Machine Learning based Dynamic Correlation on Marine Environmental Data Using Cross-recurrence Strategy

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ABSTRACT As a frequent natural disaster, red tide has attracted more and more attentions. In fact, red tide results from the joint actions of multiple complex marine environmental factors. Unfortunately, there is no work on the interaction analysis between these factors. To inaugurate a systematic research of this area, a novel machine learning based framework is developed for marine environmental series analysis. It combines cross recurrence plot (CRP), cross recurrence quantification analysis (CRQA) and statistical analysis. This framework provides a general way to transform two marine series into a high-dimensional space. CRP is used to visualize internal dynamics, while the influence of factors is quantitatively analyzed through CRQA. Finally, the representative factors in each field are statistically determined by boxplot. This is the first analysis framework attempting to reveal the similarity in intrinsic dynamics of marine factors. Experimental results show that the framework is competent to perform the visualization of marine time series. Besides, the results also demonstrate the degree of similarity between different marine factors through quantitative analysis.

INDEX TERMS Marine time series, phase space reconstruction, CRP, CRQA, statistical analysis, machine learning.

I. INTRODUCTION

THE protection of marine environment has become a worldwide common concern. As a kind of common disaster, red tide has attracted wide attention of scholars. Red tide is an abnormal and frequent ecological phenomenon, which is considered to have effects on marine ecosystem and human health. It is caused by abundant concentration and rapid propagation of phytoplankton. Currently, reasons for the rapid growth of phytoplankton have been studied for many years, including the effects of meteorological phenomenon, hydrology, nutritive salt and water quality. The analysis and evaluation of marine environmental factors have essential value and significance for preventing red tide. It has become a hot topic in current research.

As is known, red tide is caused by complex environmental factors. Generally, it can be measured by the concentration of chlorophyll a (ChlA). When red tide occurs, there exists excessive ChlA concentration. At present, a great many of machine learning based works focus on the red tide prediction. For example, Karki et al. exploited some models to forecast harmful algal blooms occurrences, they combined spatiotemporal remote sensing and field data [1]. Different red tide forecasting models were analyzed by Feki-Sahoun et al., including general linear model, Bayesian Network and Naive Bayes classifier [2]. Hu et al. integrated the theory of the minimum mean distance and partial minimum data density into fuzzy c-means algorithm, and applied this algorithm to the forecast of red tide [3]. Kwon et al. let ChlA represent...
coastal algal blooms, and used artificial neural network and support vector machine techniques to develop a prediction model [4]. The combination of empirical dynamic modeling and an extensive dataset was introduced in [5], which was used to predict algal blooms. Qin et al. made a fusion of autoregressive integrated moving average and deep belief network for red tide forecasting [6]. Given these, most works concentrate on developing satisfactory prediction methods. However, there is no special research on the internal dynamic characteristics of marine environmental data related to red tide.

Recurrence theory is a powerful tool of dynamic measure on complex systems [7]–[9]. Cross recurrence plot (CRP) is a classical visualization method to capture inherent relations between different time series. It has been applied to a great diversity of domains widely, such as chemistry, medicine and ecology. For example, the sulfur-induced localized corrosion of the alloy 718 was explored and valued in the case of high-temperature brine through the CRP method [10]. Kanakambaran et al. applied CRP on signals captured using fiber bragg grating sensors, frequencies of single as well as multiple-tones signals were extracted successfully [11]. Iwaniec et al. did a study on the sensitivity of CRP to damage size and location, then applied it to damage detection and tracking changes in the natural frequencies of system [12]. Shalba et al. used CRP to characterize brain dynamics during anesthesia, focusing on the concentration-dependent effect of the propofol [13]. In [14], CRP was used to categorize normal people and patients, which also described dysfunction during memory tasks in people with schizophrenia. Spiridonov applied CRP for testing the tentative of mutual forcing of the mulde event on conodont enrichment mechanics [15].

Additionally, cross recurrence quantification analysis (CRQA), being a quantification expression of CRP, is an important part of recurrence theory. It can elucidate the recurrences characterized by dynamic systems. Wang et al. extracted CRQA value from bearings vibration signals, aiming at constituting the regression trend for bearing degradation evaluation [16]. In [17], Hobbs et al. proved that the behaviours of CRQA measures could represent major jumps in crustal displacement rate, which is beneficial to crustal deformation prediction. Curtin et al. analyzed the difference between the elemental nutrient-nutrient interactions and the toxicant-nutrient interactions through CRQA [18]. CRQA had been shown to be an adaptable tool for identifying the pupil size oscillations in non-luminance conditions, this contributed to a better observation of the cortical state activity at rest [19]. Haworth et al. employed CRQA to investigate the coupling between postural sway and visual stimulus position, which supported the notion that the periodicity of body sway provided interactivity to complex environmental dynamics behavior [20]. In [21], CRQA was used to evaluate the intermuscular coupling between abductor pollicis brevis and first dorsal interosseus. Inspired by these obvious advantages and broad prospects, we consider CRP and CRQA to study the correlation between marine environmental factors and red tide.

