Analysis of Self-Similarity, Memory and Variation in Growth Rate of COVID-19 Cases in Some Major Impacted Countries

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Abstract. In the present work investigation of self-similarity as well as scaling analysis have been performed over daily number of new confirmed cases of COVID-19 in some major impacted countries viz. USA, Brazil, India, Russia, Spain, UK, Italy, Germany and France from their respective dates of first report of COVID-19 till June 30, 2020. To reduce uncertainty and irregular fluctuations in these present time series seven-point moving averages are taken and the entire analysis has been further performed over these seven-point moving average data. Scale invariance and self-similarity or self affinity manifests the fractal nature. For these time series, investigations of fractal nature have been performed by means of Higuchi method and corresponding fractal dimensions have been obtained. Also scaling analysis has been applied to understand the nature of the memory in these by means of Hurst exponent. Next, on the basis of these seven-point moving average data cumulative profiles of confirmed cases of COVID-19 for these countries have been generated. An effort has been made to understand the initial exponential growths in them. Study does not yield constant growth rates of infection; rather it shows time dependent profiles with variable functional representations at different windows of time for all these countries. Finally an effort has been made to predict the scenario for certain upcoming days for all the nine countries considered within a pre-assigned tolerance level continuing with the last obtained exponential growth rates. Results are not persistent in most of the cases. This might point towards a difficult scenario of prediction of future impacts in these countries.

Keywords: COVID-19, Fractal, Scaling Analysis, Memory, Initial Exponential Growth, Growth Rate of Infection
1. Introduction

On 29 December, 2019 Chinese officials noticed a bunch of alike pneumonia cases of unfamiliar aetiology in the city of Wuhan, Hubei Province, China [1, 2]. Eventually, a new type of coronavirus was identified in a patient on 07 January, 2020 [1, 2]. Initially it was named as 2019-nCoV (full form: 2019-novel coronavirus) by World Health Organization (WHO) on 12 January, 2020 [3]. On 21 January, 2020 WHO officially reported the chance of sustained human to human transmission [4]. On 30 January, 2020 WHO declared that the disease spreading by 2019-nCoV is a “public-health emergency of international concern” [5]. Eventually on 11 February, 2020 International Committee on Taxonomy of Virus (ICTV) announced the new name of this virus as “severe acute respiratory syndrome coronavirus 2” (SARS-CoV-2). WHO announced ‘COVID-19’ (Coronavirus Disease-19) as the name of this disease caused by SARS-CoV-2 on 11 February, 2020 [6]. On 11 March, 2020, anticipating the severity and vastness in the outbreak WHO declared COVID-19 as pandemic [7].

In the present work we have performed the analysis of self-similarity as well as scaling analysis over the daily number of new confirmed cases of COVID-19 in some major impacted countries viz. USA, Brazil, India, Russia, Spain, UK, Italy, Germany and France. We have taken the data from their respective dates of first report of COVID-19 till June 30, 2020[8]. Due to certain misreporting or late reporting some amount of uncertainty and irregularity often arises in these data. To reduce these uncertainty and irregular fluctuations seven-point moving averages are taken for all the nine time series and the all the present calculations have been further performed over these seven-point moving average data. Scale invariance and self-similarity or self affinity reveals the fractal nature. Exploration of fractal nature has been executed by means of Higuchi method and corresponding fractal dimensions have been obtained. Also scaling analysis has been employed to comprehend the nature of the memory in these time series and corresponding Hurst exponents have been identified. Next, using these seven-point moving average data cumulative profiles of confirmed cases of COVID-19 for these nine countries have been sketched to understand the initial exponential growths in them. Finally an attempt has been made to capitalize the last obtained exponential growth rates for all the nine countries considered to predict the scenario for certain upcoming days within a pre-assigned tolerance level.

2. Theory

2.1 Higuchi Method and Estimation of Fractal Dimension

To examine whether a time series obeys self-similarity or self-affinity and if yes then to calculate its fractal dimension Higuchi [9, 10] invented a method as follows:

We start with a finite set of time series \( \{x(t_n)\} \) where \( n = 1, 2, \ldots, N \) and \( t \) characterizes time chosen at a regular interval, i.e.; \( t_n = t_i + (n-1)\tau \) where \( \tau \) represents the constant gap between two consecutive observation instants.

