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Does the “Delta Variant” affect the nonlinear dynamic characteristics of 
SARS-CoV-2 transmission?

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Abstract

In this paper, we analyzed the difference of nonlinear dynamic characteristics of SARS-CoV-2 transmission caused by “Delta Variant”. We selected the daily new diagnostic data of SARS-CoV-2 from 15 countries. Four different kinds of complexity metrics such as Kolmogorov complexity, Higuchi’s Hurst exponent, Shannon entropy, and multifractal degrees were selected to explore the features of information content, persistence, randomness, multifractal complexity. Afterwards, Student’s t-tests were performed to assess the presence of differences of these nonlinear dynamic characteristics for periods before and after “Delta Variant” appearance. The results of two-tailed Student’s t-test showed that for all the nonlinear dynamic characteristics, the null hypothesis of equality of mean values were strongly rejected for the two periods. In addition, by one-tailed Student’s t-test, we concluded that time series in “Delta period” exhibit higher value of Kolmogorov complexity and Shannon entropy, indicating a higher level of information content and randomness. On the other hand, the Higuchi’s Hurst exponent in “Delta period” was lower, which showed the weaker persistent in this period. Moreover, the multifractal spectrum width after “Delta” emergence were reduced, representing a more stable multifractality. The sources for the formation of multifractal features are also investigated.

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1. Introduction

The novel coronavirus pneumonia (COVID-19) epidemic caused by New Coronavirus (SARS-CoV-2) has been widely spread worldwide since the end of 2019. With the research of medical medicine and the strengthening of epidemic prevention measures in various countries, the virus has been controlled to some extent. However, since the “Delta Variant” was discovered in India in October 2020, “Delta” has spread to most countries and regions of the world, and has become a major variant of the new global pneumonia epidemic. Syed, A. M. et al. [1] modified virus-like particle (VLP) technology and found that a little-known mutation in Delta virus, the R203M mutation, can significantly enhance its infectivity. Due to its immune evasion ability, almost all currently marketed vaccines have a reduced ability to produce neutralizing antibodies against the Delta strain, resulting in lower protection rates. For example, the serum samples of Zhifei three-dose vaccine recipients showed that neutralizing antibodies were reduced by 1.2 times, and the British Johnson also decreased by 1.6 times. It has brought new problems to the global epidemic prevention and control. The virus can still spread despite the use of personal protective equipment and a high two-dose COVID-19 vaccination.

Confronting such a threatening threat, scholars in various fields have done corresponding researches on the virus to reduce the impact of the mutant virus on human body and activities [2-8]. The particularity of delta variant is that it is still transmissible to people injected with COVID-19 vaccine. In the investigation of the individuals in India, Thangaraj et al. [9] found that whether inoculated and not vaccinated COVID-19 vaccine, “Delta” mutants can break through vaccine protection and cause infection to individuals. Secondly, there was no significant difference in the prevalence of Delta mutation between the vaccinated group and the unvaccinated group. However, compared with the unvaccinated group, the case of COVID-19 in vaccine group is less likely to develop severe illness and mortality. In addition, in studying the impact of “Delta Variant” on vaccine efficacy and response strategy, Bian et al. [10] pointed out that improving vaccination coverage is an effective means to control the transmission of virus variants. However, only vaccination with SARS-CoV-2 vaccine without intervention may lead to continuous transmission and the emergence of new variants.

Nevertheless, we observed that most of the research reports on “Delta” mutants are analyzed from the perspective of virus gene sequence or vaccine, and few do nonlinear analysis on the transmission
characteristics of “Delta Variant” by using statistical analysis methods. We believe that extracting and analyzing the nonlinear characteristics of time series of infected people can play a key role in controlling and preventing the transmission of SARS-CoV-2.