In this paper, we provide a valuable insight of some main influencing factors of red tide occurrence. It is achieved by evaluating the similarity degree between ChlA and marine environmental factors. A novel analysis framework is proposed for marine environmental data processing. This framework can achieve a unified and consistent operation for marine data with functional entities of phase space reconstruction, establishment of CRP and corresponding quantitative analysis. To the best of our knowledge, this is the first attempt to apply CRP and CRQA to the study on dynamics characteristics of marine environmental series. Experimental results show that this framework provides an excellent visualization as well as effective quantitative analysis of dynamic implied in marine data. Meanwhile it can also determine the influence degree of different factors on red tide. The key contributions of this work can be summarized as follows.

- High dimensional phase space reconstruction for marine series is provided in this paper. The parameters of reconstruction are established by mutual information method and false nearest neighbor method. The experiments prove that correct parameter selection is the key to the construction of phase space.
- We provide an approach to visualize dynamics features of marine series. It is demonstrated that this method can reflect the dynamic behaviors between each factor visually. These behaviors are embodied by the degree of correlation in different graphic features.
- The quantitative analysis of marine environmental data is accomplished through CRQA. It is a qualitative measurement of dynamic behavior, aiming at accessing the similarity degree between marine data. Compared to intuitional graph representation, qualitative expressions can provide more specific descriptions of the red tide cause.

The rest of this paper is formed as follows. A brief summary about some relevant concepts in the process of marine factors visualization is presented in Section II. In the next section, a review of quantitative analysis method is given briefly, with special regard to evaluate metrics. Section IV gives the experimental results of dynamic characteristics analysis on marine environmental data. We discuss the correlation between each factor in this part. Finally, Section V offers conclusions and prospective research directions.

II. RECURRENCE ANALYSIS FOR MARINE DATA

In this section, CRP analysis framework is introduced firstly for marine series processing, followed by descriptions of parameter selection, including embedding dimension and delay time. Finally, the most important step of two-dimensional graph construction is given through a two dimension matrix.

A. ARCHITECTURE

Fig. 1 shows the CRP analysis framework for marine data processing. On the whole, the analysis process consists of
three important stages, namely phase space reconstruction, two-dimensional matrices representation and dynamic visualization.

Firstly, low-dimensional marine data is mapped into high-dimensional space by means of reconstruction, respectively, including ChlA and the related influencing factors. Generally, the false nearest neighbor and mutual information methods are used to achieve this operation, aimed at determining embedding dimension and delay time. In the flowing step, cross recurrence matrix is constructed by comparison of the distance between tracing points and the customized threshold, composed of 0 and 1. Finally, the effects of the considered marine factors on ChlA are visualized through CRP.

**B. RECONSTRUCTION**

Phase space reconstruction is regarded as a pre-condition for CRP in the visualization task of marine environmental data. Its purpose is to project the corresponding marine series into the high-dimensional phase space to obtain chaotic attractors [22]–[25]. For $w = 1, 2, \ldots, M - (r - 1) l$, the high dimensional space after reconstruction can be expressed as follows:

$$F_w(r) = \{f_w, f_{w+l}, \ldots, f_{w+(r-1)l}\}$$

where $l$, $r$ and $M$ represent the delay time, the embedding dimension and the marine series length, respectively.

As is known, the choices of embedding dimension and delay time play a key role in the reconstruction of phase space. Their determination methods are described in the following parts.

1) DELAY TIME

The mutual information method is employed to choose the suitable delay time. It is a classical method of information theory [26]–[27]. Firstly, for $D = \{d_1, d_2, \ldots, d_n\}$, the entropy of series is defined as Eq. (2).

$$E(D) = -\sum_{i=1}^{n} p(d_i) \log_2 (p(d_i))$$

where $D$ is a time series varying from 1 to $n$, $p(d_i)$ is a probability mass function.