From \( \{x(t_n)\} \), another time series can be generated as \( \{X(m), X(m+k), X(m+2k), \ldots, X(m+[\lfloor(N-m)/k\rfloor.k]\} \) where \( [ \ldots ] \) is the well-known greatest integer function, \( k \) and \( m \) (\( m = 1, 2, 3, \ldots, k \)) being integers indicate the initial time and the interval time respectively. In this course, for each \( k \), we can get \( k \) sets on new time series. We set the length of the curve analogous to each \( m \) for a particular value of \( k \) of theses new \( k \) time series as follows:

\[
L_m(k) = \left( \sum_{i=1}^{\lfloor(N-m)/k\rfloor} \left| X(m+ik) - X(m+(i-1)k) \right| \right) / k
\]

(1)
The length of the curve for the time interval \( k \), \( \langle L(k) \rangle \) is set as the average value over \( k \) sets of \( L_m(k) \) as obtained in equation (1). If we have \( \langle L(k) \rangle \propto k^{-D} \) we can infer that curve is of fractal nature and \( D \) is its fractal dimension. We can derive fractal dimension \( D \) estimating the gradient of the regressed straight line obtained from the plot of \( \log(\langle L(k) \rangle) \) against \( \log k \). Usually for a self-similar time series, \( 1 < D < 2 \).

### 2.2 Scaling Analysis and Estimation of Hurst Exponent

For the scaling analysis of a given time series Finite Variance Scaling Method (FVSM) is an efficient technique [11-15].

Finite Variance Scaling Method (FVSM) is a popular form of the Standard Deviation Analysis (SDA) (Sarkar e. al., 2005). For a given finite time series \( \{x(t_i)\} \) (where \( n = 1, 2, ..., N \) and \( t \) represents time), this method gives rise to a sequence of cumulative standard deviations \( D(t_j) \) associated with the partial time series \( \{x(t_i)\} (n = 1, 2, ..., j) \) by the following manner:

\[
D(t_j) = \left[ \frac{\sum_{i=1}^{j} x^2(t_i)}{j} - \left( \frac{\sum_{i=1}^{j} x(t_i)}{j} \right)^2 \right]^{\frac{1}{2}}
\]

for \( j=1,2...N \).

For a self-similar time series, eventually, we can find that this \( D(t) \) follows a power law by the following way [11-15]:

\[
D(t) \propto t^H
\]

Here, \( H \) is the Hurst exponent which can be estimated from the slope of the best fitted straight line in the plot of \( \log D(t) \) versus \( \log t \).

The value of the Hurst exponent \( (H) \) ranges between 0 and 1. A value of 0.5 indicates a true random walk implying the time series is Brownian in nature. A Hurst exponent value \( 0<H<0.5 \) indicates a discrete time series with anti-persistent behaviour where autocorrelation is negative. In this situation the time series is ruled by a short memory process. If the Hurst exponent is \( 0.5<H<1.0 \), the time series is governed by long memory process pointing towards a persistent behaviour influenced by positive correlation. If \( H=0 \), we have a white noise and \( H=1 \) indicates a smooth time series.

### 2.3 Variable Growth Rate of Infection During Initial Exponential Growth Phase

During initial exponential growth, the growth of infection altogether follows the following rule:

\[
I(t)=I_0 e^{\mu t}
\]

where \( I \) is the total number of infected at time \( t \), \( I_0 \) is the total number of infected at the initial time, \( \mu \) is the growth rate of infection. Eventually, if this growth rate changes with time then we can have the following:

\[
I(t)=I_0 e^{\mu(t) t}
\]

Here the strategy is to first fix the initial point of time and then find the variable growth rate \( \mu(t) \) at different \( t \) by the following formula:

\[
\mu(t) = \frac{1}{t} \log \left( \frac{I(t)}{I_0} \right)
\]
Next task is to fit a polynomial of certain convenient degree for this $\mu$ as obtained in equation (7). This process is continued till the measure of goodness of fit $R^2$ for the polynomial stays greater than 0.97 and also the percentage of error at each position for the estimated $I$ as counted by equation (6) based on the estimated $\mu$ over the polynomial against the actually observed $I$ stays within 5%.