We sort out the number of newly diagnosed patients per day of COVID-19 in 15 countries and formed it into a time series. The time length of the series covered the two periods including before and after the occurrence of “Delta Variant”. We utilize statistical analysis on the time series of two periods respectively, and various algorithms such as Kolmogorov complexity, Higuchi’s Hurst exponent, Shannon entropy, and multifractal degree are adopted. Then, we use the Student’s t-test to compare the differences of nonlinear dynamic indicators before and after “Delta Variant” occurrence in 15 countries.

Based on nonlinear dynamic characteristics are often employed in the analysis of time series, the nonlinear dynamics has been widely used in various problems before [11–24]. In this study, the number of newly diagnosed patients per day of COVID-19 in each country are organized as the time series, and it is likely to use these nonlinear metrics to mine the transmission pattern of “Delta Variant” in various countries, and then compare the differences of nonlinear transmission characteristics before and after the emergence of “Delta Variant”.

The remainder of the paper is structured as follows. We introduce the methodology in Section 2. Section 3 presents the data information. Section 4 contains the empirical results. Section 5 reports the conclusion.

2. Methodology

To explore the nonlinear characteristics of four investigated objects, we select four different kinds of complexity metrics such as Kolmogorov complexity [25], Higuchi’s fractal dimension [26], Shannon entropy [27], and multifractal degree [28]. The four processes assess the fund time series of infected people can play a key role in controlling and preventing the transmission of SARS-CoV-2.

2.1. Kolmogorov complexity

Kolmogorov complexity was discovered by Andrei Nikolaevich Kolmogorov in 1963. In algorithmic information theory, the Kolmogorov complexity of an object, such as a sequence of time, is a measure of the amount of information required to describe this object, and measure the informational value of the code string by calculating the algorithmic complexity, that is, the shortest program to calculate it on a fixed universal Turing machine. Kolmogorov complexity was calculated via the algorithm proposed by Lempel and Ziv [29] in 1976. The detailed definition is stated as follows.

Step 1. Consider a time series \( x_i \), \( i = 1, 2, ..., N \), and construct the time series \( s(i) \) of characters 0 and 1, where \( i = 1, 2, ..., N \), the construction rule is accorded by

\[
s(i) = \begin{cases} 
0, & \text{if } x_i < x', \\
1, & \text{if } x_i \geq x'.
\end{cases}
\]

(1)

Here, \( x' \) is the threshold which is used by the mean value of the time series.

Step 2. Calculate \( C(N) \), where \( C(N) \) is the minimum number of distinct patterns contained in the given sequence. When \( N \) approaching infinite, the value of \( C(N) \) is close to an ultimate value \( B(N) \), that is

\[
C(N) = \mathcal{O}(B(N)),
\]

\[
B(N) = \frac{N}{\log_2 N}.
\]

Step 3. The normalized information measure \( KC(N) \) is defined by

\[
KC(N) = \frac{C(N)}{B(N)} = C(N) \log_2 N.
\]

(4)

\( KC(N) \) denotes the information quantity of the given sequence, and the value of \( KC(N) \) varies asymptotically between 0 and 1. If \( KC(N) = 0 \), then it indicates a regular series; if \( KC(N) = 1 \), then it represents a random series.

2.2. Higuchi’s Hurst exponent

The algorithm of the Higuchi’s Hurst exponent is introduced as follows. Consider a time series \( X(1), X(2), ..., X(N) \) with length \( N \), the first step is to reconstruct the given time series into \( k \) groups of new time series. Each self-similar sequence \( Y_k \) is built as

\[
Y_k = \left\{ X(m), X(m + k), ..., X\left[m + \left\lfloor \frac{N-m}{k} \right\rfloor \right] \right\},
\]

(5)

where \( k \) is window interval, and \( m \) denotes the initial location, here, \( m = 1, 2, ..., k \). Besides, \( \lfloor \cdot \rfloor \) represents the integer part \( \frac{N-m}{k} \). Then calculate the length of the original sequence as

\[
L_k = \sum_{i=1}^{\left\lfloor \frac{N-m}{k} \right\rfloor} \left| Y(m + ik) - Y[m + (i - 1)k] \right| \cdot \frac{N-1}{\left\lfloor \frac{N-m}{k} \right\rfloor}.
\]

