



A new information dimension of complex network based on Rényi entropy

Shuyu Duan, Tao Wen, Wen Jiang*

School of Electronics and Information, Northwestern Polytechnical University, Xi'an, Shaanxi 710072, China



HIGHLIGHTS

- Rényi dimension is proposed based on Rényi entropy and the generalized box-covering algorithm.
- SWF and PWF can explain the changing trend of Rényi dimension and Tsallis dimension.
- The concept of network attractors and absolute attraction network (AAN) are proposed in this paper.
- The physical meaning of the parameter α , SWF and PWF are discussed according to attractors in the network.
- Some experiments of the real networks and theoretical networks are applied in this paper.

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ABSTRACT

With the development of high technology and artificial intelligence, it evolves into an open issue to calculate the dimension of the complex network. In this paper, a new dimension — Rényi dimension, combined with Rényi entropy and information dimension is proposed. A modified box-covering algorithm is introduced to calculate the minimum number and the length of the boxes needed to cover the whole network. Additionally, the self weight factor (SWF) and the positive weight factor (PWF) are defined to illustrate the change of the dimension value based on the perspective of both topology structure and dynamic property. The concept of attractors is proposed to illuminate the physical meaning of the weighted parameter in the formula of Rényi entropy — α , PWF and SWF. Finally, to demonstrate the efficiency of our method, it is applied to calculate the dimension of Sierpinski weighted fractal network, BA networks and many real-world networks. The results show that attractors exist in the network researched and α can access the attractiveness of attractors as a criterion. The SWF quantifies the total attractiveness of attractors. The comparison results with Tsallis dimension indicate the stability of the Rényi dimension.

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1. Introduction

Recently, complex networks have aroused great interests since they are applied to describe a wide range of systems in nature [1] and society [2]. The topology of complex network [3,4] can clearly illustrate many complicated systems in many subjects such as the social network of interpersonal relationships [5], the WWW [6] and the Food Web [7]. The small world [8,9] and the scale-free [10] have been acknowledged to be two fundamental properties of complex network. The small-world property of complex networks has many applications in the real world such as brain work mechanism [11,12].

* Corresponding author.

E-mail address: jiangwen@nwpu.edu.cn (W. Jiang).

and information flow [13]. Similarly, the free-scaling of network is often used for testing the network performance under attacking [14,15], reaction-diffusion [16,17] and the targeted safeguard strategy [18]. BA network model is proposed by AL Barabási and R Albert to illustrate the scale-free property of the complex network [10,19]. In addition, the fractal [20] and self-similarity [21] firstly discovered by Song et al. [22] have also attracted many researchers. Many researches have been done about the properties [23,24]. In order to quantize the two properties above and demonstrate the structure of the complex network, entropy is introduced to calculate the uncertainty and the complexity of network [25,26]. With the further study of the nature of complex networks, many researches have been carried about the approach to estimate the importance of nodes [27] based on TOPSIS [28] and evidence theory [29,30] and lots of practical applications especially in ClusterRank [31], LeaderRank [32], the dynamic control strategies [33] and the construction of co-author networks [34].

The concept of dimension is developed after the discover of space-filling curves [35]. The fractal dimension value extends to the positive real number range as the theory of fractals is developed and improved by many mathematicians such as Mandelbrot [36] and Hutchinson [37]. The fractal dimension is introduced to many fields [38,39]. It is widely used in the field of complex network as an important network evaluation parameters [40,41]. To calculate the dimension of complex networks, the box-covering algorithm is proposed by Song et al. [22] and many improvement solutions have been designed to complete the algorithm including the way of finding the minimal [42] and maximal sizes of covering boxes [43] and the minimal partition coverings method [44].

The classical dimension, such as information dimension [45] and Hausdorff dimension [46], is designed to quantize the degree of fractal and complexity of the networks [47]. However, these dimensions are usually used for calculating the network dimension in planar area. It is segmentary to study a complex network in this way for some important information will be neglected unavoidably. So the modified box-covering algorithm proposed by Wei [48] is introduced to fill the requirements of comprehensiveness of network information and computational efficiency and some researches related to information dimension of weighted network [49] are studied. Additionally, compared with other dimensions combined with information entropy [50] or Tsallis entropy [51], the existence of parameter α makes the proposed method more flexible and expands its use in many different situations. Tsallis' entropy is another general form of Shannon entropy [52] controlled by q [53], which was firstly proposed by Tsallis in 1988. Now, with the development of information theory, Tsallis' entropy [54] is applied in many aspects, such as medical image analysis [55] stellar polytropes [56], cardiovascular physics [57] and communities detection [58]. Meanwhile, the generalized dimension attracts much attention [44,59,60]. Due to the mathematical qualities of Rényi entropy [61,62], the Rényi dimension values are more stable than that of Tsallis dimension.

Generalized dimension refers to the dimension which is controlled by certain parameter and degrades into fractal dimension, information dimension when setting the parameter as some fixed values. It can be divided into different types according to the various deductive methods and diverse application domains. Two of the most commonly adopted generalized dimension are Tsallis information dimension and Rényi dimension. In literature [63], Liu and Yu applied the generalized dimension to characterize the complexity of complex networks with the help of multi-fractal analysis and sandbox algorithm. In the recent work of Rosenberg [44], a generalized dimension proposed by Grassberger and by Hentschel and Procaccia in 1983, is adopted to calculate the densest part of complex network and solve the problem about minimal partition covering in box-covering algorithm. Wu [64] studied lossless analog compression in information-theoretic framework by strict theoretical derivation under the fundamental limit of the information dimension proposed by Rényi in 1959. Compared with the research results of similar study field mentioned above, we focus on the close integration of Rényi dimension of complex network and the modified box-covering algorithm. The discussion about the physical meaning of parameter and dimension takes both the topology structure and the dynamic property into account in order to illuminate the changing rule of the dimension from a practical perspective.