If that is violated at any stage, we stop at its previous stage and refresh the origin at that end point to start the same procedure afterwards. This strategy is continued till the last observation if all the windows of time thus obtained maintain some significant lengths. If it appears not to be maintained we stop the process till the limit of acceptability with an assertion that the initial exponential growth stage may have been terminated at this level.

3. Results

For the present analysis we have chosen four mostly affected countries by COVID-19 viz. USA (total number of cases: 2,537,636), Brazil (total number of cases: 1,344,143), Russia (total number of cases: 647,822) and India (total number of cases: 566,840) along with five most affected European countries who have already crossed the peak in first phase of attack and in stable condition now viz. UK (total number of cases: 283,545), Spain (total number of cases: 249,463), Italy (total number of cases: 240,436), Germany (total number of cases: 194,259) and France (total number of cases: 156,930) - as per the record till June 30, 2020 [8].

Analysis has been done on daily number of new confirmed cases of COVID-19 in the respective countries from the date of first report of COVID-19 till June 30, 2020 [8].

Table 1 describes the data for the daily new cases of COVID-19 for USA, Brazil, Russia, India, UK, Spain, Italy, Germany and France.

| Country | Starting Date | End Date | No. of Datapoints |
|---------|---------------|----------|------------------|
| USA     | 20th January, 2020 | 30th June, 2020 | 163              |
| Brazil  | 26th February, 2020 | 30th June, 2020 | 126              |
| Russia  | 31st January, 2020 | 30th June, 2020 | 152              |
| India   | 30th January, 2020 | 30th June, 2020 | 153              |
| UK      | 31st January, 2020 | 30th June, 2020 | 152              |
| Spain   | 2nd February, 2020 | 30th June, 2020 | 150              |
| Italy   | 29th January, 2020 | 30th June, 2020 | 154              |
| Germany | 28th January, 2020 | 30th June, 2020 | 156              |
| France  | 24th January, 2020 | 30th June, 2020 | 159              |

Figures 1-9 give the profile of daily new confirmed cases of COVID-19 for USA, Brazil, Russia, India, UK, Spain, Italy, Germany and France.
Figure 1. Daily new confirmed cases of COVID-19 in USA

Figure 2. Daily new confirmed cases of COVID-19 in Brazil

Figure 3. Daily new confirmed cases of COVID-19 in Russia

Figure 4. Daily new confirmed cases of COVID-19 in India

Figure 5. Daily new confirmed cases of COVID-19 in UK

Figure 6. Daily new confirmed cases of COVID-19 in Spain
To reduce uncertainty and irregular fluctuations in the present time series, seven-point moving average is taken and the entire analysis has been further performed over this seven-point moving average data. Number of data points in seven-point moving average data for USA, Brazil, Russia, India, UK, Spain, Italy, Germany and France are 157, 120, 146, 147, 146, 144, 148, 150 and 153 respectively.

Figures 10-18 give the profile of seven-point moving average of daily new confirmed cases of COVID-19 for USA, Brazil, Russia, India, UK, Spain, Italy, Germany and France respectively.
Figure 10. Seven-point moving average of number of daily new confirmed cases of COVID-19 in USA

Figure 11. Seven-point moving average of number of daily new confirmed cases of COVID-19 in Brazil

Figure 12. Seven-point moving average of number of daily new confirmed cases of COVID-19 in Russia

Figure 13. Seven-point moving average of number of daily new confirmed cases of COVID-19 in India

Figure 14. Seven-point moving average of number of daily new confirmed cases of COVID-19 in UK

Figure 15. Seven-point moving average of number of daily new confirmed cases of COVID-19 in Spain
For these time series, investigation of fractal nature has been performed by means of Higuchi method and corresponding fractal dimensions have been calculated. As we have observed from Figure 12 and Figures 15-18 that for those countries number of confirmed cases initially inclined for a certain period, then achieved pick and then started to decline steadily, testing fractal nature for the whole set of data may be misleading as fractal nature may be different for different phases of data. So, for those countries, data is classified in two groups; first data range is from start date to date of achieving its pick and last data range is from next day after attaining its pick to rest of the data till June 30, 2020. From Figure 14, it is evident that for UK, the number of confirmed cases initially started to incline (from day 1 to day 70), attained pick (at day 70), then had a rough behaviour for relatively shorter period (from day 71 to day 92) and then started to decline steadily. So, we have not considered that middle period of turmoil (from day 71 to day 92) for UK as interpretation of self-similarity in that period may be improper.