(6)

The length of \( L(k) \) shall be asymptotically as

\[
L(k) = C \cdot \left( \frac{1}{k} \right)^D,
\]

(7)

where \( C \) is a constant. Subsequently, transfer Eq. (7) to

\[
\ln \left( L(k) \right) = D \ln \left( \frac{1}{k} \right) + \ln \left( C \right),
\]

(8)

where \( D \) represents the fractal dimension, which can be estimated by least squares regression with slope of the log-log plots of \( L(k) \) against \( k \). Then Higuchi’s Hurst exponent is derived by \( H = D = 2 \).

2.3. Shannon entropy

Shannon solved the problem of quantitative measurement of information using the concept of information entropy in 1948. The amount of information in a piece of information is directly related to its uncertainty. In a time series, the greater the uncertainty of the time series, the greater the entropy, and the larger the degree of randomness. The Shannon entropy is defined as follows.

Let \( x_i \) be a time series, where \( i = 1, 2, ..., N \), \( p_i \) be a probability measure that \( \sum p_i = 1 \). The Shannon entropy \( SNE \) of \( x \) is

\[
SNE(x) = \sum_{i=1}^{N} p_i \log \left( \frac{1}{p_i} \right).
\]

(9)

If all the values of time series \( x_i \) are equally, then \( SNE \) reaches maximum. Thus, when the time series is nearly random, \( SNE \) approaches \( \log(N) \). In contrary, if any \( x_i \) is definitely occur, \( SNE \) reaches minimum.

2.4. Multifractal degree

As an important method of multifractal analysis, Kantelhardt proposed the multifractal detrended fluctuation analysis(MF-DFA), which can effectively know whether the time series has multifractal properties. The general MF-DFA procedure can be conducted by five steps. The first four steps are the same as DFA, for more details, please refer to [30,31]. The last step is:
Calculating the mean of $2N_s$ segments, obtain the $q$ order fluctuation function $F_q(s)$ as

$$F_q(s) = \left\{ \frac{1}{2N_s} \sum_{v=1}^{2N_s} F^2(s,v) \right\}^{1/2}.$$

When $q = 0$, according to Lopida’s law,

$$F_0(s) = \exp \left\{ \frac{1}{2N_s} \sum_{v=1}^{2N_s} \ln F^2(s,v) \right\}.$$

$F_q(s)$ is a function of segment $s$ and fractal order $q$. With the increase of $s$, the series are long-range power-law correlated, the generalized Hurst exponent $h(q)$ is defined by $F_q(s) \propto s^{h(q)}$, when $q = 2$, $F_2(s)$ is the standard DFA.

When the original sequence is monofractal, the scales of variance $F^2(s,v)$ in each segment $s$ is constant, therefore, $h(q)$ is a constant independent of $q$. The range of $h(q)$ indicates the extent to which the series is multifractal. A higher $\Delta H = h(q_{\text{max}}) - h(q_{\text{min}})$ means stronger multifractal feature. Furthermore, the multifractal degree can also be described between the singularity strength $\alpha$ and the fractal dimension $f(\alpha)$ [32]. The fractal strength $\Delta \alpha$ reflects the degree of multifractal complexity. The two features are characterized by

$$\alpha = h(q) + q h'(q),$$

$$f(\alpha) = q(\alpha - h(q)) + 1.$$

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Table 1
Selected country samples.

| Country       | India | Brazil | Colombia | United States | Russia | Turkey | Argentina | Netherlands | South Africa | United Kingdom | Germany | Italy |
|---------------|-------|--------|----------|---------------|--------|--------|-----------|-------------|--------------|---------------|---------|-------|

