**Structural Engineering and Mechanics**, *Vol. 57, No. 3 (2016) 529-541*
DOI: http://dx.doi.org/10.12989/sem.2016.57.3.529


# Fractal behavior identification for monitoring data of dam safety

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*(Received September 15, 2015, Revised December 20, 2015, Accepted January 11, 2016)*

**Abstract.** Under the interaction between dam body, dam foundation and external environment, the dam structural behavior presents the time-varying nonlinear characteristics. According to the prototypical observations, the correct identification on above nonlinear characteristics is very important for dam safety control. It is difficult to implement the description, analysis and diagnosis for dam structural behavior by use of any linear method. Based on the rescaled range analysis approach, the algorithm is proposed to identify and extract the fractal feature on observed dam structural behavior. The displacement behavior of one actual dam is taken as an example. The fractal long-range correlation for observed displacement behavior is analyzed and revealed. The feasibility and validity of the proposed method is verified. It is indicated that the mechanism evidence can be provided for the prediction and diagnosis of dam structural behavior by using the fractal identification method. The proposed approach has a high potential for other similar applications.

**Keywords:** dam safety; observed structural behavior; fractal feature; identification method; rescaled range analysis

## 1. Introduction

Dam body and dam foundation make up a complex dynamic system. Under the comprehensive influence of material and loads, the dam structural behavior presents the time-varying nonlinear characteristics (Su *et al*. 2007). It is very important for dam safety control to identify accurately dam structural behavior. According to the prototypical observations on deformation, seepage, stress, water level, temperature, rainfall, etc., some mathematical methods are usually adopted to analyze and identify the data characteristics in prototypical observations, and the statistical models are built to fit and forecast dam structural behavior. It can be regarded as an effective alternative tool for monitoring dam safety (Ranković *et al*. 2014).

The conventional approaches, which are used to fit and forecast dam structural behavior, focus on the random characteristics in prototypical observations of dam structural behavior (Kao and Loh 2013, Karimi *et al*. 2010). Under the assumption that the observed data series obeys the normal distribution, some standard statistical methods are adopted to analyze the prototypical

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http://www.techno-press.org/?journal=sem&subpage=8 ISSN: 1225-4568 (Print), 1598-6217 (Online)

observations of dam structural behavior. In fact, the observed data series does not obey strictly the normal distribution. Some nonparametric statistical methods need to be introduced to implement the data characteristics identification. Their analysis results are not affected whether the observed data series accords with normal distribution or not.

With the development of nonlinear science since the 1990s, more and more research results show that the scale invariance widely exists in natural systems. Traditional deterministic and random research methods have shortcomings in identifying the long-term service behavior characteristics of the nonlinear systems such as dam engineering. The independence test methods, which are used to identify the short-term correlation of observed data, cannot always identify correctly the long-term correlate behavior characteristics (Huang *et al*. 2010). The fractal theory, which is adopted to analyze the nonlinear law of dam structural behavior, can have a better discovery for the ordered and inherent law contained in observed data series of dam structural behavior and reveal more comprehensively the complex time-varying characteristics of dam system. In the time respect, the fractal time series shows the self-similarity. The statistical self-similarity can be scored with the similarity between different scale density functions, which has a unique advantage in describing the nonlinear systems such as dam engineering. Therefore, it is necessary to understand the dynamic characteristics in prototypical observations of dam structural behavior so that the reasonable data resources can be provided for analyzing and evaluating dam structural behavior based on the prototypical observations.

So far the research on the fractal theory application of hydraulic structure engineering is insufficient (Su *et al*. 2012). The research interests are mainly focused on fractal dimension and fractal correlation dimension combining the fractal dimension with the chaos theory. Considering the field feature monitoring dam safety, the rescaled range (*R/S*) analysis method is introduced to analyze the data characteristics in prototypical observation series of dam structural behavior. This paper studies the identification algorithm and corresponding criterion on the fractal characteristics of prototypical observations of dam structural behavior. The proposed method is used to reveal the time-varying fractal characteristic rule in prototypical observations of dam structural behavior. The formation mechanism on fractal characteristics of observed dam structural behavior is analyzed preliminarily so that the evidence can be provided for forecasting and diagnosing the dam structural behavior with the methods in fractal theory.