In the following part of the paper, the Rényi entropy and the classical dimension are introduced in Section 2. The modified box-covering algorithm is also illustrated in the same part as a preparation for the proposed method. The Rényi dimension of complex network inspired by Rényi entropy is proposed in Section 3. The SWF and PWF are also discussed in this part in order to figure out the changing rules of dimension. The definition of absolute attraction network (AAN) is clarified in the same part. Some applications in the theoretical network and real networks are listed in Section 4. Additionally, in Section 5, the Tsallis information dimension is also studied and explained by the SWF and PWF as a contrast. Proper interpretation about the physical meaning of parameter α are added as an analysis of the mass dimension results. Finally, Section 6 summarizes the conclusions of the whole paper.

2. Preliminaries

2.1. Rényi entropy and Tsallis' entropy

Shannon firstly defined the concept of Shannon entropy in order to calculate the uncertainty of a probability distribution [61]. The Shannon entropy has become one of the best-known measures of uncertainty, the headstone of the modern communication theory so far and it is commonly used for describing the uncertainty relations [65,66] and quantum mechanics predictions.

Definition 2.1. Shannon entropy is defined as follows [67]:

$$H(X) = \sum_k^n p_k \log_2 \frac{1}{p_k} \quad (1)$$

Where $X = (p_1, p_2, \dots, p_k)$ is finite discrete probability distribution, which means $p_k \geq 0 (k = 1, 2, \dots, n)$ and $\sum_{k=1}^n p_k = 1$

As information science advances, Shannon entropy may not meet all the requirements of diverse application domains. For further application of the entropy and more options to calculate the uncertainty of generalized distribution, Alfréd Rényi proposed a new entropy inspired by Shannon entropy. Rényi entropy is a family of entropies, which can be reduced to several important special cases by changing the parameter α [68]. This entropy conserves many convenient mathematical properties such as additivity.

Definition 2.2. The Rényi entropy of order α is given as [61]:

$$H_\alpha(X) = \frac{1}{1-\alpha} \log \sum_{k=1}^n p_k^\alpha \quad (2)$$

For $\alpha \in (0, 1) \cup (1, \infty)$, and the corresponding limit for $\alpha \in \{0, 1, \infty\}$. For $\alpha = 1$, the limit of Rényi entropy can degenerate to the Shannon entropy, so the Rényi entropy is the generalization of Shannon entropy.

Definition 2.3. The Tsallis' entropy of order q is shown as follows [51]:

$$S_q \equiv k \frac{1 - \sum_{i=1}^N p_i^q}{q-1} \quad (3)$$

Where N is the total number of the elements of the probability set and p_i represents the corresponding probabilities. When the order q equals to 1, the Tsallis' entropy degenerates to the Shannon entropy.

The order α in the Rényi entropy is usually compared with the order q in the Tsallis' entropy to analyze the stability of them in the rapidly and slightly changing situation [69,70]. In this paper, the two entropies are applied to calculate the dimension of complex network and evaluated according to the value of dimension in Section 4.

2.2. Box-covering algorithm

Given a complex network, $G = (N, V)$ and $N = (1, 2, \dots, n)$, $V = (1, 2, \dots, m)$ where n is the number of nodes and m is the number of edges. G is a matrix which can express all the necessary information of a complex network.

Definition 2.4. The strength of a weighted network is presented as follows:

$$S_i = \sum_{j=1}^n w_{ij} \quad (4)$$

where i is the focal node and j represents all other nodes, w_{ij} is the weight between i and j directly.

Definition 2.5. The shortest path between two nodes i and j , d_{ij} is defined as follows:

$$d_{ij} = \min(w_{ij_1} + w_{j_1 j_2} + \dots + w_{j_k j}) \quad (5)$$

where $j_k (k = 1, 2, \dots)$ represents the IDs of the other nodes except i and j . The maximum of d_{ij} is defined as the diameter of a complex network.

Song et al. [22] have proposed a box-covering algorithm to calculate the fractal dimension of complex network by choosing a beginning node randomly and averaging the results of huge amount of experiments which takes rather long time to get the final result. Usually to get a representative value of dimension, we must repeat the algorithm over 1000 times and get the average value. So here we adopt Wei's method [48], which is modified to be easily calculated the weighted network. The total running time and space complexity of Wei's algorithm are nearly 5 times shorter than that of the box coverage algorithm which takes 0.023 s to calculate the dimension of a BA network with 1000 nodes. What is more, the result of the theoretic network – Sierpinski network in the fourth section is 1.4663 which is close to the theoretic value 1.5850. As a result, the algorithm can not only save computing time but can also represent the average result. The procedure is illustrated as follows:

1. Calculate the size of box l_B by adding up the weights from small to large until the sum is greater than the diameter of the network.

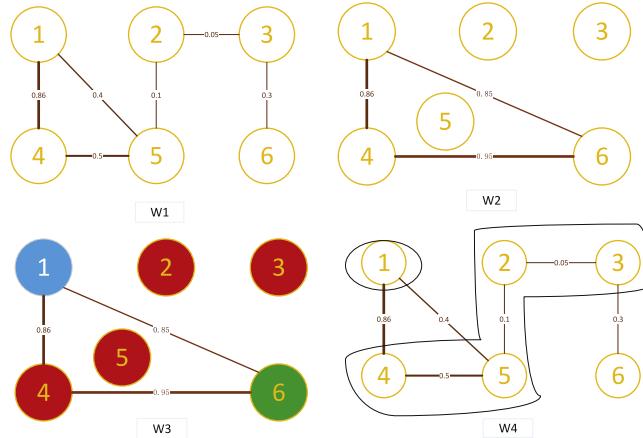


Fig. 1. The process of coloring the network. \$W_1\$ is a weighted network with six nodes and six edges. The diameter of the network is 0.95. So we choose \$0.85(0.05 + 0.1 + 0.3 + 0.4 = 0.85)\$ as the box size and connect the nodes \$i, j\$ with \$d_{ij} \leq 0.85\$ and obtain \$W_2\$. Color the nodes connected in \$W_3\$. The nodes 1, 4, 6 have different colors and the other nodes share the same color with node 4 because it has the maximum strength.