Table 2
Descriptive statistics.

| Period          | Statistics parameter | KC   | HHE | SHE | $\Delta H$ | $\Delta \alpha$ |
|-----------------|----------------------|------|-----|-----|------------|-----------------|
| Non-Delta period| Max                  | 7.88 | 0.96| 7.88| 2.81       | 4.58            |
|                 | Min                  | 7.17 | 0.38| 7.65| 0.68       | 1.09            |
|                 | Mean                 | 7.60 | **0.67** | 7.79 | **1.72** | **2.37**        |
|                 | $\sigma$             | 0.22 | 0.15 | 0.07 | 0.50      | 0.85            |
| Delta period    | Max                  | 7.88 | 0.78| 7.88| 2.23       | 3.08            |
|                 | Min                  | 7.68 | 0.06| 7.83| 0.31       | 0.42            |
|                 | Mean                 | 7.83 | 0.47| **7.96** | 1.05 | 1.42        |
|                 | $\sigma$             | 0.06 | 0.20| 0.01 | 0.55      | 0.81            |

We display the larger value in bold.

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Fig. 1. Daily new COVID-19 infections in 15 countries of (a) maximum daily increase exceeds 35000, and (b) maximum daily increase less 35000.

Fig. 2. Kolmogorov complexity of 15 countries for “non-Delta period” and “Delta period”.

Fig. 3. Hurst exponent estimated by Higuchi’s method of 15 countries for “non-Delta period” and “Delta period”.

Fig. 4. Shannon entropy of 15 countries for “non-Delta period” and “Delta period”.

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3. Data collection

In order to ensure the balance of samples, we covered all continents of the world while selecting the samples. We selected 20 countries which are suffering serious epidemic situation, and the total number of confirmed cases in each of these countries exceeds 2 millions. Please refer to Table 1 for details. The time period we selected covers a total of 470 days from March 11, 2020 to June 23, 2021, and the collection object

Fig. 5. Log-log plots between $s$ and $F_q(s)$ of 15 countries for "non-Delta period".
is the number of daily new diagnosed people of COVID-19. The time series of daily new COVID-19 infections in 15 countries is shown in Fig. 1. To better distinguish the daily numbers of newly diagnosed patients for each country, we depict the countries whose maximum daily increase exceeds 35000 in Fig. 1(a); otherwise, plot in Fig. 1(b). “Delta” mutant was first discovered in India in October 2020. Considering that it takes a certain time window from discovery to transmission to many countries around the world, we take November 1, 2020 as the intermediate

Fig. 6. Log-log plots between $s$ and $F_q(s)$ of 15 countries for “Delta period”.

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dividing point and divide the overall time series into “non-Delta period” and “Delta period”. In order to ensure the comparability of two periods, we set the data length of the two periods to the same, with the length of 235 for each period. According to Fig. 1, we can clearly see that there are obvious differences in the distribution of time series curves on the left and right sides with November 1, 2020 as the midpoint. We preliminarily judge that the emergence of “Delta Variant” may lead to the change of the trend of daily new confirmed cases in various countries.

Fig. 7. Generalized Hurst exponent $H(q)$ of 15 countries for “non-Delta period” and “Delta period”.
4. Computational results

We first estimate the nonlinear complexity by Kolmogorov complexity. According to Fig. 2, we observe that whether in “non-Delta period” or “Delta period”, the Kolmogorov complexity in each period is greater than 5, which means both periods achieve high level of information content. Besides, the statistics indicators of estimated populations of Kolmogorov complexity across two periods are described in Table 2. One may observe that the estimated Kolmogorov complexity are different across two periods, and the “Delta period” indicates a higher nonlinearity and the volatility of the metrics of “Delta period” is three times lower than the “non-Delta period”, indicating the “Delta period” has relatively higher level of information content. The higher value in bold is listed in Table 2.