## 2. Key fractal characteristics

### *2.1 Long-range correlation*

The long-range correlation of measured time series fluctuation is used to describe the continuous effects of the current conditional variances of measured values on the conditional variances in all forecast periods.

A wide-sense stationary random process, $X=\{X_t:\ t=0,\ 1,\ \ldots\}$, is taken. $r(k)$ represents the autocorrelation function, which is only related to $k$. $r(k)=E[(X_i-\mu)(X_{i+k}-\mu)]/\sigma^2$, $k=0, 1, 2, \ldots$, where $\mu$ and $\sigma$ are the mean value and the variance of random process, respectively. Assume that the autocorrelation function of $X$ can be described as follows.

$$r(k) \sim k^{-\beta}L_1(k),\ k\to\infty \tag{1}$$

where $0<\beta<1$; $L_1$ is the slowly varying function, namely the equation, $\lim_{t\to\infty} L_1(tx)/L_1(t)=1$, is true for all $x>0$. Then $X$ has the long-range correlation characteristics.

### *2.2 Self-correlation*

The self-correlation of one system means that the characteristics of some structures or processes from different spatial scale or time scale are similar, or the local property or local structure of one system or structure is similar with the whole.

For a wide-sense stationary random process, $X=\{X_t: t=0, 1, \ldots\}$, its autocorrelation function is $r(k)$ and the autocorrelation function of its smoothing process, $X^{(m)}(k)$, is $\gamma^{(m)}(k)$. If the autocorrelation function of $X$ can be described as follows

$$\gamma(k)=\frac{\sigma^2}{2}\left(|k+1|^{2H}-2|k|^{2H}+|k-1|^{2H}\right)=\lim_{m\to\infty}\gamma^{(m)}(k),\ k\geq 0, 0<H<1 \tag{2}$$

then $X=\{X_t: t=1, 2, \ldots\}$ can be called the progressive second order self-similar process, namely, when $m\to\infty$, $X=\{X_t: t=1, 2, \ldots\}$ is similar to the second-order statistics of $X^{(m)}(k)$ and is not relevant to the scale. The parameter $H$ is also called the Hurst exponent.

It can be seen from Eq. (2) that when $k\to\infty$

$$\lim_{m\to\infty}\gamma(k)/[H(2H-1)k^{2H-2}]=1,\ 0<H<1 \tag{3}$$

When $H$ is taken as different values, there are the following cases.

1) If $1/2<H<1$, the progressive second order self-similar process is equivalent to the long-range correlation process, namely, the second order progressive self-similar process has the long-range correlation characteristics and is the special case of long-range dependence. The follows can be seen easily from Eq. (2).

$$\sum_{k\to\infty}\gamma(k)=\infty \tag{4}$$

That is, the sum of autocorrelation functions of random process with long-range correlation tends to infinity and the autocorrelation functions decrease slowly. For a series with persistence or enhancing trend, if the series is going up (down) in the former period, then it will continue to go up (down) in the next one. The long memory of time sequence does not change with time scale. The same statistical law exists between the time sequences for different time increments (days, weeks, months, years, etc. ), that is, the daily changes have the effects on the ones in the future and the weekly changes also have the effects on any week in the future. The time sequences have the key characteristics of fractal time series. The strength or persistence of enhancing trend behavior increases with $H$ close to 1.

2) If $H=1/2$, the random process is not the autocorrelation one, that is, the present situation does not affect the future. The familiar white noise series is so. In this case, the follows need be satisfied.

$$\sum_{k\to\infty}\gamma(k)=0 \tag{5}$$

3) If $0<H<1/2$, the random process, $X=\{X_t: t=1, 2, \ldots\}$, only has the short-range correlation

characteristics. In this case, the follows need be satisfied.

$$\sum_{k \to \infty} \gamma(k) < \infty \tag{6}$$

It is an anti-permanent sequence, that is, if the trend of one sequence goes up during one period, it will go down during next period.

The interval, $1/2<H<1$, namely that the long-range correlation of observed sequence is considered, is discussed emphatically in this paper. It can be seen from above analysis that the parameter $H$ can reflect the fractal feature of one random process, namely the strength of self-similar process. So the parameter $H$ obtained with different methods has different effects on the identification result on fractal characteristics of time series.