Figures 19-27 give the profile of fractal nature of seven-point moving average daily new cases of COVID-19 for USA, Brazil, Russia, India, UK, Spain, Italy, Germany and France respectively.
Figure 19. Fractal nature of seven-point moving average of daily new confirmed cases of COVID-19 in USA from day 1 to day 157

Figure 20. Fractal nature of seven-point moving average of daily new confirmed cases of COVID-19 in Brazil from day 1 to day 120

Figure 21. Fractal nature of seven-point moving average of daily new confirmed cases of COVID-19 in Russia (a) from day 1 to day 97; (b) from day 98 to day 146

Figure 22. Fractal nature of seven-point moving average of daily new confirmed cases of COVID-19 in India from day 1 to day 147
Figure 23. Fractal nature of seven-point moving average of daily new confirmed cases of COVID-19 in UK (a) from day 1 to day 70; (b) from day 93 to day 146

Figure 24. Fractal nature of seven-point moving average of daily new confirmed cases of COVID-19 in Spain (a) from day 1 to day 54; (b) from day 55 to day 144

Figure 25. Fractal nature of seven-point moving average of daily new confirmed cases of COVID-19 in Italy (a) from day 1 to day 55; (b) from day 56 to day 148
Figure 26. Fractal nature of seven-point moving average of daily new confirmed cases of COVID-19 in Germany (a) from day 1 to day 64; (b) from day 65 to day 150

Figure 27. Fractal nature of seven-point moving average of daily new confirmed cases of COVID-19 in France (a) from day 1 to day 66; (b) from day 67 to day 153

Next, scaling analysis has been applied to understand the nature of the memory in the time series by means of Hurst exponent.

Figures 28–36 give the profile of scaling analysis of seven-point moving average daily new cases of COVID-19 for USA, Brazil, Russia, India, UK, Spain, Italy, Germany and France respectively.
**Figure 28.** Scaling analysis of seven-point moving average of daily new confirmed cases of COVID-19 in USA.

**Figure 29.** Scaling analysis of seven-point moving average of daily new confirmed cases of COVID-19 in Brazil.

**Figure 30.** Scaling analysis of seven-point moving average of daily new confirmed cases of COVID-19 in Russia.
Figure 31. Scaling analysis of seven-point moving average of daily new confirmed cases of COVID-19 in India from day 1 to day 147

Figure 32. Scaling analysis of seven-point moving average of daily new confirmed cases of COVID-19 in UK (a) from day 1 to day 70; (b) from day 93 to day 146

Figure 33. Scaling analysis of seven-point moving average of daily new confirmed cases of COVID-19 in Spain (a) from day 1 to day 54; (b) from day 55 to day 144
Figure 34. Scaling analysis of seven-point moving average of daily new confirmed cases of COVID-19 in Italy (a) from day 1 to day 55; (b) from day 56 to day 148

Figure 35. Scaling analysis of seven-point moving average of daily new confirmed cases of COVID-19 in Germany (a) from day 1 to day 64; (b) from day 65 to day 150

Figure 36. Scaling analysis of seven-point moving average of daily new confirmed cases of COVID-19 in France (a) from day 1 to day 66; (b) from day 67 to day 153
Then on the basis of seven-point moving average data, a cumulative profile of confirmed cases of COVID-19 in different countries has been generated and visualized in Figures 37-45.

Figure 37. Cumulative number of confirmed cases of COVID-19 in USA obtained from seven-point moving average data.

Figure 38. Cumulative number of confirmed cases of COVID-19 in Brazil obtained from seven-point moving average data.

Figure 39. Cumulative number of confirmed cases of COVID-19 in Russia obtained from seven-point moving average data.

Figure 40. Cumulative number of confirmed cases of COVID-19 in India obtained from seven-point moving average data.

Figure 41. Cumulative number of confirmed cases of COVID-19 in UK obtained from seven-point moving average data.