Subsequently, in order to quantitatively evaluate the dimensions of the fractal, we check the Higuchi-based Hurst exponent of two periods. From Fig. 3, two periods exhibit comparable different levels of persistence. According to Table 2, the mean values of HHE in two periods are 0.67 and 0.47, respectively, and the volatilities are similar. One may observe that the value of Hurst exponent in “non-Delta period” is higher, which means the self-similarity of this period is greater, and also illustrates a stronger persistence. This may be related to the increasingly mature global epidemic prevention policies and the substantial increase of global vaccination rate.

Then we calculate the Shannon entropy for both the two periods with COVID-19 transmission before and after “Delta Variant” emergence, respectively. In Fig. 4, all the the Shannon entropy are greater than 5, showing both the periods have high level of randomness, and the nonlinear complexity in “Delta period” is higher than “non-Delta period”. According to Table 2, by the mean values calculated for each period, we notice that the Shannon entropy of “Delta period” also achieves a greater value, implying “Delta period” exhibits a relatively higher level of randomness. Here, the volatility σ of “Delta period” is three times smaller than “non-Delta period”.

Finally, we consider the multifractal metrics to further investigate the nonlinear dynamic characteristics of “Delta Variant” on epidemic spread. We first examine whether multifractal features exist in the time series of all countries. This can be reflected by analyzing the log-log plots curve of fluctuation function $F_q(s)$ and segment size $s$. It can be seen from Fig. 1 that the time series has obvious oscillations, Horvatic et al. [33] proposed to use polynomials of different orders to remove the trend, and higher order polynomials are required in multifractals to correctly decompose the oscillations. Therefore the scale range $[s_1, s_0]$ contains several complete oscillations of the time series and will cope well with the corresponding effects. If the oscillation part is filtered out, the multifractal features of the time series will be greatly affected, and the self-similar properties of the calculated model will not be well exploited. Suggested by [28], the parameters used in the MF-DFA are selected as follows. Segment size $s$ from 5 to 15 with 1 increment, and fractal order $q$ varies from $-20$ to 20, the interval of $q$ is divided into 10 equal parts. Figures 5 and 6 show that in all the countries, $ln (F_q(s))$ increases with the increase of $ln (s)$, and the slope of the curve decreases with the increase of $q$, which exhibits the multifractals natures in all the time series of these countries. The curves in the each figure denotes $q = -20, -16, ..., 16, 20$, respectively. Figs. 5 and 6(a)-(o) represent India, Brazil, United States, Russia, Argentina, Iran, Colombia, Poland, Turkey, Indonesia, Netherlands, South Africa, United Kingdom, Germany, Italy, respectively.

Next, we calculate the generalized Hurst exponents according to the slope of the curves, as shown in Fig. 7. The blue dots represent “non-Delta period”, and the red dots represent “Delta period”. Color version of figure is available in web version of this article. It is obvious that the variation range of $H(q)$ in “Delta period” is narrower than that in “non-Delta period” for almost all countries.

Afterwards, we calculate the fluctuation ranges of $H(q)$ of two periods for the 15 countries respectively, measured by $\Delta H$. It can be observed from Fig. 8 that the multifractal degree of COVID-19 in the transmission process between countries before the emergence of “Delta Variant” is higher than that in the Delta transmission stage. Moreover, from Table 2, we can also see that in “non-Delta period”, the mean value of $\Delta H$ is much higher than that in “Delta period”, reflecting that the multifractals of the time series of daily new COVID-19 infections after “Delta” emergence are more stable, and the narrower multifractal spectrum width in “Delta period” implies an increase in the effectiveness of global epidemic prevention and control. The same situation can be analyzed by $\Delta \alpha$, and we can get the same conclusion from Fig. 9.