2. Connect those pairs of nodes in the original network whose distance is equal or greater than \$l_B\$ and a new network \$G'\$ will be obtained.
3. Color the nodes which are connected directly in network \$G'\$ with different colors which means they belong to different boxes. The left isolated nodes will be arranged to the box with the node which holds the maximum strength.
4. Count the number of colors used to cover the boxes and then yield the number of boxes needed to cover the whole network. Calculate the information content \$I\$ according to the color scheme.
5. Add the edge weights again until the sum is less than the first \$l_B\$ and get the refreshed box size. Then repeat the step 2 to 4 in order to get a series of information content and box size respectively.
6. Perform a linear regression of \$\ln(I)\$ and \$\ln(l_B)\$. Choose the slope as the dimension of the complex network.

The detailed algorithm to calculate the box number is given in Fig. 1.

After calculating the minimum number of the boxes \$N_B\$ of a complex network, the Hausdorff dimension, also known as the box dimension, can be obtained through the formula written as follows:

$$d_H = - \lim_{l_B \rightarrow 0} \frac{\log N_B}{\log l_B} \quad (6)$$

2.3. Information dimension and Tsallis information dimension

Information dimension is firstly used for estimating the information load on decision making [71] and measure strange attractors. Wei et al. [72] defined an information dimension based on information entropy and box-covering algorithm.

Definition 2.6. The information content concluded in a complex network can be calculated as follows:

$$I = - \sum_{i=1}^{N_B} p_i \ln p_i \quad (7)$$

Where \$p_i\$ represents the probability of nodes in the \$i\$th box, which can be written as follows:

$$p_i = \frac{n_i}{n} \quad (8)$$

Where \$n_i\$ is the number of nodes in the \$i\$th box, and \$n\$ is the total number of nodes in the network. So the information dimension of the network is defined as follows:

$$d_I = - \lim_{l_B \rightarrow 0} \frac{I}{\log l_B} = \lim_{l_B \rightarrow 0} \frac{\sum_{i=1}^{N_B} \frac{n_i(l_B)}{n} \log \left(\frac{n_i(l_B)}{n} \right)}{\log l_B} \quad (9)$$

Where \$l_B\$ represents the length of the boxes needed to cover the network, \$\frac{n_i(l_B)}{n}\$ is the probability of nodes in the \$i\$th box when the box edge is \$l_B\$.

The Tsallis information dimension is proposed by Zhang et al. [73], inspired by the Tsallis' entropy, with the aim of explaining the structure complexity of the complex network and reflecting the degree of self-similarity and fractal properties.

Definition 2.7. The Tsallis information dimension is defined as follows [73]:

$$d_T = \lim_{l_B \rightarrow 0} \frac{\frac{1 - \sum_{i=1}^{N_B} p_i(l_B)^q}{q-1}}{\ln l_B} \quad (10)$$

According to the Eq. (10), the information content of the Tsallis' entropy is rewritten as follows:

$$I_T = \frac{\sum_{i=1}^{N_B} p_i(l_B)^q - 1}{1 - q} \quad (11)$$

Where l_B represents the length of the covering boxes and the p_i is the probability associated with the box-covering results. q is the restraining parameter of the generalized entropy.

3. Rényi dimension

There are many dimensions which can be used for illustrating the complexity and the uncertainty of the complex network. However the existing dimensions generally have two drawbacks – one is that they lack of flexibility because of the fixed formula (For instance, the information dimension is a certain value when it is applied on one complex network while the Rényi dimension can change as the variation of α), while another is that the topology structure and the dynamic feature of complex network cannot be balanced and the computing time is usually too long because of the average box-covering algorithm.

With the aim of improving the situation mentioned above, a new dimension is proposed to calculate the complexity of complex network which is more flexible to use than some dimensions of the same kind because of its weighted parameter α in this section. The new dimension is inspired by the Rényi entropy and the information dimension.

3.1. Basic method

Definition 3.1. The Rényi dimension is defined as follows:

$$d_R = \lim_{l_B \rightarrow 0} \frac{\frac{1}{1-\alpha} \log \sum_{k=1}^n p_k^\alpha}{\log l_B} \quad (12)$$

where l_B is the box size of the box-covering algorithm. The numerator is the Rényi entropy defined in Eq. (2).

When $\alpha = 1$, the Rényi dimension degenerates to information dimension which can be easily proved using L'Hospital's rule. When $\alpha = 0$, the dimension is exactly the classical Hausdorff dimension. Just as the Eq. (12) shows, the change trend function of dimension cannot be judged directly. In other words, it is confusing to view the whole formula as an entire part. As a result, it is a simple and intuitive approach to separate the Rényi entropy into two impact factors according to the connection between the network structure and the mathematical property which are defined as positive weight factor and self weight factor. Here we dismantle the Rényi entropy in order to illustrate the meaning of α in the process of dimension calculation.

Definition 3.2 (Positive Weight Factor (PWF)). In order to distinguish the influence of the weight parameter α , a positive weight factor (PWF) w_p is defined as

$$w_p = \frac{1}{1 - \alpha} \quad (13)$$

where α is the parameter of Rényi entropy.

This factor is completely decided by the value of α , which can be given by different researchers according to different analysis measures they apply to complex network. According to the formula of the function of PWF, the value of PWF increases with the increasing of α .

Case 1 When $\alpha \in (0, 1)$, the value of PWF is positive, which contributes to the increase of the final result of Rényi entropy. The more belief the expert gives to a certain measure, the more important PWF will be;

Case 2 When $\alpha \in (1, \infty)$, the value of PWF becomes negative. So the factor influences the entropy in an opposite way, though the function is still incremental. And the importance of α begins to descend, since too much weight will be taken as invalid measure.

Definition 3.3 (Self Weight Factor(SWF)). Considering the structural features of complex network, a self weight factor w_s is proposed, indicated by

$$w_s = \sum_{k=1}^N p_k^\alpha \quad (14)$$

Table 1
The dimension of different network with different complexity.

