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Algorithms of Time Series Network: Approaches Reproduction and Networks Topology

Li-Na WANG[a,b,1], Yuan-Yuan CHENG[a] and Gui-Min TAN[a]
[a]*Science College, Inner Mongolia University of Technology, Hohhot, 010051, China*
[b]*Inner Mongolian Key Laboratory of Statistical Analysis Theory for Life Data and Neural Network Modeling, Hohhot, 010051, China*

Abstract. Network analysis methods of time series provide a new analytical framework on describing complex behaviors using sample data. Reproducibility is one of the important principles in scientific research. This work focuses on the algorithm review and reproduction of time series network. We paid special attention to the applicability and data characteristics of the five typical algorithms: visibility graph, phase space reconstruction, fluctuation mode, symbolic representation and coarsened multidimensional time series. It provides a reference and inspiration for future analysis of time series with various characteristics. Although two pioneer methods are widely applicable, while the directed weighted network established by coarsening thoughts contains more information about time series. In addition, coarseness process makes these approaches perform better for massive data analysis. It should be noted that: the process of data coarsening needs to ensure that the data characteristics of the original time series are inherited.

Keywords. Time series, network science, complex system, scale free, small world, visibility graph, phase space reconstruction

1. Introduction

In statistics, economics, sociology, physics and other fields, time series analysis is an important research direction. With the increase of time series length and system complexity, some methods are no longer applicable, and a series of new methods have being proposed constantly. Among them, time series analysis based on network science has become a hot research topic.

The construction process of the network is to abstract the components and dynamic relationships between components into the node set V and edge set E, forming the graph G = (V, E). The characteristics of time series can be analyzed by the topological features of network, which makes the time series analysis methods based on networks applied to various fields. Literatures on the time series analysis methods based on networks is growing rapidly. In 2016, Gao et al[1] wrote a short review article on network approaches to time series analysis, which briefly summarized the methods and applications. They divided the time series analysis methods based on networks into two

[1] Corresponding Author, Li-Na WANG, Mathematics Department, Inner Mongolia University of Technology, AiMin Road #49, Hohhot, China; E-mail: wanglina@imut.edu.cn.

categories, single-variant time series analysis and multivariate time series analysis. In 2019, Zou et al[2] wrote a long review article on complex network approaches to nonlinear time series analysis. They reviewed the existing approaches of time series networks and mainly explored three approaches: phase space based recurrence networks, visibility graphs and Markova chain based transition networks.

Reproducibility is one of the important principles in scientific research. We believe that it is not only suitable for experimental sciences such as biology and medicine, but also suitable for algorithm studies. The reproducibility of scientific results is also an important principle for algorithm. The focus of this article is on the algorithm reproduction of classical time series network. 1) Pay attention to the algorithm itself, including the characteristics of the data. 2) Reproduce the algorithm to realize the time series network. 3) Study the topological characteristics of the network. We choose five classical models of time series network, including visibility graph[3], phase space reconstruction method[4], fluctuation mode approach[5], symbolic representation method[6] and the method of coarsened multidimensional time series[7]. The visibility graph[3] and phase space reconstruction method[4] are the pioneer achievements of time series network. The fluctuation mode approach[5], symbolic representation method[6] and coarsened multidimensional sequences[7], based on coarse-grained thought, are newly proposed in recent years.

2. Data

Visibility graph[3] is an efficient method and suitable for various types of data. Phase space reconstruction[4] method can be used to analyze chaotic time series to mining the characteristics of chaotic systems. The fluctuation mode[5] approach is based on a class of data with change rate and it can reflect the changes of time series. Symbolic representation method[6] is effective for analyzing the jumping data. The method of coarsened multidimensional[7] time series can be used to assess the evolutions of the correlations between multi-variable time series. When reproducing the above five classical approaches, we choose random numbers with normal distribution as experiment data. The length of time series is 1000. Due to uncertainties in the process to generating the random numbers, it can be considered that the time series has characteristics of randomness, fluctuation and jumping. The initial time series is denoted as $\{ x_t, t = 1, 2, \ldots, n \}$, where n is the length of the time series.