### *2.3 Scale invariance*

The scale invariance means that, for a local area chosen arbitrarily in fractal, its enlarged graph can still display the morphological characteristics of original graph. Namely, no matter the fractal is amplified or reduced, its properties, such as morphological characteristics, irregularity, complex degree, will not change. So the scale invariance is also called the expansion symmetry. The self-similarity and the scale invariance are closely related. The structure with self-similarity must satisfy the scale invariance. The scale invariance of observed data series on dam structural behavior, such as deformation, stress and strain, shows that the development of dam structural behavior is a process under the interaction between internal and external factors. The past structural behavior has the influence on current and future status, which can be regarded as a biased random walk.

## 3. Fractal characteristics identification method for observed data series on dam structural behavior

It has been known that many natural systems have the typical scale invariance characteristics. The existence of scale invariance shows that the system development is a process under the comprehensive influence of internal and external factors. The influence of system events which have happened in the past will last to the future. It is a biased random walk. To describe and forecast reasonably the dam structural behavior, the long-range correlation of observed prototypical data series needs to be analyzed and identified deeply. To analyze the long-range correlation of time series, the Fourier transform for time series is usually implemented and the logarithmic relationship between energy and frequency is calculated. However, the Fourier method is not a good method for parameter estimation in the sense of statistical stability, because its parameter estimation is lack of robustness. At present, the long-range correlation of time series can be analyzed with the following methods such as the rescaled range (*R/S*) analysis method, the periodic chart method, the detrended fluctuation analysis (DFA) method, the absolute value smoothing method, the Higuchi method, the estimation maximization (EM) analysis method of wavelet domain (Chamoli *et al*. 2007, Chang *et al*. 2006, Shi *et al*. 2008, Weng *et al*. 2008). The analysis for observed data series on dam deformation is taken as an example in this paper. The rescaled range (*R/S*) analysis method is introduced to identify the long-range correlation of dam deformation behavior.

### *3.1 R/S analysis*

For a system with the random characteristics and normal distribution, it can be analyzed with some standard methods. However, for a nonlinear system with the characteristics between randomness and certainty, some nonparametric statistical methods need to be used. When the *R/S* analysis method is adopted to implement the characteristics analysis for observed data series on dam deformation, it is not necessary to assume the distribution feature of *R/S* measured time series, that is, the stability of *R/S* analysis results are not affected by the time series with normal distribution or non-normal distribution. It has important theoretical significance for revealing the long-range effect of dam deformation and exploring the law and persistent measurement of dam deformation.

When Hinstein builds the random walk model on Brownian movement, it is known that the distance of random molecules is proportional to the square root of interval time.

$$R = T^{0.5} \tag{7}$$

where $R$ represents the covered distance; $T$ is the time parameter.

Because it is assumed in Eq. (7) that the mean value and variance for potential sequence are 0 and 1, respectively, for a time series, Hurst rescales the local range $R$ according to the local standard deviation and mean value of the subsequence. Above operation implemented can eliminate the possible influences of different measurement scales and guarantee the range comparability during different periods. The core idea in the *R/S* analysis method is as follows. The time scale of researched object is changed. The statistical changing law within the range of different scales is analyzed. So the law obtained from the small scale can be applied to the large scale, or the law obtained from the large scale can also be applied to the small scale (Couillard and Davison 2005, Wang *et al*. 2006, Rehman 2009, Yin *et al*. 2009, Ienco *et al*. 2013, Oldrich *et al*. 2013, Vlastimil 2013). This method can distinguish the random sequence and non random sequence from fractal time series. Its general expression can be described as follows.

$$R/S = K(n)^H \tag{8}$$

where *R/S* represents the rescaled range value of time series studied; $n$ is the interval length of time increment; $K$ is a constant; $H$ is the Hurst exponent.

The calculation problem on Hurst exponent for time series of observed dam deformation is solved as follows. When a positive integer $\tau$ is given, the mean value of observed dam deformation time series, $\{\xi(t)\}$, $t$=0, 1, …, can be calculated as follows.

$$\langle \xi \rangle_r = \frac{1}{T}\sum_{t=1}^{\tau} \xi(t) \tag{9}$$

At the moment $\tau$, the accumulation deviation of observed variable, $X(t, \tau)$, can be calculated as follows.

$$X(t,T) = \sum_{k=1}^{t}\left[\xi(k) - \langle \xi \rangle_T\right],\ t = 1,2,...T \tag{10}$$

Its range, $R(\tau)$, can be obtained as follows.

$$R(T) = \underset{1 \le t \le T}{\mathrm{Max}}\, X(t,T) - \underset{1 \le t \le T}{\mathrm{Min}}\, X(t,T) \tag{11}$$

Its standard deviation, $S(\tau)$, can be calculated as follows.

$$S(T) = \left| \frac{1}{T} \sum_{t=1}^{T} \left( \xi(t) - \langle \xi \rangle_T \right)^2 \right|^{1/2} \tag{12}$$

Then the rescaled range of every subsequence, namely *R/S*, can be calculated. For the different values of *n*, the different subsequences will be generated and the corresponding rescaled ranges will be different.