α	Probability distribution	SWF
0.5	(1,0)	1.000
0.5	(0.6,0.4)	1.407
0.5	(0.5,0.2,0.3)	1.702
0.5	(0.4,0.3,0.2,0.1)	1.943
0.5	(0.3,0.3,0.2,0.1,0.1)	2.175
2.0	(1,0)	1.000
2.0	(0.6,0.4)	0.520
2.0	(0.5,0.2,0.3)	0.380
2.0	(0.4,0.3,0.2,0.1)	0.300
2.0	(0.3,0.3,0.2,0.1,0.1)	0.240

The SWF is influenced by the complexity of the network construction and the given parameter α . $X = (p_1, p_2, \dots, p_k)$ represents the original feature of a network, while α indicates the weight given by the users. For each p_k belongs to $(0, 1)$, the value of SWF increases when α pertains to $(0, 1)$ and decreases when α belongs to $(1, \infty)$. Also the value of SWF is greater than 1 when α belongs to $(0, 1)$, while the value is less than 1 when α changes in the domain of definition greater than 1.

For the Tsallis information dimension, Eq. (11) can be regarded as the combination of SWF and PWF when the parameter α is replaced by the parameter q in the Tsallis' entropy. α and q play quite similar roles in the two dimensions. The two information content based on the Rényi entropy and Tsallis' entropy can be rewritten as:

$$I_R = w_p \log w_s \quad (15)$$

$$I_T = w_p(w_s - 1) \quad (16)$$

Where w_p and w_s are the positive weight factor and the self weight factor.

3.2. Example explanation

A succinct example is taken to interpret the effect of SWF. It is assumed that there are four different networks, the edge of the boxes needed to cover the whole network is a fixed value. When setting the length of the covering box as a fixed value, the metric is certain, the original characteristic of complex network is the only factor that influences the SWF. As a result, the increment of the number of the elements means the complexity of the networks is increasing. According to Table 1, two values of α are chosen to show the changing rule dominated by SWF. It is revealed by the data in Table 1 that when setting α as 0.5, the increase of the boxes leads to the amplification of the complexity of network and the value of SWF. The result is exactly the reverse when $\alpha = 2.0$.

Case 1 When $\alpha \in (0, 1)$, the value of SWF can directly reflect the complexity of network. However, restricted by the formula of SWF, the increment is not quite large. It remains rather steady when the weight parameter changes.

Case 2 When $\alpha \in (1, \infty)$, the value of SWF is degressive so the SWF must be taken as a negative feedback of the structure of network.

For a network, the degree of complexity is decided by the nodes and the edges it has. SWF, a factor connects closely with the structure, can reflects the property of the structure cell and the similarity of the cells. As is demonstrated in Table 1, the more complex the networks become, the less increment the SWF has. This can demonstrate that the complex networks will have more similar parts when the number of nodes and edges grow, which is a proof of the existence of the complex networks' fractal property. The feature is evident especially when calculating the SWF of some typical fractal networks. Some detailed explanations are listed in the Section 4.

Taking both of the factors into consideration, the final trend of Rényi entropy can be deduced. Nevertheless, it remains to be proved when one of factors plays a decisive role with the increase of weight parameter α . Therefore there emerges a milestone in the series of Rényi dimension.

3.3. The physical meaning of the weight parameter α and SWF

Inspired by strange attractors that cause nonlinear effects of the dynamical system, we try to find attractors in a growing network. The nodes which maintain the larger degree (in unweighted network) or strength (in weighted network) during the process of growth are defined as the attractors of the network, because having greater degrees is more likely to have an impact on the growth of the network and the connection of other nodes, which symbolizes greater appeal of the attractors. The attractors are usually the nodes which are colored firstly in the box-covering algorithm. In this way, the ordinary parameter α gets the new physical meaning and represents the parameters for assessing the attractiveness of the attractor. According to the definition of SWF in Eq. (5), the meaning of α is illustrated as follows.

- When $\alpha > 1$, with the evaluation criteria α increasing, the boxes with less attractors are being phased out because it does not reach the attractiveness required by α , it means that p_k^α will be small enough to be ignored for some weak attractors. And the SWF value gradually becomes smaller, so α exhibits strong screening ability.
- When $1 > \alpha > 0$, α also reflects weak screening ability, but the requirement of the value of p_k^α is not very demanding. Take a pellucid example, $0.1^{0.1} = 0.79432$ is not quite different from $0.9^{0.1} = 0.98952$ while $0.1^{10} = 10^{-10}$ has ten orders of magnitude difference with $0.9^{10} = 0.34867$.

As a result, the physical meaning of SWF refers to the total attractiveness of the attractors in the network under the evaluation of a certain attracting ability index α .

Case 1: $\alpha = 0$, SWF is equal to the number of boxes required by the box-covering algorithm, indicating the number of potential attractors.

Case 2: $\alpha = 1$, SWF equals to 1, the attractor is in equilibrium and does not exhibit attractive qualities, which only reflects the sum of p_k .

Case 3: $\alpha > 1$, SWF embodies attractiveness under strong screening conditions.

Case 4: $1 > \alpha > 0$, SWF reflects attractiveness while the screening condition is weak.

In order to clearly give an index that quantifies attractors and attractive forces, we give the following definition according to α and SWF.

Definition 3.4 (Absolute Attraction Network (AAN)).

$$w_{sA} = \sum_{k=1}^N p_k^{10} \quad (17)$$

A absolute attraction network (AAN) is a network whose w_{sA} is greater or equal to 0.10737 ($0.8^{10} + 0.2^{10} = 0.10737$). When $w_{sA} < 0.10737$, the network is defined as non-absolute attraction network (NAAN).

The definition shows that the complex network which has attractors with rather great degree or strength is more likely to become AAN. This can be proved by the box-covering algorithm described in Section 2. The isolated nodes are arranged to the boxes which contains the nodes with largest degree or strength, then the p_k of these boxes will be large enough to influence the final result – SWF and make the network become AAN eventually.