To show the clear distributions of “non-Delta period” versus “non-Delta period”, we depict the boxplot charts for 15 countries. As shown in Fig. 10, the boxplot chart is used to show the data information of 15 countries under each statistical index, which consists of “box” and “whisker”. Straight line in the “box” represents the median of the 15 statistical values, and its upper and lower boundaries represent 75% and 25% values respectively. The two “whisker” lines are the maximum and minimum values of the statistical values. Outliers are usually drawn separately and represented by “+”. Results in Fig. 10 supports our above conclusions.

Since the global anti-epidemic work lasted more than a year, the level of epidemic control, vaccination and economic recovery in various countries has been continuously improving. During the initial epidemic of COVID-19, countries all over the world once encountered “mask panic”, the supply of epidemic prevention equipment was less than demand, and then expanded the production capacity of epidemic prevention and control materials, while the production capacity of medical materials such as the medical masks and protective clothing increased...
significantly, and even overcapacity appeared in some countries. On the other hand, in terms of new crown vaccination, the global vaccination rate has been on the rise since the end of 2020, both daily and cumulative. In addition, countries united and cooperated in the COVID-19 pandemic, which vividly interpreted the concept of the community of common destiny for mankind. The enhancement of the effectiveness of epidemic prevention and control all over the world caused by these factors may reasonably explain the reduction of multifractal intensity in “Delta period”.

To verify whether the above conclusions about Kolmogorov complexity, Higuchi’s Hurst exponent, Shannon entropy, and multifractal degrees are incredible across the two periods, we adopt Student’s t-test to test the null hypothesis of equal means. The probability value refers to the probability that the observed sample rejects the null hypothesis when the null hypothesis is true, and the probability value is calculated at the significance level of 5%. It should be noted that there exists evidence of rejection of the null hypothesis if the p-value below 5%.

Table 3 reports the p-values by two-tailed Student’s t-test. The p values computed between “Non-Delta period” and “Delta period”

| Nonlinear metric | KC  | HHE | SHE  | ΔH   | Δα   |
|------------------|-----|-----|------|------|------|
| p value          | 0.0006 | 0.0052 | 0.0009 | 0.0018 | 0.0038 |

Fig. 10. Boxplot of statistical indicators for “non-Delta period” and “Delta period” of (a) Kolmogorov complexity, (b) Higuchi’s Hurst exponent, (c) Shannon entropy, (d) ΔH, and (e) Δα.
indicate that the null hypothesis of equality of mean values is strongly rejected for all the nonlinear dynamic characteristics. This shows that there is a significant difference between the time series of statistical characteristics of the number of newly diagnosed patients per day after the emergence of “Delta Variant” and before the emergence of “Delta Variant”.

However, we still cannot determine the magnitude of the nonlinear strength between the two periods. Because we cannot assume that the time-series data of the statistical characteristics of the daily newly diagnosed patients in 15 countries has changed. The two-tailed Student’s t-test only emphasizes the difference, not the directionality, and can only determine that the nonlinear strength of the two periods is significantly different. The one-tailed t-test emphasizes a test in a certain direction, and can be used to effectively test whether the difference between the mean values of Kolmogorov complexity, Higuchi’s Hurst exponent, Shannon entropy, and multifractal degrees before and after “Delta Variant” is greater or less than 0. In this regard, we conduct the one-tailed Student’s t-test, and the probability values $p$ are also computed with a 5% statistical significance level. The $p$ values presented in Table 4 can derive conclusions such that “Delta period” > “non-Delta period” for Kolmogorov complexity and Shannon entropy, indicating a higher level of information content and stronger randomness than the other period. Moreover, for Higuchi’s Hurst exponent, and multifractal degrees $\Delta H$, $\Delta\alpha$, all the results show “Delta period” < “non-Delta period”, which represent the “Delta period” has a lower level of persistence. Besides, weaker multifractal strength of “Delta period” reflects the improvement of the effectiveness of global epidemic prevention and control.