The following result can be obtained by using the logarithm function on both sides of Eq. (8).

$$\log \frac{R(t)}{S(t)} = \log(K) + H \log(n) \tag{13}$$

log ($n$) and log $R(t)/S(t)$ can be regarded as the independent variable and the dependent variable, respectively. A line fitting the scattered points can be obtained by the least square estimation. $H$ is the slope of above line.

The follows can be known from the $H$ exponent explanation under different cases in Section 2. The Hurst exponent can reveal the trend components of time series, namely the long-range correlation of time series. And the degree of above trend can be judged according to the value of $H$. Some research work has showed that the relationship between the Hausdorff dimension $D$ and the Hurst exponent $H$ can be expressed as follows.

$$D = 2 - H \tag{14}$$

Namely the relationship between the scale transformation factor $H$ and the fractal dimension for time series can be determined above. The fractal dimension is a quantitative parameter which can be used to describe the self-similarity of one fractal structure. And its value can reflect the complexity degree of one system. Eq. (14) also reveals that the Hurst exponent can be adopted to measure the jaggy degree of a time series to some extent.

### 3.2 V statistic

$V$ statistic, which is proposed by Hurst, is a variable testing the series period. It can be expressed as follows.

$$V = (R/S)_N \big/ N^{1/2} \tag{15}$$

$V$ statistic is originally used to test the stability of *R/S* analysis. It is later applied to the length estimation of long-term memory, which means that the system memory for initial conditions will disappear after one point.

If the *R/S* statistic undergoes a uniform change with the time root ($N^{1/2}$), $H$=0.5, the displayed graph of $V$ statistic is level. If the process is sustained, namely the *R/S* statistic changes faster than the ratio of the time root ($N^{1/2}$), $H$>0.5, the displayed graph of $V$ statistic is upward-sloping. The time series is a long-term changing process. The corresponding result of Hurst exponent depends on the order of data arrangement. The exponent of the time series with changed order is less than that of the original series. If the process is unsustainable, the displayed graph of $V$ statistic is downward-sloping.

Some inflection points, which represent the critical points on periodic cycle of time series, will appear in the $V$ statistic graph. $N$ corresponding to the critical point is the average cycle length of time series.

### *3.3 Significance test of R/S analysis*

For the hypothesis of random walk, $H$=0.5 represents a gradual process. When the analyzed sample number is finite, the $H$ value of random series always deviates 0.5. The $H$ value of time series with random walk can be calculated as follows.

$$E[(R/S)_n] = [(n-0.5)/n](n\pi/2)^{-0.5}\sum_{r=1}^{n-1}\sqrt{(n-r)/r} \tag{16}$$

$E(H)$ can be obtained using of the regression analysis for $\log E[(R/S)_n]\sim\log n$.

$(R/S)_n$ represents a random variable with normal distribution. So $\mathrm{E}(H)$ also obeys the normal distribution. The expected variance is $\mathrm{Var}(H)_n=1/T$, where $T$ represents the total number of analyzed sample.

For a significance test, its null hypothesis $H_0$ is $H=E(H)$, namely the series is a Gaussian process with random walk. Its alternative hypothesis $H_1$ is $H\neq E(H)$, namely the series is a biased random walk with the characteristics such as persistence and memory effect. The hypothesis testing statistic $t$ is

$$t = \frac{H - \mathrm{E}(H)}{\sqrt{1/T}} \tag{17}$$

### *3.4 R/S analysis-based fractal characteristics identification process for observed data series on dam structural behavior*

According to the principle introduced above, a $R/S$ analysis-based process identifying the fractal characteristics for observed data series on dam structural behavior needs to be implemented as Fig. 1.