4. Application

In this section, the proposed Rényi dimension is applied to calculate the series of dimension of a theoretical network – Sierpinski weighted fractal network, BA networks of different types and five real weighted networks, namely, the 500 busiest commercial airports in the United States (*top500*) [74], the *Caenorhabditis elegans* worm's neural network (*celeg*) [75], the collaboration scientists working on network theory weighted network (*Netscience*) [76], the collaboration scientists in computation geometry weighted networks (*goem*) [76] and the US Air-line network [76]. For comparison, the Tsallis' dimension is also applied in the real networks to show how the two factors mentioned effects the value of dimension. Also we discuss the physical meaning of two parameter α and SWF according to the dimensions of different networks. The PWF in Table 3 is fit for all the network and is only related to the weight parameter α .

4.1. Applications on Sierpinski network

Sierpinski network is a theoretical weighted network, which is featured by its regular fractal structure referring to Fig. 2. The length of the edge halves and the number of nodes increases threefold when the number of iterations increases by one at a time. As a result, the Hausdorff dimension can be precisely calculated according to its iterative rule, as follows.

$$d_H = -\lim_{l_H \rightarrow 0} \frac{\log N_B}{\log l_H} = \frac{\log 3}{\log 2} \doteq 1.585 \quad (18)$$

In Table 4, the Rényi dimension of Sierpinski weighted fractal network is listed. Furthermore, according to the result of Table 5, though the iteration is increasing from G5 to G9, the gap between two SWF is lower than 0.0035. This phenomenon also reveals that for a certain theoretical fractal network, the degree of self-similarity is quite high, and the self structure is merely decided by the most fundamental cell of the iteration no matter how larger the number of iteration is. For a network which has strong fractal property, SWF works as both a measure to testify the character and a reference to ascertain the primary geometry.

Influenced by both the SWF and PWF, the dimension of Sierpinski network progressively increases as the weight factor α increases. From G5 (which is contained by 40 nodes and 121 edges) to G9 (which consists of 3280 nodes and 9841 edges), the larger the number of iterations is, the lower the theoretical value and the actual value gap is for the ideal network is infinite. In order to reflect the average changing trend and the closest dimension to the theoretical network, the dimension of G9 is shown by Fig. 4.

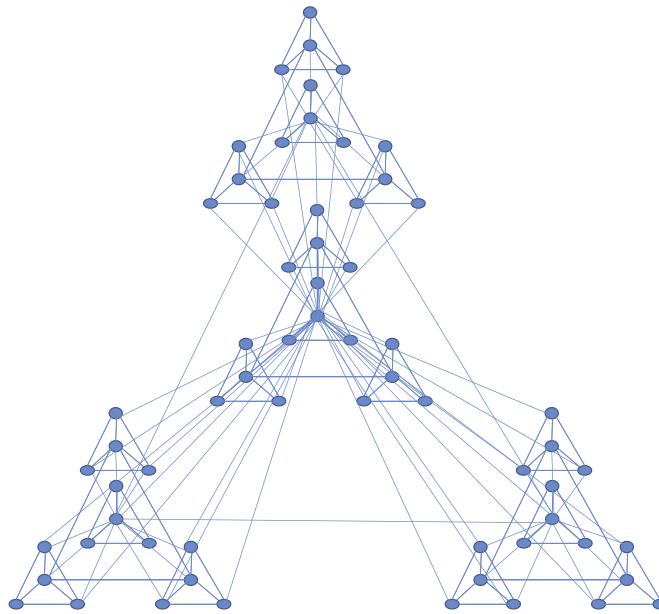


Fig. 2. Sierpinski weighted fractal network.

Table 2

The SWF of BA network as α changes.

α	0	0.5	0.8	1	1.5	2	3	5	10
SWF(BA66361)	6	2.0295	1.2733	1	0.6478	0.4799	0.3013	0.1318	0.0173
SWF(BA66362)	5	1.8636	1.2362	1	0.6801	0.5185	0.3401	0.1616	0.0261

4.2. Applications on BA networks of different types

AL Barabási and R Albert proposed a scale-free network model (BA model) to explain the power law generation mechanism [19]. The BA model has two characteristics. One is growth which refers to the continuous increase of the network size. In the research network, the nodes of the network are continuously increasing; The second is the preferential connection mechanism which means that the new nodes that are continuously generated in the network are more likely to be connected to those nodes that are more connected. It can be seen in Fig. 3. Rényi dimension increases as the parameter α increases except when α equals to 1. The information dimension is much smaller than other dimension.

This can be explained by the generating rules of the BA network. The BA network is generated according to the power law, so it will obey the rules called "Rich get richer". It means that the node with the greater degree at the beginning is more likely to connect the new node during the growth of the network scale. As a result, the average path length of the BA network is rather short, and the cluster coefficient is also quite small. From the perspective of information entropy, the source information is mastered in a few important nodes which can be seen as attractors in the network, the uncertainty in the propagation process is reduced, so the entropy is smaller, and the dimension is smaller.

The result of SWF is a reflection of how many attractors the network has. The network with the name ended by 1 like BA66361, is the network whose initial network nodes are isolated nodes. The networks with the name ended by 2 like BA66362 begin with complete networks. According to Table 2, the SWF of BA66362 is larger than that of BA66361 when α is greater than 1. This shows that when α performs strong screening ability, the more complicated the initial structure of the BA network is, the larger the SWF is.