Then we also analyze the source of multifractality of the 15 countries in two periods. Two types of multifractality are possible to be distinguished in the time series [28], one stems from long memory features in the and fluctuations, another arises from the fat-tail probability density function. Now we adopt shuffled and surrogated time series to reveal the source of multifractality in these countries. When the width of multifractality is removed by the shuffling procedure in the original time series, indicating the source stems from the long memory. When arising from the fat tails, the width of multifractality is lower by surrogate the original time series.

Fig. 11 shows the path of the generalized Hurst exponent $H(q)$ versus $q$ order for the original, shuffled, and surrogated series in India. The shuffled and surrogated series have lower multifractality features than the original data, which exhibits that some multifractalities are removed. Besides, we observe that in Fig. 11(a), the multifractality is more reduced when surrogating the original series, which implies the fat-tail distributions contribute to the multifractality in “non-Delta period”. Nevertheless, in Fig. 11(b), the shuffled time series has a lower multifractality, indicating the multifractality arises from the long memory in “Delta period”. We investigate the main multifractal sources of time series in all the 15 countries and list the results in Tables 5 and 6.

Since the pandemic is still expanding and the dynamics is not stable, to show that the difference of nonlinear dynamic characteristics of SARS-CoV-2 transmission is really caused by “Delta Variant”, we change the time period of the “Delta period. We use a moving window with a size of 13 to move to the right until “Omicron Variant” appears. We set the deadline of the moving window to October 31, 2021. Before the emergence of “Omicron Variant”, we consider that the nonlinear dynamic index was completely caused by “Delta Variant”. As shown in Figs. 2, 3, and 4, the nonlinear indicators of Germany in the two periods are obviously different displayed, thus, we focus on explaining the phenomenon in Germany. The time period selection of different “Delta period” is shown in Table 7. The statistical indicators under these time

Table 4

| Nonlinear metric | KC  | HHE | SHE | $\Delta H$ | $\Delta\alpha$ |
|------------------|-----|-----|-----|------------|---------------|
| $\theta$         | <   | >   | <   | >          |               |
| $p$ value        | 0.0003 | 0.0026 | 0.0005 | 0.0009 | 0.0019 |

Table 5

| Country | Original | Shuffled | Surrogated | Non-Delta period | Main source |
|---------|----------|----------|------------|------------------|-------------|
| India   | 2.5468   | 2.3923   | 0.8187     | Fat-tail         |             |
| Brazil  | 2.9309   | 2.4736   | 2.6725     | Long memory      |             |
| United States | 3.5879 | 2.3973   | 2.8738     | Long memory      |             |
| Russia  | 1.8459   | 1.9125   | 1.935      | Fat-tail         |             |
| Argentina | 2.1412 | 1.5964   | 1.3384     | Fat-tail         |             |
| Iran    | 1.6780   | 1.6512   | 1.2666     | Fat-tail         |             |
| Colombia | 4.5759  | 1.9622   | 2.8738     | Long memory      |             |
| Poland  | 1.0876   | 0.8392   | 0.6552     | Fat-tail         |             |
| Turkey  | 2.1201   | 1.2644   | 1.8324     | Long memory      |             |
| Indonesia | 1.6809  | 1.6634   | 0.9618     | Fat-tail         |             |
| Netherlands | 2.3668 | 1.8298   | 2.0216     | Long memory      |             |
| South Africa | 2.7077 | 1.9198   | 1.6504     | Fat-tail         |             |
| United Kingdom | 1.8032 | 1.3279   | 1.6302     | Long memory      |             |
| Germany  | 2.2313   | 1.5773   | 1.3297     | Fat-tail         |             |
| Italy    | 2.3797   | 2.0849   | 1.8064     | Fat-tail         |             |
periods are shown in Fig. 12. We note that the statistical indicators tended to be stable in different “Delta Variant” time periods, and there is an obvious level of comparison with the values of the statistical indicators in the “non-Delta period”, which further shows that the transmission of “Delta period” changes the nonlinear characteristics of SARS-CoV-2.