Figure 42. Cumulative number of confirmed cases of COVID-19 in Spain obtained from seven-point moving average data.
After that, an effort has been made on cumulative number of confirmed cases from seven-point moving average data for different countries to understand the initial exponential growth and also the growth rate of infection. At first, initial point of time (origin) has been fixed to that day after which exponential growth rate has been first observed and variable growth rate $\mu(t)$ at different $t$ is found using equation (7). Then a polynomial of degree 3 is fit for these $\mu(t)$’s as long as till the measure of goodness of fit $R^2$ for this fitted polynomial stays greater than 0.97 and also the percentage of error at each position for the estimated $I(t)$ as counted by equation (6) for the estimated $\mu(t)$ over this polynomial against the actually observed $I(t)$ stays within 5%.

We have stopped to the previous stage at which that is violated and have refreshed the origin at that end point of the previous stage to start the same procedure afterwards. This strategy is continued till the last observation (on June 30, 2020) if all the windows of time thus obtained maintain some significant lengths. If it appears not to be maintained we stop the process till the limit of acceptability with an assertion that the initial exponential growth stage may have been terminated at this level.
Figures 46-54 demonstrate the profile of growth rate in different time windows for cumulative number of seven-point moving average daily new confirmed cases of COVID-19 for USA, Brazil, Russia, India, UK, Spain, Italy, Germany and France respectively.

**Figure 46.** Profile of growth rate of cumulative number of confirmed cases of COVID-19 in USA obtained from seven-point moving average data (a) from day 58 to day 82 taking day 57 as origin; (b) from day 83 to day 157 taking day 82 as origin

**Figure 47.** Profile of growth rate of cumulative number of confirmed cases of COVID-19 in Brazil obtained from seven-point moving average data (a) from day 39 to day 81 taking day 38 as origin; (b) from day 82 to day 120 taking day 81 as origin
Figure 48. Profile of growth rate of cumulative number of confirmed cases of COVID-19 in Russia obtained from seven-point moving average data from day 64 to day 146 taking day 63 as origin

Figure 49. Profile of growth rate of cumulative number of confirmed cases of COVID-19 in India obtained from seven-point moving average data (a) from day 63 to day 119 taking day 62 as origin; (b) from day 120 to day 147 taking day 119 as origin

Figure 50. Profile of growth rate of cumulative number of confirmed cases of COVID-19 in UK obtained from seven-point moving average data (a) from day 44 to day 105 taking day 43 as origin; (b) from day 106 to day 146 taking day 105 as origin
Figure 51. Profile of growth rate of cumulative number of confirmed cases of COVID-19 in Spain obtained from seven-point moving average data (a) from day 36 to day 52 taking day 35 as origin; (b) from day 53 to day 98 taking day 52 as origin; (c) from day 99 to day 144 taking day 98 as origin.
Figure 52. Profile of growth rate of cumulative number of confirmed cases of COVID-19 in Italy obtained from seven-point moving average data (a) from day 30 to day 56 taking day 29 as origin; (b) from day 57 to day 110 taking day 56 as origin; (c) from day 111 to day 148 taking day 110 as origin.
Figure 53. Profile of growth rate of cumulative number of confirmed cases of COVID-19 in Germany obtained from seven-point moving average data (a) from day 41 to day 48 taking day 40 as origin; (b) from day 49 to day 68 taking day 48 as origin; (c) from day 69 to day 129 taking day 68 as origin; (d) from day 130 to day 134 taking day 129 as origin; (e) from day 135 to day 150 taking day 134 as origin.
Figure 54. Profile of growth rate of cumulative number of confirmed cases of COVID-19 in France obtained from seven-point moving average data (a) from day 41 to day 56 taking day 40 as origin; (b) from day 57 to day 82 taking day 56 as origin; (c) from day 83 to day 153 taking day 82 as origin.

Lastly, taking the final estimated $\mu(t)$ calculated over the last window of time and last considered $I_0$ we tried to estimate $I(t)$ for certain number of days after June 30, 2020 and compared with the actually observed $I(t)$ [8] to check how long the next estimated values of $I(t)$ stay within 5% error level when compared with the actually observed $I(t)$. Results are summarized in Figures 55-63.

Figure 55. Comparison between actual data and predicted data of 11 days from last estimated $\mu(t)$ and last considered $I_0$ staying within 5% error level for cumulative number of confirmed cases of COVID-19 in USA obtained from seven-point moving average data.