3. Approaches reproduction and networks topology

Classical network-based time series analysis includes visibility graph analysis and phase space reconstruction method. Furthermore, network construction approaches based on symbolized time series have become a new research hotspot in recent years. We reproduce three approaches include fluctuation mode approach, symbolic representation method, and network based on coarsened multidimensional time series. On the one hand, these networks have directed edges and weighted edges. Thus, the constructed network can reflect the reality better. On the other hand, these approaches perform better for massive data, because the scale of the network can be effectively controlled.

Table 1. The topological characteristics of the five typical time series networks. N, |E|, <k>, <s>, C, L denotes the number of nodes, number of edges, average degree, average strength, average clustering coefficient and average link distance. p(k), P(k), P(s) denotes the degree distribution, cumulative degree distribution, and cumulative strength distribution.

Methods	**Topological characteristics of the networks**							
	N	**|E|**	**<k>**	**<s>**	**C**	**L**	**p(k) or P(k)**	**P(s)**
Visibility graph	1000	4365	8.730	—	0.707	4.608	log-normal	—
Phase space reconstruction	200	519	5.216	—	0.052	3.481	Gaussian	—
Fluctuation mode	99	238	2.404	2.475	0.088	4.130	power law	power law
Symbolic representation	320	586	1.831	3.075	0.008	7.103	exponential	power law
Coarsened multi-dimensional time series	23	59	2.565	6.913	0.211	3.164	exponential	exponential

3.1. Visibility graph analysis

Visibility graph[3, 8], proposed in 2008, is a simple and faster method for analyzing time series by network methods. The properties of time series are inherited in the process of network construction. In recent years, the extended models of the visibility graph brought into sharp focus, for instance, horizontal visibility graph[9], horizontal visibility graph with limited traversing[10], limited penetrable visibility graph[11] and multivariate horizontally visibility graph[12]. Where, limited traversing visibility graph with distance one is equivalent to visibility graph and multivariate horizontally visibility graph is the extension of horizontal visibility graph, which can be applied to analyze nonlinear time series.

Visibility graph and its extension have been successfully applied to many fields, for example analyzing problems on earthquake[13, 14], finance[15, 16], or medical science[17, 18]. In addition, on dynamics of two-phase flow, the additional information on the dynamical properties of hemispheric asymmetry is obtained by using visibility graph[19].

The principle of visibility graph[3] is: the time series is presented as a histogram. Each bar in the histogram is treated as a node in the network and a connection exists when two bars can "see" each other unobstructedly. In this way, a time series can be transformed into an undirected and unweighted network. Mathematically, if two data bars (x_a, y_a) and (x_b, y_b) can "see" each other unobstructedly, then any data point (x_c, y_c) between them satisfies: $y_c < y_b + (y_a - y_b)(x_b - x_c)/(x_b - x_a)$.

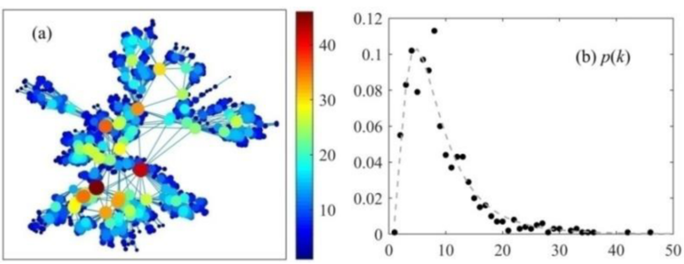

Figure 1. (a) The time series network based on visibility graph; (b) The degree distribution of the network.

According to the classical visibility graph method mentioned above, we reproduce the network from random numbers of standard normal distribution. An unweighted and undirected network is obtained, as shown in Figure 1(a). The basic topological characteristics of the network are shown in Table 1. Obvious, it is small-world network.

The degree distribution is lognormal distribution $p(k) = 0.1e^{-((\ln k-1.6)/0.9)^2}$, and goodness of fit $R^2 = 0.9386$. As shown in Figure 1 (b), about ten percent nodes have degree value around 8, and the proportion of large degree nodes is small.