5. Conclusions

In this study, we investigated the nonlinear dynamic natures of the time series of daily new diagnosed people of COVID-19. 15 countries on different continents of the world were selected. Four different kinds of complexity metrics such as Kolmogorov complexity, Higuchi’s Hurst exponent, Shannon entropy, and multifractal degrees ($\Delta H$ and $\Delta \alpha$) were employed to check the features of information content, persistence, randomness, and multifractal strength. By the mean values of these metrics, the assessed nonlinear features were generally not statistically similarly across components of two different periods. Furthermore, to further estimate the magnitude of the nonlinear strength between every two periods, we adopted Student’s t-test to assess the presence of differences. The results of two-tailed Student’s t-test indicated that for all the Nonlinear metrics, the null hypothesis of equality of mean values is strongly rejected. Afterwards, one-tailed Student’s t-test was performed and the $p$ values showed the “Delta period” exhibited higher value of Kolmogorov complexity and Shannon entropy than the “non-Delta period”, which implied that “Delta period” had higher level of information content and randomness than the “non-Delta period”. Besides, the calculated results of Higuchi’s Hurst exponent indicated the “Delta period” had a lower level of persistence, and the width of multifractal strength $\Delta H$, $\Delta \alpha$ in “Delta period” was narrower, which reflected its multifractal stability, and also revealed the enhancement of the effectiveness of global epidemic prevention and control.

| Table 6 | Width Values of multifractal degree $\Delta \alpha$ in “Delta period”. |
|---------|---------------------------------------------------------------|
| Country | Original | Shuf | Surrogated | Main source |
| India   | 0.7760   | 0.5422 | 0.7711 | Long memory |
| Brazil  | 1.3486   | 0.9409 | 1.2214 | Long memory |
| United States | 3.0831   | 1.7755 | 2.8738 | Long memory |
| Russia  | 0.9229   | 0.8809 | 0.6126 | Fat-tail |
| Argentina | 2.3878   | 2.2254 | 1.7110 | Fat-tail |
| Iran    | 1.6203   | 1.5772 | 1.3149 | Fat-tail |
| Colombia | 0.4907   | 0.4302 | 0.2319 | Fat-tail |
| Poland  | 0.6081   | 0.6002 | 0.3065 | Fat-tail |
| Turkey  | 0.9477   | 0.5532 | 0.9187 | Long memory |
| Indonesia | 0.4225   | 0.3962 | 0.2162 | Fat-tail |
| Netherlands | 1.6753   | 1.5142 | 1.0248 | Fat-tail |
| South Africa | 2.7610   | 1.8893 | 2.5369 | Long memory |
| United Kingdom | 1.4532   | 1.4440 | 1.1328 | Fat-tail |
| Germany | 1.6508   | 1.6622 | 1.3022 | Fat-tail |
| Italy   | 1.0848   | 0.9545 | 0.6539 | Fat-tail |

| Table 7 | Time series intervals for different “Delta period”. |
|---------|---------------------------------------------------|
| Non-Delta | 2020/03/11-2020/10/31 | Delta6 | 2021/01/05-2021/08/27 |
| Delta1 | 2020/11/01-2021/06/23 | Delta7 | 2021/01/18-2021/09/09 |
| Delta2 | 2020/11/14-2021/07/06 | Delta8 | 2021/01/31-2021/09/22 |
| Delta3 | 2020/11/27-2021/07/19 | Delta9 | 2021/02/13-2021/10/05 |
| Delta4 | 2020/12/10-2021/08/01 | Delta10 | 2021/02/26-2021/10/18 |
| Delta5 | 2020/12/23-2021/08/14 | Delta11 | 2021/03/11-2021/10/31 |

Fig. 12. Statistical indicators for “non-Delta period”, and “Delta pandemic expanding period” of (a) Kolmogorov complexity, (b) Higuchi’s Hurst exponent, and (c) Shannon entropy in Germany.
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