## 4. Case study

One roller compacted concrete gravity dam is taken as an example. The maximum dam height is 113.0 m, the length of dam crest is 308.5 m, and the elevation of dam crest is 179.0 m. This dam as Fig. 2 consists of 6 dam sections which are numbered 1~6 from left bank to right bank. The normal storage water level and the check flood level are 173.00 m and 177.80 m respectively. The dam construction officially began in April 1998, and the first unit was put into operation on April 29, 2001. The pendulum measurements as Fig. 2 were installed to measure the horizontal displacement of dam crest and dam body. The monitoring system was put into operation in October, 2002.

In this paper, the fractal characteristics for observed horizontal displacement along the river of No. 4 dam section crest is analyzed with the proposed method. The sign (+) indicates the

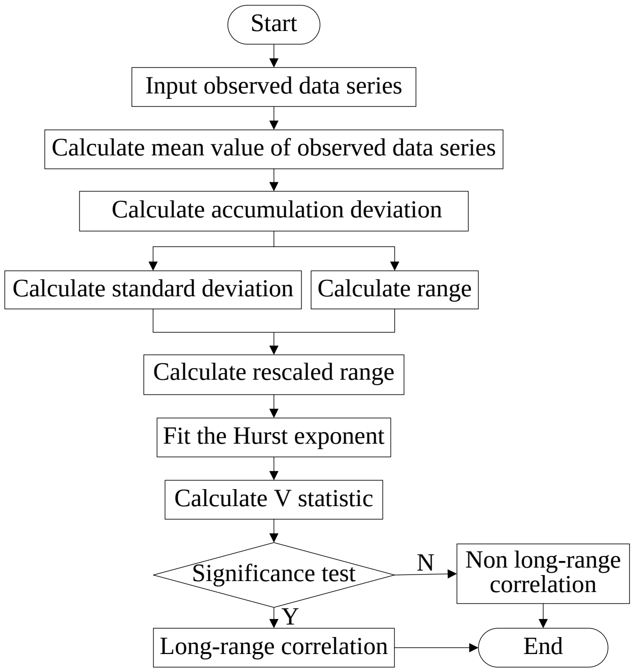


Fig. 1 Fractal characteristics identification flowchart

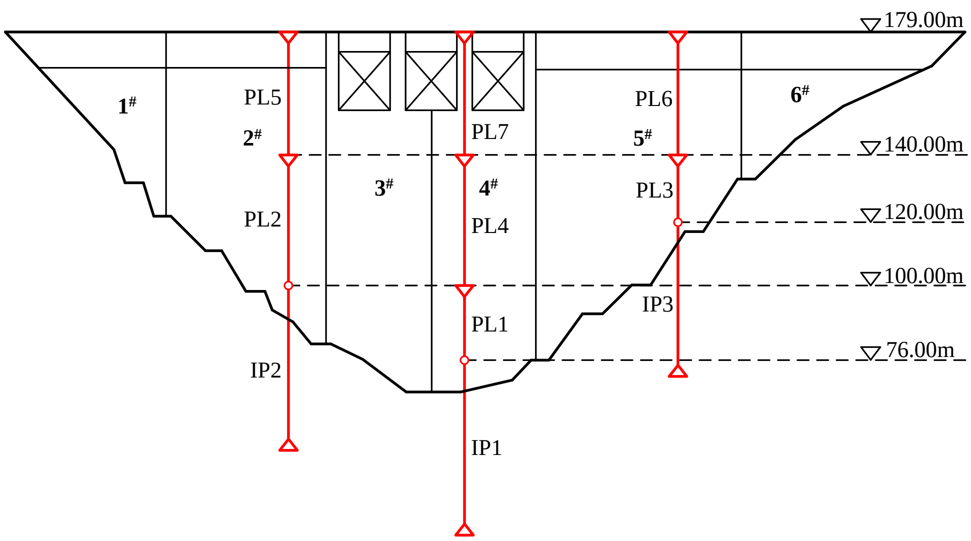


Fig. 2 Layout of pendulum measurements observing horizontal displacement

displacements downstream and the sign (-) indicates the displacements upstream. The 2105 observations, which are obtained from January 1, 2003 to December 31, 2008, are taken as the analyzed samples. The 72 monthly mean values are used to implement the comparison. Fig. 3 shows the time curve of horizontal displacement measured from January 1, 2003 to December 31, 2008. Fig. 4 shows the time curve of monthly mean value.