3.2. Phase space reconstruction method

In order to mining the characteristics of chaotic systems, some scientists have analyzed chaotic time series in phase space. Since the phase space reconstruction method[4] was proposed in 2008, it has been further developed. Gao et al[20] analyzed the dynamic characteristics of chaotic time series according to the network constructed by phase space reconstruction method. Wang et al[21] proposed a coarse-grained phase space reconstruction to map the time series into a directed weighted network. Furthermore, the phase space reconstruction method is applied to analyze specific practical problems.[22-25] For instance, the phase space reconstruction method was used to study the nonlinear characteristics and cognitive functions of the patient's brains[24], and to study the air quality in Beijing based on PM2.5 data[25].

When modeling chaotic time series to network by the phase space reconstruction method, the key part of network construction is to reconstruct vectors, using delay time and embedding dimension. Then, vectors are taken as nodes, and relations between vectors are taken as edges. The process of network construction based on phase space reconstruction[4] is as follows:

Step 1: Vector reconstruction. A new vector is constructed based on the delay coordinate embedding method. The equation is $Y_i = (x_i, x_{i+\tau}, \dots, x_{i+(m-1)\tau})$, where i = 1, 2, ..., n-(m-1)τ, m is the embedding dimension, τ is the delay time and Yi is the recombined vector.

Step 2: Parameter determination. Parameter determination includes determination of the delay time τ and determination of the embedding dimension m.

Step 3: Network construction. Vectors are regarded as nodes and edges are determined by the correlation of vectors. When $|r| \geq r_c$, $e_{ij} = 1$ indicates that nodes i and j are connected; When $|r| < r_c$, $e_{ij} = 0$ indicates that there is no connection between nodes i and j. Where r is Pearson correlation coefficient of two different vectors, r_c is the threshold, and e_{ij} is the element of adjacency matrix. Then, an unweighted and undirected network can be obtained.

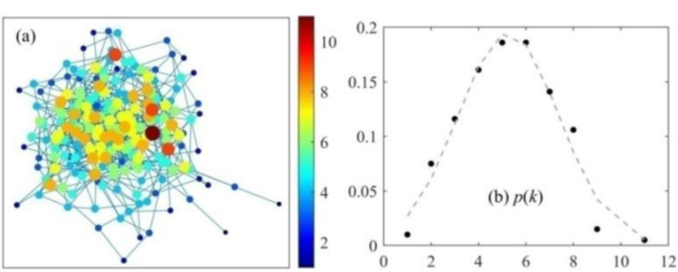

Figure 2. (a) The time series network based on phase space reconstruction; (b) The degree distribution of the network.

Using random numbers of standard normal distribution as the experimental data, we reproduce the network by the classical phase space reconstruction method. The time series data with length of 1000 is reconstructed into two hundred vectors with length of

50. The vectors are mapped as nodes. If the correlation coefficient of two vectors is greater than 0.9 ($r_c = 0.9$), the corresponding nodes will be connected. The unweighted undirected network is obtained, as shown in Figure 2(a). The topological characteristics are shown in Table 1. The degree distribution of the network follows the Gauss distribution $p(k) = 0.2e^{-((k-5.3)/3.0)^2}$ (R^2 = 0.9624). As shown in Figure 2(b), the degree values are relatively centralized, and near the value of five and six.

3.3. Fluctuation mode approach

The fluctuation mode approach can reflect the change rate of time series intuitively. Yao et al.[5] studies the exchange rate of RMB based on the fluctuation mode approach. Liu et al.[26] analyzed the changes of six stock indexes in Shanghai according to the characteristics of the network.

According to the extent of fluctuation, the time series are divided into intervals and represented as symbols. The approach details[5] are as follows:

Step 1: Change rate. In order to reflect the fluctuation of data, the initial data is transformed into the change rate data. The change rate is defined as $y_i = (x_i - x_{i-1})/x_{i-1}$.

Step 2: Symbolization. The change rate data is converted into symbolic data. If the change rate is more than 1%, it is considered that the data increase greatly, and denoted as symbol "a". If the change rate is between 0.1% and 1% (or -1% and -0.1%), it is considered that the range of changes is moderate, and denoted as symbol "b" (or "d"). If the change rate is between -0.1% and 0.1%, it is indicates that the data is almost unchanged, and denoted as symbol "c". If the change rate is less than -1%, it is considered that the data decreases significantly, and then denoted as symbol "e".