Figure 56. Comparison between actual data and predicted data of 3 days from last estimated $\mu(t)$ and last considered $I_0$ staying within 5% error level for cumulative number of confirmed cases of COVID-19 in Brazil obtained from seven-point moving average data.
Figure 57. Comparison between actual data and predicted data of 1 day (day 147) from last estimated $\mu(t)$ and last considered $I_0$ staying within 5% error level for cumulative number of confirmed cases of COVID-19 in Russia obtained from seven-point moving average data.

Figure 58. Comparison between actual data and predicted data of 3 days (day 148-150) from last estimated $\mu(t)$ and last considered $I_0$ staying within 5% error level for cumulative number of confirmed cases of COVID-19 in India obtained from seven-point moving average data.

Figure 59. Comparison between actual data and predicted data of 11 days (day 147-157) from last estimated $\mu(t)$ and last considered $I_0$ staying within 5% error level for cumulative number of confirmed cases of COVID-19 in UK obtained from seven-point moving average data.
Figure 60. Comparison between actual data and predicted data of 23 days (day 145-167) from last estimated $\mu(t)$ and last considered $I_0$, staying within 5% error level for cumulative number of confirmed cases of COVID-19 in Spain obtained from seven-point moving average data.

Figure 61. Comparison between actual data and predicted data of 22 days (day 149-170) from last estimated $\mu(t)$ and last considered $I_0$, staying within 5% error level for cumulative number of confirmed cases of COVID-19 in Italy obtained from seven-point moving average data.
Figure 62. Comparison between actual data and predicted data of 7 days (day 151-157) from last estimated $\mu(t)$ and last considered $I_c$ staying within 5% error level for cumulative number of confirmed cases of COVID-19 in Germany obtained from seven-point moving average data

Figure 63. Comparison between actual data and predicted data of 4 days (day 154-157) from last estimated $\mu(t)$ and last considered $I_c$ staying within 5% error level for cumulative number of confirmed cases of COVID-19 in France obtained from seven-point moving average data

4. Discussion and Conclusion:

The present work deals with the investigation of self-similarity as well as scaling analysis over seven-point moving average data corresponding to daily number of new confirmed cases of COVID-19 in some major impacted countries viz. USA, Brazil, Russia, India, UK, Spain, Italy, Germany and France from their respective dates of first report of COVID-19 till June 30, 2020. Application of Higuchi method revealed that fractal dimensions of all the time series for all time windows are within admissible range $(1, 2)$ (Figures 19-27). So the all the time series possess self-similarity or fractal nature which possibly designates a statistical replication of patterns from micro stage to macro stage. Hurst exponent values for Brazil, Russia, UK, Spain, Italy, Germany and France in all time windows are greater than 0.5 (Figures 29-30, Figures 32-36) indicating long or persistent memory which suggests essential dependence between the present and past data. The scaling analysis of USA (Figure 27) and India (Figure 31) gives the Hurst exponent less than 0.5 showing short or anti-persistent memory which in turn indicates an essential dependence between the present and only some near points in past. Possibly this also suggests on an average a relatively shorter incubation period for COVID-19 in USA and India. Also this magnitude in the context of India is somehow very near to 0.5 showing a tendency towards randomness and possibly this observation indicates a more uncertain behaviour in terms of predictability.

Next, on the basis of these seven-point moving average data cumulative profiles of confirmed cases of COVID-19 for these countries have been generated and an effort has been made to understand the initial exponential growths in them (Figures 46-54). Study does not yield a constant growth rate of infection except in the case of Russia; rather it shows a time dependent profile with variable functional representation at different windows of time. This supports the observation of short memory as well as in some cases possible tendency towards randomness which altogether in turn might point towards a complexity in the inherent process. For Russia, a constant growth rate of infection is maintained throughout the time period which may be a quite interesting future scope of study.

Lastly, taking the final estimated growth rate calculated over the last window of time we tried to speculate daily confirmed cases of COVID-19 for the upcoming days beyond our considered range and compared with the actually observed data to check how long the future prediction of the data stays
within 5% error level when compared with the actually observed data (Figures 55-63). Using this technique, the number of days of successful prediction within 5% error level for USA, Brazil, Russia, India, UK, Spain, Italy, Germany and France are 11 days, 3 days, 1 day, 3 days, 11 days, 23 days, 22 days, 7 days and 4 days respectively. So, it is quite evident in general that the growth rate is still very much changing with time making the task of forecasting altogether very uncertain and intricate.

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