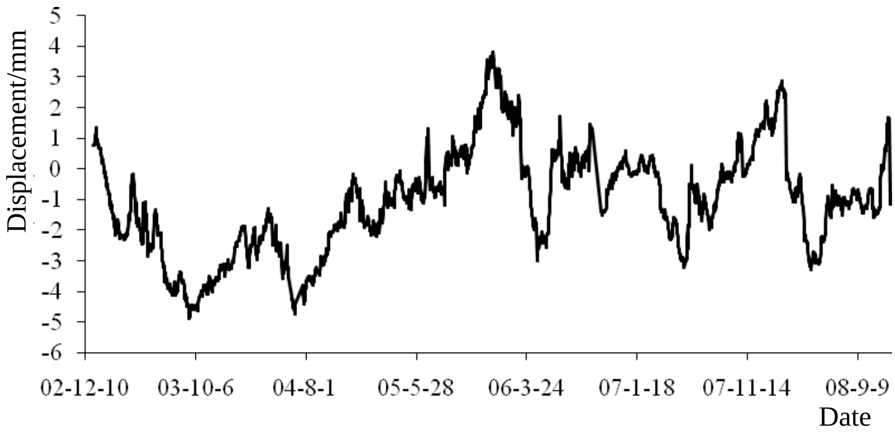


Fig. 3 Time curve on observed horizontal displacement of No. 4 dam section crest

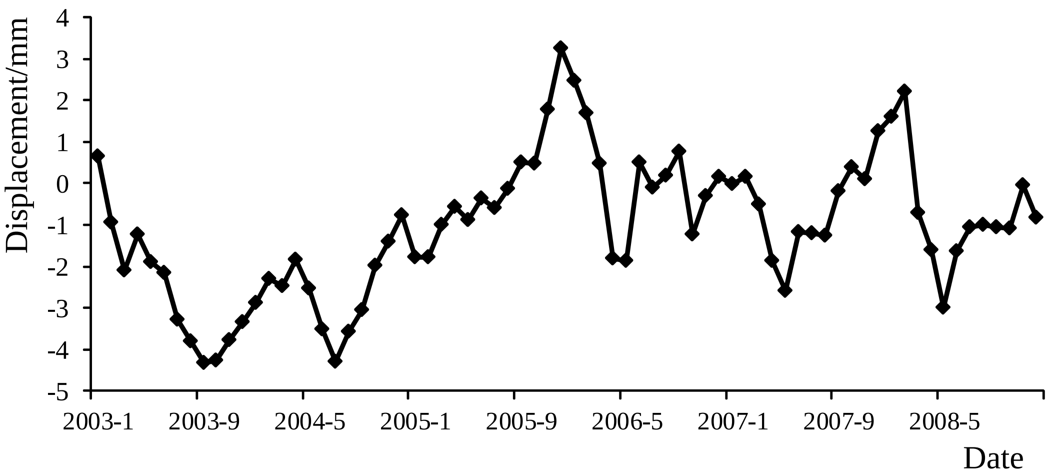


Fig. 4 Time curve on monthly mean value of observed horizontal displacement of No. 4 dam section crest

The Hurst exponent is calculated. The *V* statistic graphs, which are shown in Fig. 5 and Fig. 6, are drawn with log(*N*) as *X* axis and $\log(R/S)_n$ as *Y* axis, or with log(*N*) as *X* and the statistic log(*V*) as *Y* axis. The latter is same with the former in essence. It can be seen from Fig. 5 that the *V* statistic of daily measured value is divided into three sections obviously. According to above analysis in Section 3, the inflection points in the *V* statistic graph can be regarded as the critical points of periodic cycle. However, it can be seen from Fig. 6 that the *V* statistic of monthly mean value cannot reflect the second inflection point. The length of periodic cycle can be determined if enough displacement observations can be obtained and are relatively stable in the subsequent analysis. A detailed analysis is given as follows.