4.3. Applications on real networks

The result of real network dimension is presented in Table 7. In Table 7, d_I represents the information dimension. The value of d_I is the same as the Rényi dimension when the weighted parameter α equals 1, which suggests that in this case, the Rényi dimension degenerates to the box dimension. And it is evident that when setting $\alpha = 0$, the dimension is exactly the box dimension. The results show that there will emerge a inflection point with the increase of the parameter α . In summary, the trend of the dimension will increase at first and then decrease. The trend is caused by the irregular variation of the distance between two nodes and the uneven growth of the length of the boxes used to cover the whole network. Thus the SWF and the PWF cannot have a certain change rule and for different networks, the rule of the emergence of inflection

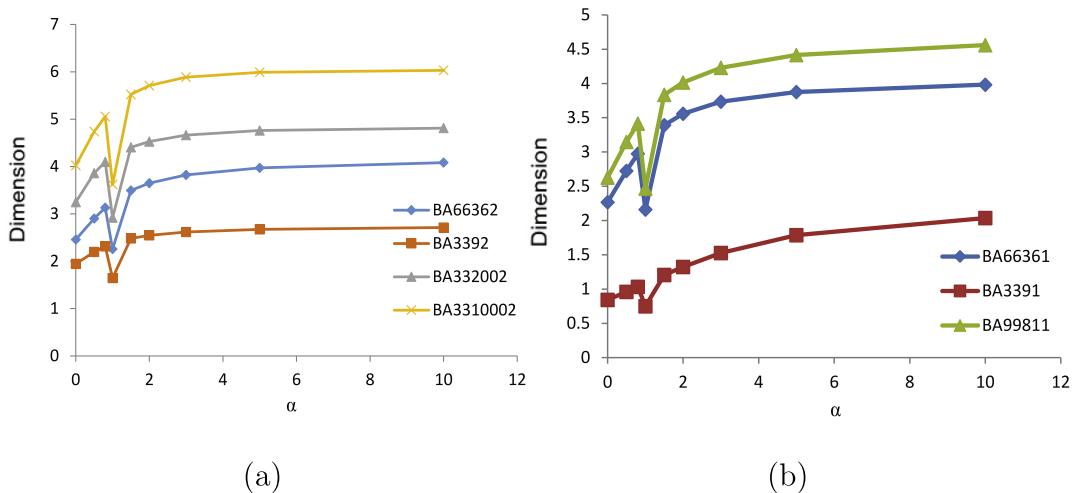


Fig. 3. The Rényi dimension of BA network belongs to two different types when the parameter α changes. (a) shows the dimension of BA networks whose initial nodes constitutes a complete graph while (b) refers to the dimension of BA networks with isolated nodes at the very beginning.

Table 3

The value of PWF.

α	0	0.5	0.8	1.0	1.5	2.0	3.0	5.0	10.0	100.0
PWF	1.0	2.0	5.0	–	–2.0	–1.0	–0.5	–0.25	–0.11	–0.01

Table 4

Rényi dimension of Sierpinski weighted fractal networks with different iterations.

d_I	G5	G6	G7	G8	G9
$d_R(\alpha=0)$	1.2425	1.3077	1.3558	1.3940	1.4245
$d_R(\alpha=0.5)$	1.2673	1.3272	1.3749	1.4122	1.4414
$d_R(\alpha=0.8)$	1.2763	1.3341	1.3798	1.4154	1.4434
$d_R(\alpha=1.0)$	1.2814	1.3378	1.3822	1.4170	1.4443
$d_R(\alpha=1.5)$	1.2920	1.3451	1.3871	1.4202	1.4465
$d_R(\alpha=2.0)$	1.3003	1.3509	1.3912	1.4233	1.4489
$d_R(\alpha=3.0)$	1.3124	1.3599	1.3981	1.4287	1.4532
$d_R(\alpha=5.0)$	1.3270	1.3713	1.4037	1.4362	1.4593
$d_R(\alpha=10.0)$	1.3424	1.3838	1.4174	1.4445	1.4663
$d_R(\alpha=100.0)$	1.3589	1.3968	1.4277	–	–

point is ambiguous. What is more, the PWF and SWF effect the final dimension in different degrees for different structure of networks. This two main reasons make the prediction of the inflection point remain an unsolved problem.

The Tsallis information dimension is combined with SWF and PWF. The SWF of Tsallis information dimension is exactly the SWF of Rényi dimension, and the value of SWF in the same real network decreases as the parameter increases according to Table 6. The PWF is fixed when given the weighted parameter and increases when the parameter increases. The final changing rule of Tsallis information dimension is discussed into two cases as follows:

Case 1 When $q \in (0, 1)$, $(w_s - 1)$ attenuates with q grows while w_p changes inversely. The changing rate of $(w_s - 1)$ is greater than w_p . So the SWF plays a conclusive role in the attenuation of the Tsallis information content and the Tsallis information dimension.

Case 2 When $q \in (1, \infty)$, $(1 - w_s)$ aggrandizes but $-w_p$ decreases more drastically when q expands gradually. In this way, the Tsallis information dimension is decided by the PWF and reduces accordingly.

Taking both the results in Table 8 and analysis above into consideration, the Tsallis information dimension monotonically decreases when the weight parameter q increases. Comparing the dimension proposed in this paper with Tsallis information dimension, the Rényi dimension is more stable because the logarithmic structure of Rényi information content imposes restrictions on the variation of the dimension.

5. Discussion

Through the comparison of the Sierpinski weighted fractal network and the real networks, the law of change about Rényi dimension is decided by the SWF and the PWF. The PWF is only decided by the parameter α which can be considered to be