Step3: Mode. The symbolized data will be transformed into the mode data in this step. Taking four as the time window, the symbolized time series is divided into the mode time series $g(y)_1g(y)_2g(y)_3g(y)_4$, $g(y)_5g(y)_6g(y)_7g(y)_8$, …. Where, $g(y)_i$ belongs to the set {a, b, c, d, e}.

Step 4: Network. A directed weighted network will be obtained. Different modes are treated as nodes. Mode conversion relationship is treated as edge. The direction and the frequency of conversion are treated as the direction and the weight of edge respectively.

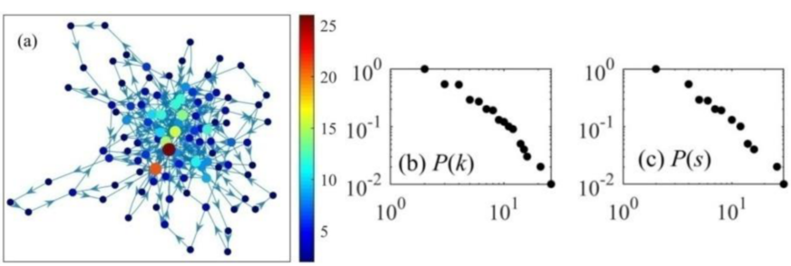

Figure 3. (a) The time series network based on fluctuation mode approach; (b) The cumulative degree distribution of the network; (c) The cumulative strength distribution of the network

Here, we reproduce the fluctuation mode approach by using random number from the standard normal distribution. Firstly, the time series with length of 1000 is transformed into change rate data. According to intervals $(-\infty, -1]$, (-1, 0], (0, 1] and (1,

∞), the change rate data is transformed into symbolic data. Then, taking four as the time window, the symbolic data is transformed into the mode data. Taking different modes as nodes, there will be an edge linked with two nodes if the former mode is different from the latter. The direction of the edge is from the former mode to the latter. The weight of the edge is the total number of the modes transformation. The directed weighted network is shown in Figure 3(a). The cumulative degree distribution is power law $P(k) = 2.5k^{-1.3}$ ($R^2 = 0.9761$), which indicates that there is large number of small degree nodes (blue color in Figure 3(a)) and a few nodes with large degree (warm color in Figure 3(a)). The cumulative strength distribution is power law $P(s) = 2.4s^{-1.2}$ and $R^2 = 0.9781$. As shown in Figure 3(b) and Figure 3(c), the scatter points are straight lines in log-log coordinates.

3.4. *Symbolic representation method*

The symbolic representation method was proposed by Zeng et al.[6]. This method is fit for a class of jumping data and by the topological characteristics of the network, the periodic time series and chaotic time series can be distinguished. Furthermore, Zhang et al. [27] studied air quality index by using symbolic representation method.

The symbolic representation method is a combination of coarsening technology and slide-window technology. This method can map time series into a directed weighted network and the details are as follows:

Step 1: Coarsening. By standardizing the initial time series, the standardized time series $\{y_i, i = 1, 2, \ldots, n\}$ can be obtained, where $y_i = (x_i - \bar{x})/s$, $\bar{x}$ is the mean and s is standard deviation. Using equal probability partition, the standardized time series are coarsened and then the coarsened time series $\{s_1, s_2, ..., s_n\}$ is obtained. Where s_i is the coarse-grained data and can be represented by symbols a, b, c, d, etc.

Step 2: Network. Set the slide-window with a certain length ω and slide along the time series. Then, the time series composed of patterns is obtained. Different pattern fragments are taken as nodes, and the transformation between patterns are defined as edges. The direction of the transformation is defined as the direction of the edge, and the frequency of the transformation is defined as the weight of the edge. A directed weighted network can be obtained.