Considering another series $U = \{u_1, u_2, \ldots, u_m\}$, the joint entropy between $D$ and $U$ is computed as

$$E(D, U) = -\sum_{j=1}^{m} \sum_{i=1}^{n} p(d_i, u_j) \log_2 (p(d_i, u_j))$$

where $p(d_i, u_j)$ is a joint probability mass function.

The mutual information is the amount of information that both series share, given by

$$S(D, U) = E(D) + E(U) - E(D, U)$$

As is demonstrated in [28], the first minimum value of $S$ is the optimal delay time $l$ of these considered series.

2) EMBEDDING DIMENSION

The false nearest neighbor (FNN) is considered to be an exact method for dimension selection [29]–[31]. Theoretically, it eliminates false neighbors in reconstructed phase space, aimed at obtaining dimensionality information on the series.

<table>
<thead>
<tr>
<th>Factors</th>
<th>MP</th>
<th>HYD</th>
<th>NA</th>
<th>WQ</th>
</tr>
</thead>
<tbody>
<tr>
<td>RaiF</td>
<td>0.4019</td>
<td>0.5684</td>
<td>0.5483</td>
<td>0.4956</td>
</tr>
<tr>
<td>AirT</td>
<td>0.2975</td>
<td>0.5497</td>
<td>0.4063</td>
<td>0.4879</td>
</tr>
<tr>
<td>AirP</td>
<td>0.2123</td>
<td>0.5437</td>
<td>0.3154</td>
<td>0.4832</td>
</tr>
<tr>
<td>MWP</td>
<td>0.2975</td>
<td>0.5497</td>
<td>0.4063</td>
<td>0.4879</td>
</tr>
<tr>
<td>SWH</td>
<td>0.1681</td>
<td>0.5429</td>
<td>0.2313</td>
<td>0.4832</td>
</tr>
<tr>
<td>MWH</td>
<td>0.0858</td>
<td>0.5384</td>
<td>0.1719</td>
<td>0.4832</td>
</tr>
<tr>
<td>NIT</td>
<td>0.0954</td>
<td>0.5376</td>
<td>0.1388</td>
<td>0.4832</td>
</tr>
<tr>
<td>NH3-N</td>
<td>0.0369</td>
<td>0.5358</td>
<td>0.08651</td>
<td>0.4832</td>
</tr>
<tr>
<td>PHO</td>
<td>0.0835</td>
<td>0.5283</td>
<td>0.06272</td>
<td>0.4832</td>
</tr>
<tr>
<td>WT</td>
<td>0.0820</td>
<td>0.5193</td>
<td>0.05418</td>
<td>0.4832</td>
</tr>
<tr>
<td>SalN</td>
<td>0.08223</td>
<td>0.5172</td>
<td>0.05514</td>
<td>0.4832</td>
</tr>
</tbody>
</table>

FIGURE 2: Delay time measurement.

Here, initially, $Q(r)$ is given as the average distance between the false nearest neighbor and the real point after increasing one dimension, given by

$$Q(r) = \frac{1}{M - r} \sum_{w=1}^{M-r} \frac{\|F_w(r+1) - F_{w'}(r+1)\|_2}{\|F_w(r) - F_{w'}(r)\|_2}$$  \hspace{1cm} (5)

where $F_{w'}(r)$ is the false nearest neighbor of $F_w(r)$. After that, the average distance ratio has the following definition, given by

$$A(r) = \frac{Q(r+1)}{Q(r)}$$  \hspace{1cm} (6)

It is used to determine the best embedding dimension. The rule is that if $A$ becomes stable, the most suitable embedding dimension occurs.

Notably, in order to reconstruct two series into a same phase space, unified reconstruction parameters should be selected. The higher embedding dimension and smaller delay time should be chosen in our scenario [10].

C. CRP

Once the phase space reconstruction is completed, the data visualization is performed based on CRP. Similar to the traditional RP [32] [33], CRP is also determined by a recurrence matrix. For $i = 1, 2, \ldots, N$ and $j = 1, 2, \ldots, M$, the elements in this matrix are calculated by the following equation

$$CR_{i,j}(\varepsilon) = \Theta(\varepsilon - \|F_i - F_j\|)$$

where $\Theta(\cdot)$ is the Heaviside function, $\varepsilon$ denotes a customized problem-dependent threshold and $\|\cdot\|$ denotes $\ell_2$-norm, measuring the distance between two series. Specially, $\varepsilon$ is set to be 0.6% of the maximum phase space diameter according to the diameter multiple method [34].