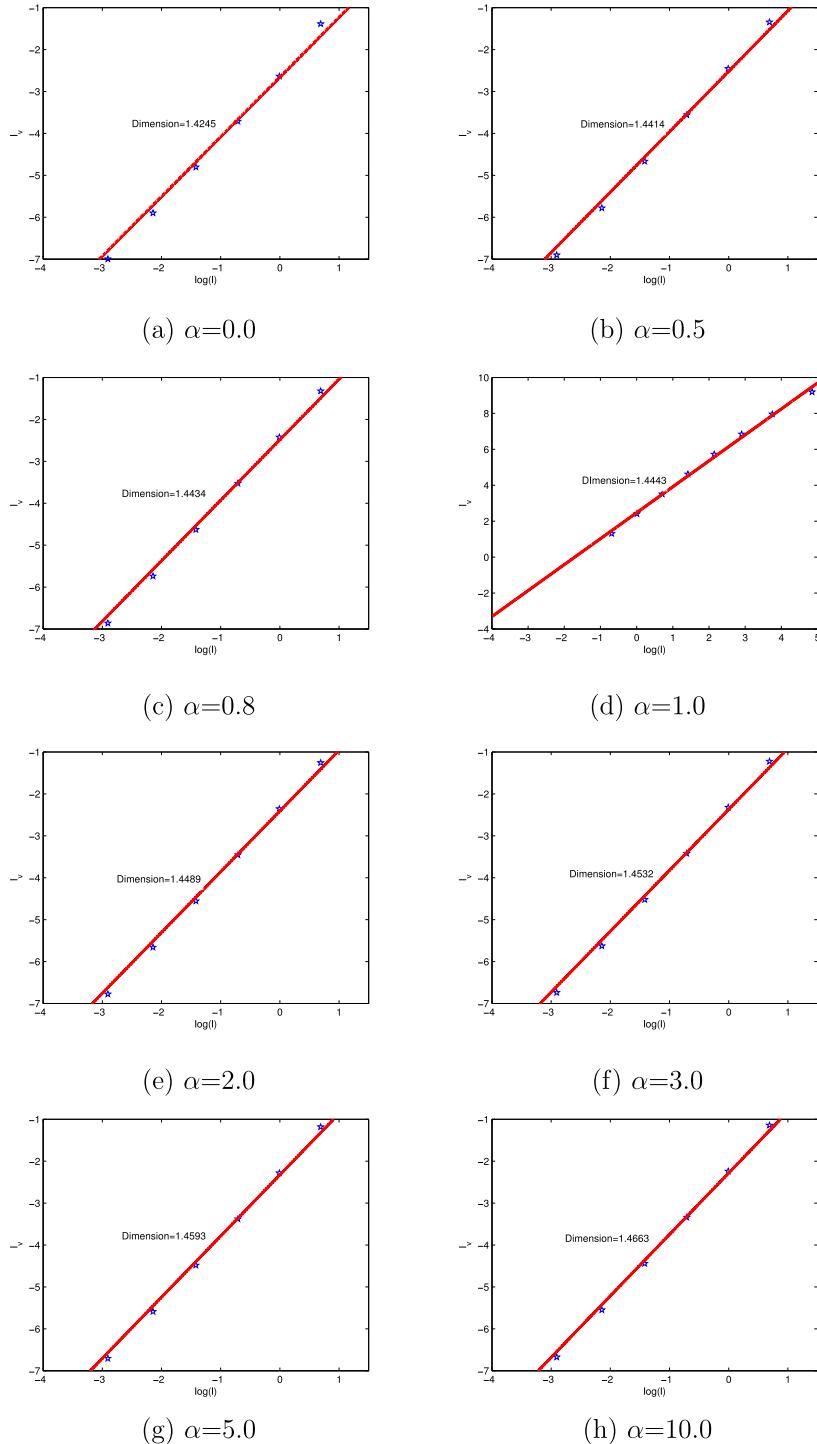


Fig. 4. The Rényi dimension of Sierpinski weighted fractal network. The x -axis — $\log(l)$ represents logarithm of the box side length and the y -axis — $I-v$ is the Rényi information content. According to the box-covering algorithm, the slope is the value of Rényi dimension.

a parameter depended on expert's decision. The SWF is a part which can reflect the parameter α and the structural feature of the network.

Table 5
SWF of Sierpinski weighted fractal networks with different iterations.

SWF	G5	G6	G7	G8	G9
$\alpha = 0$	4.0000	4.0000	4.0000	4.0000	4.0000
$\alpha = 0.5$	1.9624	1.9605	1.9598	1.9596	1.9595
$\alpha = 0.8$	1.3043	1.3035	1.3033	1.3032	1.3031
$\alpha = 1.0$	1.0000	1.0000	1.0000	1.0000	1.0000
$\alpha = 1.5$	0.5249	0.5261	0.5265	0.5266	0.5267
$\alpha = 2.0$	0.2817	0.2832	0.2837	0.2839	0.2839
$\alpha = 3.0$	0.0849	0.0859	0.0863	0.0864	0.0864
$\alpha = 5.0$	0.0085	0.0087	0.0088	0.0088	0.0088
$\alpha = 10.0$	3.15E−05	3.32E−05	3.39E−05	3.40E−05	3.41E−05

Table 6
SWF of different real networks.

	top500	USAir	Netscience	geom	celeg
$\alpha = 0$	2.0000	2.0000	397.0000	2061.0000	2.0000
$\alpha = 0.5$	1.0437	1.0534	16.3878	31.4410	1.0564
$\alpha = 0.8$	1.0053	1.0072	2.8217	3.1506	1.0078
$\alpha = 1.0$	1.0000	1.0000	1.0000	1.0000	1.0000
$\alpha = 1.5$	0.9971	0.9957	0.1627	0.3557	0.9951
$\alpha = 2.0$	0.9960	0.9940	0.0603	0.2432	0.9933
$\alpha = 3.0$	0.9940	0.9910	0.0134	0.1198	0.9899
$\alpha = 5.0$	0.9900	0.9850	7.52E−04	0.0291	0.9832
$\alpha = 10.0$	0.9802	0.9703	5.65E−07	8.48E−04	0.9667

Table 7
Rényi dimension of different real complex networks.

d_I	top500	USAir	Netscience	geom	celeg
	0.9220	1.1906	0.5964	1.5055	2.0712
$d_{R(\alpha=0)}$	0.6303	0.9600	0.3276	0.3730	1.7315
$d_{R(\alpha=0.5)}$	0.8259	1.1309	0.4170	0.6248	2.0273
$d_{R(\alpha=0.8)}$	0.9014	1.1767	0.5095	1.0378	2.0661
$d_{R(\alpha=1.0)}$	0.9220	1.1906	0.5964	1.5055	2.0712
$d_{R(\alpha=1.5)}$	0.8989	1.1972	0.8642	2.3799	2.0642
$d_{R(\alpha=2.0)}$	0.8476	1.1888	1.0558	2.5913	2.0516
$d_{R(\alpha=3.0)}$	0.7812	1.1646	1.1891	2.6624	2.0284
$d_{R(\alpha=5.0)}$	0.7288	1.1245	1.2240	2.6583	1.9975
$d_{R(\alpha=10.0)}$	0.6932	1.0674	1.2021	2.6320	1.9661