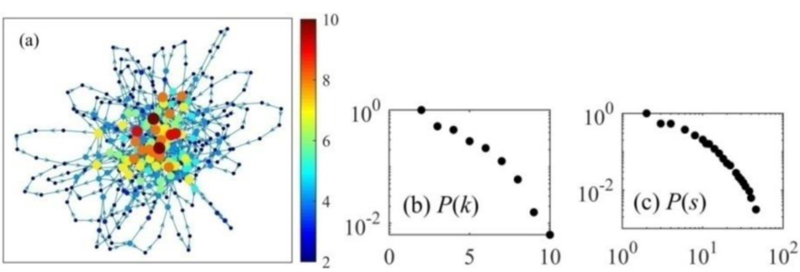

Figure 4. (a) The time series network based on symbolic representation method; (b) The cumulative degree distribution of the network; (c) The cumulative strength distribution of the network.

The random jump data are used as experimental data to reproduce the method. After normalization and equal probability division, the symbolized time series is obtained. Here we use symbols with six levels: a, b, c, d, e, f. Then the slide-window of length 4 is moved along the symbolized time series, and a series of mode segments are obtained. Since the slide-window with length 4 is used when building the network, the state of the node in the network reflects the state of the four adjacent moments in the time series. And the directed edge reflects the transition between the moments of the time series. The obtained directed weighted network is shown in Figure 4(a). The cumulative degree distribution is exponential $P(k) = 2.3e^{-0.4k}$ (R^2 = 0.9769). As shown in Figure 4(b), the scatter points are straight line in semi-log coordinates. The cumulative strength distribution is power law $P(s) = 2.1s^{-1.1}$ (R^2 = 0.9723), as shown in Figure 4(c).

3.5. Coarsened multidimensional sequence

Reconstructing a time series into a network can help uncover the dynamic information hidden in the time series.[7] Based on coarsened multidimensional sequence, Fang et al.[7] assess the evolution dynamics of the correlations among energy prices.

For multidimensional time series, the algorithm of coarsened multidimensional sequence is to construct a network combined with Pearson correlation coefficient. The extent of linear correlation between variables can be measured by Pearson correlation coefficient. There is a strong correlation between the variables if the absolute value of Pearson correlation coefficient is close to 1. The correlation between variables is considered as weak when the absolute value of Pearson correlation coefficient is close to zero. By coarsening, the nodes are determined. By the movement of slide-window, the edges are determined. The network modeling method based on coarsened multidimensional time series[7] is as follows:

Step 1: Reconstruction. The multidimensional time series are reconstructed. Three time series are recorded as X_1, X_2 and X_3 respectively. The slide-window with length ω slides along with the time series and then the time series are transformed into a series of time series fragments. In each slide-window, the length of time series is ω. The i-th slide-window of X_1, X_2 and X_3 is denoted as $(x_{1i}, x_{1i+1}, x_{1i+2}, \ldots, x_{1i+\omega})$, $(x_{2i}, x_{2i+1}, x_{2i+2}, \ldots, x_{2i+\omega})$ and $(x_{3i}, x_{3i+1}, x_{3i+2}, \ldots, x_{3i+\omega})$, respectively.

Step 2: Symbolization. Calculate Pearson correlation coefficient between the pairs of three time series fragments $(x_{1i}, x_{1i+1}, x_{1i+2}, \ldots, x_{1i+\omega})$, $(x_{2i}, x_{2i+1}, x_{2i+2}, \ldots, x_{2i+\omega})$ and $(x_{3i}, x_{3i+1}, x_{3i+2}, \ldots, x_{3i+\omega})$, and recorded as r_{12i}, r_{13i}, r_{23i} respectively. That is, the correlation is $(r_{12i}, r_{13i}, r_{23i})$ in the i-th slide-window. Then, the symbolized mode $mode_i = (g(r_{12i}), g(r_{13i}), g(r_{23i}))$ is obtained according to the correlation values and the following principles: $g(r) = a$, if $r \in (0.6, 1]$; $g(r) = b$, if $r \in (0.2, 0.6]$; $g(r) = c$, if $r \in (-0.2, 0.2]$; $g(r) = d$, if $r \in (-0.6, -0.2]$; $g(r) = e$, if $r \in (-1, -0.6]$. Where r is the value of Pearson correlation coefficient.

