+Yt+i)+Yt}{2n+1} = Yt \tag{2}$$

Yt represents the true value, Xt represents the observed value, and represents the noise. We add the observations at adjacent times and average them to reduce the impact of noise. The formula is as follows:

$$G_t = \frac{\sum_{i=1}^{n}(X_{t-i}+X_{t+i})+X_t}{2n+1} \tag{3}$$

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where Gt represents the filtering result at time t, Xt-i represents the observation value at time t-i, and n is the radius of the sliding window.

$$Gt = \frac{\sum_{i=1}^{n}(Yt - i + Yt + i) + Yt - \sum_{i=1}^{n}(\varepsilon_{t-i} + \varepsilon_{t+i}) - \varepsilon_t}{2n+1} \tag{4}$$

Since the mean of the noise is assumed to be 0, so is 0, so the 5above formula can be written as:

$$\mathrm{Gt} = \frac{\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{Yt} - \mathrm{i} + \mathrm{Yt} + \mathrm{i}) + \mathrm{Yt}}{2\mathrm{n}+1} \tag{5}$$

When the real value changes linearly or the change value is small, it can be approximated that:

$$Gt = \frac{\sum_{i=1}^{n}(Yt - i + Yt + i) + Yt}{2n+1} = Yt \tag{6}$$

It can be seen from the above that when the real value in the sliding window does not change much or is a linear relationship, the filtering result is close to the real value; when the real value in the sliding window changes greatly, using the sliding average method will lose the accuracy, and the filtering The result is close to the average expectation of the true value. Therefore, the choice of the width of the window has a great influence on the filtering result. That is, the larger the window width, the more obvious the smoothing effect, but the deviation from the real value will be larger; the smaller the window width, the closer the filtering result is to the observed value, but the noise will be larger.

In this article, the selected window width is 10.

3. Evaluation Method of Exhaust Gas Measurement Value based on Dynamic Time Warping

Affected by factors such as sensor, operator error, wind speed and direction, the collected CO2 and SO2 concentration data are divided into good and bad. Some collected data have similar changing trends in the image, while some collected data show changing trends in the image. Not close, and there are many noise points. Through dynamic time warping to calculate the overall minimum distance value combined with manual analysis, it is found that there is a certain relationship between the minimum distance and the quality of the collected data. The analysis process is as follows: first, calculate the minimum distance of the collected CO2 and SO2 concentration data, and record it, and find the higher concentration interval in the combined image. If the data has multiple higher concentration intervals, and the concentration data is formed If the trend of change is similar, the data belongs to the data with a better measurement. Use data 2019-8-20B and data 2019-3-29A to illustrate the difference between good and bad data.

The Minvalue of the data 2019-7-25B as a whole is 4.462. It can be seen from the figure that the SO2 and CO2 concentration data are generally stable in the initial stage, but the SO2 concentration fluctuates slightly in stages 43 to 55; in stages 121 to 187 , SO2 and CO2 concentration data appeared two obvious peak intervals, and the variation trends of the

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intervals were similar; the data in the stages 167 to 301 were overall smooth without large fluctuations.