Table 8
Tsallis information dimension of different real complex networks.

d_I	top500	USAir	Netscience	geom	celeg
	0.9220	1.1906	0.5964	1.5055	2.0712
$d_{T(\alpha=0)}$	68.4895	53.6739	258.0225	1.46E+03	92.3206
$d_{T(\alpha=0.5)}$	6.0820	6.2191	10.4605	32.2256	10.8002
$d_{T(\alpha=0.8)}$	1.8017	2.1435	1.7663	4.4508	3.7252
$d_{T(\alpha=1.0)}$	0.9220	1.1906	0.5964	1.5055	2.0712
$d_{T(\alpha=1.5)}$	0.2870	0.4135	0.0641	0.2499	0.7284
$d_{T(\alpha=2.0)}$	0.1471	0.2172	0.0131	0.0884	0.3926
$d_{T(\alpha=3.0)}$	0.0691	0.1025	0.0031	0.0213	0.1969
$d_{T(\alpha=5.0)}$	0.0303	0.0452	3.29E−05	0.0025	0.0972
$d_{T(\alpha=10.0)}$	0.0104	0.0157	9.33E−09	3.04E−05	0.0417

5.1. Connection between parameter α and Rényi dimension

The Rényi dimension does not only symbolize the fractal geometry of the network but also expresses the dynamic characteristics of the growth of the network.

So when the concept of attractors is introduced in the study of complex network, for theoretical networks and unweighted networks like BA networks, with the increase of the assessing parameter α , the fractal feature is weakened while the dynamic characteristics become the main factors affecting the complexity of the network. The node with the largest degree in the beginning continuously strengthens the control of the new generation nodes in the process of network growth (the rich get richer thoughts). Attraction continues to increase, and dimensions increase, but the speed of growth slows down (referring to the dimension gap between $d_{R(\alpha=1)}$, $d_{R(\alpha=10)}$ and $d_{R(\alpha=1000)}$) because the number of attractors with absolute attraction will get less and less in the screening process. As for the weighted network in the real world, the SWF holds the same

Table 9
The judgment of AAN.

	Network	The number of covered box	w_{sA}	Type
Sierpinski network	G5	4	3.15E–05	NAAN
	G6	4	3.32E–05	NAAN
	G7	4	3.39E–05	NAAN
BA networks with complete graph	BA3310002	4	0.7374	AAN
	BA3392	2	0.3079	AAN
	BA332002	4	0.56796	AAN
BA networks with isolated nodes	BA66361	6	0.0173	NAAN
	BA3391	6	1.72E–05	NAAN
	BA99811	10	0.0011	NAAN

influence as unweighted network, but the growth of the edge does not have definite pattern, the strength of attractors will be changed dramatically after a generation of nodes growth, the dynamic feature is erratic, so the changing rule of dimension is unpredictable.

According to the experiments of Sierpinski network and BA networks in Table 9, the theoretical network whose nodes grow evenly and steadily from a single source and the BA networks with isolated nodes initially are tend to be NAAN. The reason is that the existence of isolated nodes cuts down the degrees of the ordinary network and makes the number of boxes increase. Then the network will be more likely to become NAAN in the expansion of the nodes. On the contrary, the networks which need less boxes in the first round of coloring in the box-covering algorithm are usually AAN. So the type of network mainly depends on the number of the isolated nodes and the growth law of the nodes and edges.

5.2. Comparison of Rényi dimension to Tsallis information dimension

In general, Rényi dimension of complex network is monotonously increasing when the nodes and length change at a regular rule. The physical significance of α is debatable by now. As a result, in the part of application, through the change of the dimension of the theoretical network and the real networks, α is given the meaning of weighted parameter and can be chosen to be different values with different applications when calculating the complexity of a weighted network.

The values of Tsallis information dimension decrease as parameter q increases. So the physical meaning of the weight parameter in Tsallis information dimension is credibility that is given by the surveyors and would influence the standard of real networks' complexity. The changing trend is quite distinct, because the SWF and PWF control the tendency of dimension alternatively with 1 as the limit. As a result, when calculating the dimension of complex networks, the parameter q must be chosen meticulously based on the applied range and stability requirements. Though the Tsallis' entropy dominated by q shares some common properties with Rényi entropy controlled by α , the changing rule of Tsallis information dimension is fixed and the range ability of the former is greater than the latter.

The attractors exist in all kinds of network. Whether the parameter form is α or q , SWF can represent the attractiveness of the network because it is a crucial factor in both of the dimension. To some extent, SWF is a bridge that can connect all the generalized dimensions with the same structure as $\sum_{k=1}^N p_k^\alpha$. The explanation of the physical meaning in the article can be followed by other generalized dimension.

6. Conclusion

In this paper, a generalized information dimension, which can be calculated by the modified box-covering algorithm, is proposed inspired by the Rényi entropy. The existing information dimension, Hausdorff dimension and collision dimension (often used in quantum mechanics) are the special cases of Rényi dimension when α equals to 1, 0 and 2. The PWF and SWF is defined on the basis of Rényi entropy and analyzed from the perspective of both the topology structure and the dynamic feature. Additionally, the concept of attractors is proposed to expound the physical meaning of α – the assessment parameter of attractiveness. A point that should be stressed is that SWF – the attractiveness of the entire network changes under different attraction conditions as α increases. The results of BA networks of different types prove the existence of network attractors. Finally, the comparison between the Rényi dimension and the Tsallis dimension indicates that the proposed dimension fluctuates within a smaller range when the parameter α changes which shows the robustness of Rényi dimension.

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Conflict of interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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