Obviously, if the distance between two sequences in the same phase space is less than $\varepsilon$, $CR_{i,j} = 1$, otherwise,
CR_{i,j} = 0. As a result, CR is a two-dimensional matrix including 1 and 0. It can be visualized by matching black and white dots with 1 and 0. This is known as CRP, which is used to visualize similar behaviors between these two series. Specially, it can be seen from (7) that the computational complexity of this recursive matrix is closely related to the lengths of two considered series. Numerically, it is proportional to $O(MN)$.

### III. CRQA

The quantification of CRP structures is performed by CRQA. It is a bivariate correlation method, generally applies for the pattern comparison between two complex systems. In fact, it provides an evaluation of synchronization or coordination. From the point of overview, CRQA quantifies the similarity degree of patterns over time between systems. Concretely, CRQA can embody information about that two signals coexist in a state space originated from the observed time series. When two signals access the same regions of a state space simultaneously, their transitory coordination occurs in high rates of recurrence. Besides, CRQA is also used to explore the long-range dynamic between signals, where the signal similarity with long-range patterns is measured over different times.

In the scenario of marine data processing, CRQA determines how often every two marine influencing factors show similar patterns of change or movement. In this section, we provide details about three CRQA measures in this paper.

The first one is related to the recurrence points that form diagonal lines, called determinism (DET). It can be considered as a measure of the predictability and regularity of the interaction between the two factor series, expressed as

$$\text{DET} = \frac{\sum_{l=1}^{S} l P(l)}{\sum_{l=1}^{S} P(l)}$$

(8)

$$P(l) = \sum_{i,j=1}^{S} (1 - CR_{i-1,j-1}) (1 - CR_{i+l,j+l}) \prod_{k=0}^{l-1} CR_{i+k,j+k}$$

(9)

where $S$ denotes the number of diagonals, $l$ is a variable of diagonal length, and $l_{\text{min}}$ denotes the minimal diagonal length. Higher $l_{\text{min}}$ values can result in the worse DET reliability. In our scene, we define $l_{\text{min}} = 2$.

Entropy (ENTR) refers to the Shannon information entropy. In information theory, it can be roughly defined as

$$\text{ENTR} = - \sum_{l=l_{\text{min}}}^{S} p(l) \ln(p(l))$$

(10)

$$S_l = \sum_{l \geq l_{\text{min}}} P(l)$$

(11)

$$p(l) = \frac{P(l)}{S_l}$$

(12)

where $S_l$ is the amount of diagonal lines.

Mean length of diagonal lines (MDL) corresponds to the mean time, meaning that this process is deterministic. Generally, it is regarded as the primary measure of similarity.

$$\text{MDL} = \frac{\sum_{l=l_{\text{min}}}^{S} l \cdot P(l)}{\sum_{l=l_{\text{min}}}^{S} P(l)}$$

(13)

### IV. NUMERICAL SIMULATIONS

In experiments, recurrence theory is used to investigate the interconnectedness between marine data. Our purpose is to measure the influence of different marine factors on red tide, where ChlA is deemed as its representation. In this section, we recommend the sources and variety of our data firstly, followed by the determination of the phase space reconstruction parameters on two marine series. Finally, qualitative and quantitative analysis for marine series are performed considering visualization and dynamic behavior analysis.

#### A. DATA ACQUISITION

The used corresponding marine time series are originated from a certain sea area in China, covering different fields of meteorological phenomenon (MP), hydrology (HYD), nutritional salt (NA) and water quality (WQ). In fact, it is proved that red tide is the result of mutual influence between different factors [36]. For the sake of convenient discussion, ChlA is used as an important factor to indicate the occurrence of red tide. The influencing factors of different fields are specified in Table 1, where every field contains three factors.

#### B. PARAMETER DETERMINATION

Fig. 2 shows the delay time relative to each factor series based on mutual information. Taking Fig. 2(a) as an example, the delay time is 5s for RaiF, because the minimum appears in this series for the first time. Analogously, 4s is selected as the optimal delay time for ChlA, as shown in Fig. 2(e). Consider that two series are reconstructed into the same phase space, we choose a lower delay time, i.e., 4s. In Fig. 3, the embedding dimension is calculated by the FNN method, and the optimal value is selected when the curve starts to level off. Obviously, for MWH and ChlA in Fig. 3(b) and Fig. 3(e), its embedding dimensions are 5 and 4, respectively. When these two marine time series are reconstructed together, the high embedding dimension should be considered as optimal value, i.e., 5. Following the above guidelines, the parameter selection results are depicted in Table 2.
TABLE 2: Parameter determination between ChlA and marine factors.