Step 3: Network. The symbolized modes are taken as nodes and the edge is defined by the conversion between symbolized modes. The frequency of conversions is defined as the weight of the edge, and the transformation direction is taken as the direction of the edge. A directed weighted network can be obtained.

The method on coarsened multidimensional time series is reproduced in this subsection. Firstly, three time series, which are random numbers satisfying the standard normal distribution, are generated. Secondly, a slide-window with a length of 50 is set up, and a series of 50×3 time series fragments can be obtained. According to the above approach, a directed and weighted network is established, as shown in Figure 5(a). The adjacency matrix of the network is non-symmetrical, shown in Figure 5 (b). The cumulative degree distribution is exponential $P(k) = 1.5e^{-0.2k}$ (R^2 = 0.9352), shown in

Figure 5(c). The cumulative strength distribution is exponential $P(s) = 1.0e^{-0.1s}$ ($R^2 = 0.9531$), shown in Figure 5(d).

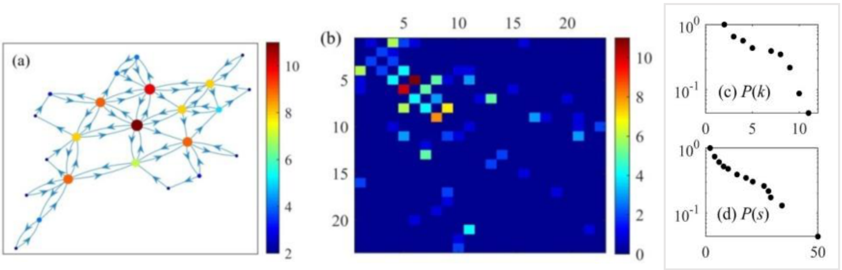

Figure 5. (a) The time series network based on coarsened multidimensional sequence; (b) The graphical representation of adjacency matrix; (c) The cumulative degree distribution; (d) The cumulative strength distribution.

4. Conclusion and discussion

In reference 3, the degree distribution of the network constructed by uniformly distributed numbers obeys the exponential distribution, and the degree distribution of the network constructed by fractal time series obeys power-law distribution. In this paper, we reproduced the visibility graph network constructed by normal distributed random numbers, and the degree distribution obeys lognormal. In addition, the network has a small world feature, which is consistent with the results of the original literature. In reference 4, the degree distribution of the network constructed by stock price time series obeys Gaussian distribution. In this paper, we reproduced the phase space reconstruction network with normal distributed random numbers, and the degree distribution obeys Gaussian distribution.

The networks based on visibility graph and phase space reconstruction are unweighted and undirected. In visibility graph network, nodes with large degree are corresponding to big value data of the time series, which can "see" many others unobstructedly. In time series network based on phase space reconstruction, nodes with large degree are corresponding to reconstructed vectors strong correlated with many other vectors. In visibility graph network, the higher the node clustering coefficient is, the stronger the visibility is among its neighbors. In time series network based on phase space reconstruction, the higher the node clustering coefficient is, the stronger the correlation is among its neighbors.

When make other three coarseness method[5-7] to model the network, the directed weighted networks are obtained. We analyzed the strength distributions of the three time series networks. In these networks, nodes with large strength are corresponding to symbolic modes with high frequency. This kind of nodes converts to other nodes more frequently. Furthermore, nodes with large clustering coefficient are corresponding to symbolic modes, among neighbors of which mode conversion occurs frequently.

The above three time series networks, proposed in recent years, have one thing in common: they all use symbolic mode, the essence of which is coarsening. Coarseness process leads to less number of nodes in the network, which can make the computational complexity of time series analysis reduced. Thus these approaches perform better for massive data analysis. It should be noted that: the process of data coarsening needs to ensure that the data characteristics of the original time series are inherited. In addition, the directed weighted network established by the latter three algorithms contains more information from time series. For example, the data of time series are related to the time order, and the edge direction in directed weighted network just contains this time order information.

Network analysis methods of time series provide a new analytical framework on describing complex behaviors using sample data. Nowadays, there are abundant data in many fields. Analyzing these data by appropriate methods will promote the development of science.

Acknowledgments

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