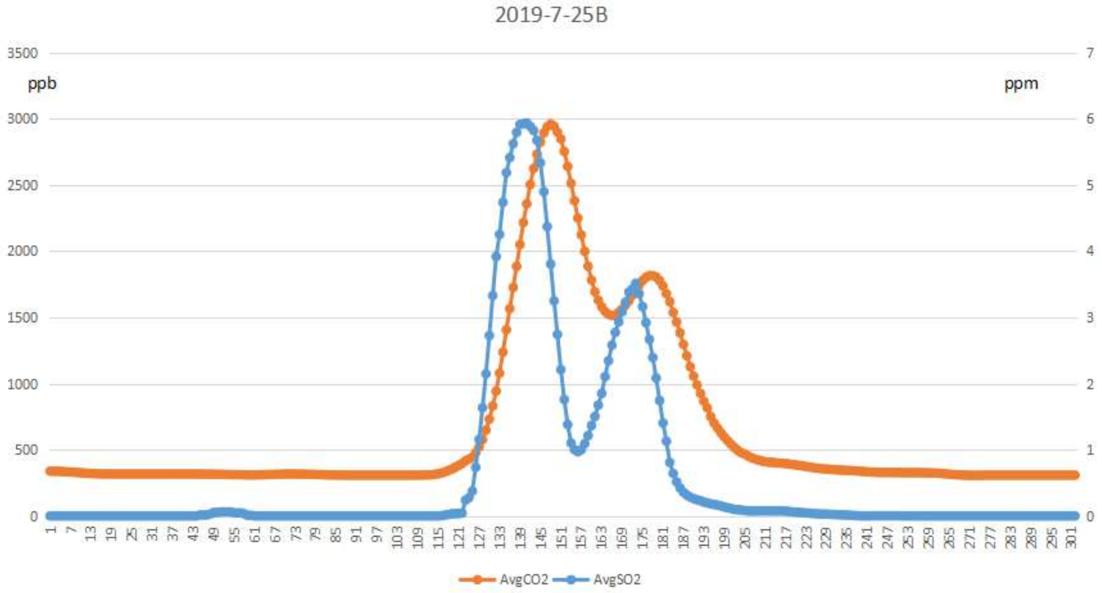

Figure 1. 2019-7-25data

The Minvalue of the data 2019-3-29A as a whole is 67.104. It can be seen from the figure that the CO2 concentration and SO2 concentration data have similar trends at the beginning, and there are differences in the changes after the abscissa 222. The overall trend of CO2 changes smoothly and does not appear sharp. The change interval of SO2, and the trend change of SO2 has many sharp changes. In the end interval of 537 to 936 on the left side of the constant, the change of SO2 concentration changes sharply in a short time, and the maximum change of SO2 concentration is 1.22ppb, measured at 885 to 936 At the end stage, the SO2 concentration changes sharply instead of ending smoothly, so there is a problem with the measurement data, which is considered to be a set of poor data.

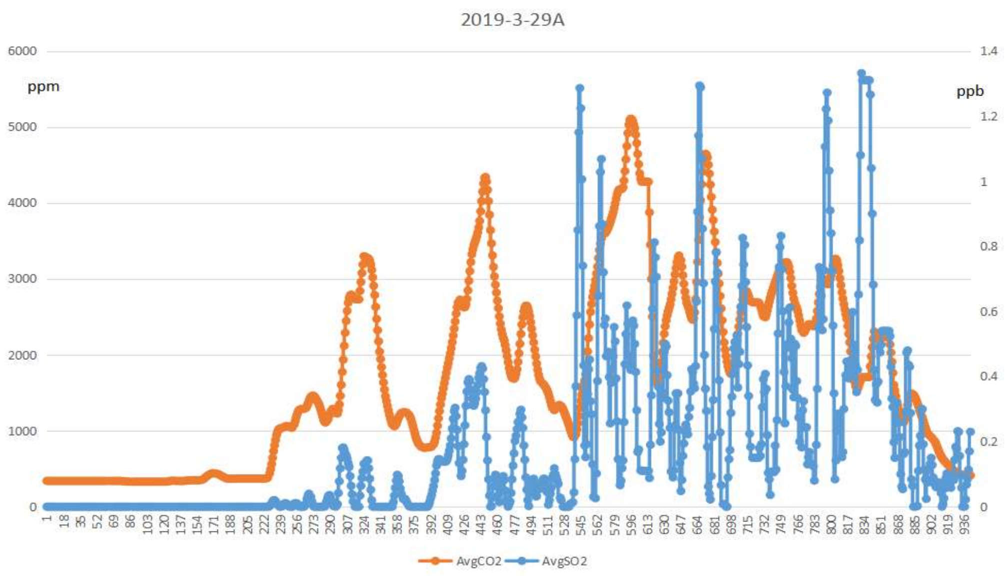

Figure 2. 2019-3-29Adata

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Table 1. Minvalue and Data quality

Data	Minvalue	Data quality
2019-3-18A	14.333	good
2019-3-22A	8.357	good
2019-3-22B	15.055	good
2019-3-29A	67.104	bad
2019-4-1A	58.130	bad
2019-4-3B	45.672	bad
2019-4-12B	26.588	good
2019-4-15B	55.118	bad
2019-7-12A	14.779	good
2019-7-15A	110.453	bad
2019-7-25A	2.566	good
2019-7-25B	4.462	good
2019-8-14A	55.189	bad
2019-8-15A	28.542	good
2019-8-16A	13.189	good
2019-8-16C	11.307	good
2019-8-16D	71.943	bad
2019-8-20A	37.570	bad
2019-8-20B	110.356	bad
2019-8-22A	29.700	good
2019-8-22B	81.167	bad
2019-8-22C	45.358	bad
2019-8-22E	49.593	bad
2019-9-17B	53.385	bad
2019-9-27B	10.659	good

The study found that the smaller the minimum distance value of the data is, the overall change trends of the CO2 concentration and SO2 concentration data are similar, and the result of the data measurement is a set of well-measured data, in which there are multiple intervals with the same change trend; The larger the minimum distance value of the data is, the overall change trend of the CO2 concentration and SO2 concentration data is not similar, and the result of the data measurement is the data with a poor measurement, in which the data has very little change trend in the same interval or no change trend is the same There are sharp changes in SO2 concentration data, which may be caused by irregular operation during measurement, uncalibrated SO2 sensor and CO2 sensor, and environmental factors such as wind speed during measurement.

4. Conclusion

Therefore, the study finds that the quality of CO2 concentration and SO2 concentration data is related to the calculation of the minimum distance value by the dynamic time warping algorithm. Generally, the minimum distance value is less than 30, then the measured data is a good set of data, and the minimum distance value The smaller the value, the more similar the overall trend of CO2 concentration and SO2 concentration data; on the contrary, if the minimum

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distance value is greater than 10, then the measured data is a group of poor data, and the larger the minimum distance value is, then the CO2 concentration and SO2 concentration The overall trend of the data is more different.

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