<table>
<thead>
<tr>
<th>Factor</th>
<th>MP</th>
<th>HYD</th>
<th>NA</th>
<th>WQ</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RaiF</td>
<td>AirT</td>
<td>AirP</td>
<td>MWP</td>
</tr>
<tr>
<td>Delay Time (s)</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>Embedding Dimension</td>
<td>15</td>
<td>6</td>
<td>7</td>
<td>4</td>
</tr>
</tbody>
</table>

FIGURE 3: Embedding dimension measurement.

C. CRP COMPARISON

The relations between ChlA and other marine influencing factors are visualized by CRP, as shown in Fig. 4. Generally, weak correlation is shown by the dispersive pattern in CRP, even if there exist few aggregation points. As is seen from Fig. 4(d), numerous irregular points appear, indicating the worse similarity between ChlA and MWP. Besides, there is also a small number of diagonal and laminar structures in this CRP. It means that these two series have some correlations over the whole time scale. Combined with two aspects, ChlA is weakly related to MWP. When a great many vertical segments and diagonal structures in CRP, indicate a strong correlation between two series. In Fig. 4(j), there exist a great deal of vertical black rectangles, meaning that motion state of WT at current moment is similar to that of ChlA at a period of time. Likewise, Fig. 4(c) shows the significant horizontal laminar pattern in the CRPs of ChlA and AirP, implying the high synchronism in this case. Specially, in Fig. 4(g), the more conspicuous similarity between ChlA and NIT emerges due to the representation of numerous black aggregations and diagonal structures, namely strong correlation.

D. QUANTITATIVE MEASUREMENT

In the subsection, CRQA is used to catch the patterns of synchrony between ChlA and each factor. Substantially, we evaluate the influence degree of different factors on ChlA.
FIGURE 4: Cross recurrence plots of marine time series.
TABLE 3: Quantitative measurement between ChlA and marine factors.

<table>
<thead>
<tr>
<th>Factor</th>
<th>MP</th>
<th>HYD</th>
<th>NA</th>
<th>WQ</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RaIF</td>
<td>AirT</td>
<td>AirP</td>
<td>MWP</td>
</tr>
<tr>
<td>DET</td>
<td>0.8211</td>
<td>0.7809</td>
<td>0.9327</td>
<td>0.2975</td>
</tr>
<tr>
<td>ENTR</td>
<td>0.9617</td>
<td>1.3591</td>
<td>2.1151</td>
<td>0.5557</td>
</tr>
</tbody>
</table>

FIGURE 5: Boxplot of each field on the considered measure, including DET, MDL and ENTR.

We focus on the following measure parameters, such as DET, ENTR, MDL.

Table 3 depicts quantitative measurement between ChlA and other marine factors. As is known, the predictability and regularity can be proved by DET. Generally, a large DET value represents strong regularity and predictability. Obviously, the correlation between pH and ChlA is the most predictable, due to the prominent DET value. ENTR measures the complexity of similarity. Clearly, ENTR has a largest value when NIT and ChlA are measured, revealing a most complicated similarity between them. Besides, Table 3 also gives the temporal duration of the ChlA series to be in synchrony with other marine factor series in the cross recurrence scenario, i.e., MDL, measuring the degree of series interaction. It is clear that NIT has the greatest impact on ChlA, followed by SalN, pH, AirP, WT, AirT, NH3-N, RaIF, SWH, MWH, MWP and PHO.

Furthermore, Fig. 5 shows a graphic representation on the effects of MP, HYD, NA and WQ on ChlA through boxplot, considering the measure parameters of DET, MDL, ENTR. From this figure, the upper quartile, median, lower quartile, minimum and maximum of each data can be observed easily [37]–[39]. Interestingly, it can be seen from these three boxplots that there exists maximum medians for WQ, marked by red lines. In other words, the factors in the field of WQ has a great influence on ChlA. It is also demonstrated the findings in Table 3.

V. CONCLUSION

In this paper, a recurrence analysis framework is proposed for the dynamic measure between marine data. It is consistently integrated with functionalities of high dimensional reconstruction, visual analysis of data, quantitative analysis and statistical analysis. Experimental results confirm the excellent visualization ability of our proposal for the dynamic correlation of marine time series. Furthermore, the quantitative results based on CRQA provide a guideline for determining the influence of different factors on red tide. Future research will focus on the combination of this framework with neural networks, aiming at proposing more accurate red tide prediction models.

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