(1) The first critical point in the *V* statistic graph on observed horizontal displacement of No. 4 dam section crest, which is shown in Fig. 5, occurs on January 19, 2001 and its value is 0.6887 mm. It can be seen from the *V* statistic graph that the *V* statistic decreases continuously before this point but increases gradually after that. The corresponding observed displacement also decreases

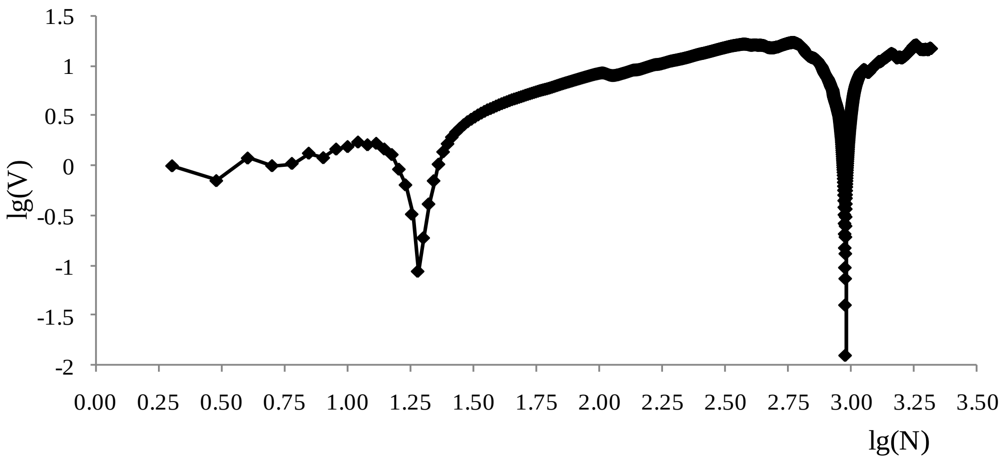


Fig. 5 *V* statistic graph on observed horizontal displacement of No. 4 dam section crest

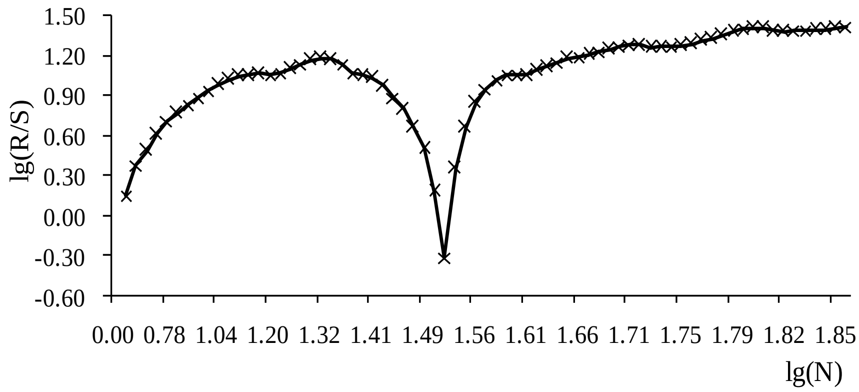


Fig. 6 *V* statistic graph on monthly mean value of observed horizontal displacement

gradually after this point. The general trend of dam deformation leads to the upstream until July 3, 2004. The increasing trend of transitory deformation appears. The main cause resulting in the first critical point is that the measured values are unstable in the early installation of automatic instrument. The dam displacement increases gradually and has the cycle characteristics of upstream and downstream deformation after July 2004. However, the second critical point reflects the changing process of dam displacement from negative value to positive value. It can be known from above analysis for long range dependence in Section 3 that the dam deformation before or after the critical point is long-range correlated. And the trend of dam deformation can be judged with the preceding monitored results. However the data of this cycle has no relationship with next cycle. The *V* statistic graph can reflect well the dam deformation trend.

(2) The *V* statistic value at the critical point in the *V* statistic graph on monthly mean value of observed horizontal displacement of No. 4 dam section crest, which is shown in Fig. 6, is -0.3166 mm. The corresponding monthly mean value of observed horizontal displacement in September 2005 is 0.4917 mm. It can be seen from the time curve on monthly mean value of observed horizontal displacement of No. 4 dam section crest, which is shown in Fig. 4, the monthly mean

Table 1 Hurst exponent of observed displacement for whole process

| Time series | Hurst exponent | Confidence interval | Fitting variance | Hausdorff dimension |
|---|---|---|---|---|
| Daily observation | 0.6927 | [0.6629,0.7226] | 0.5060 | 1.3073 |
| Monthly mean value | 0.5920 | [0.4122,0.7177] | 0.3848 | 1.4080 |

Table 2 Hurst exponent for trend segment

| Time series | Hurst exponent | Confidence interval | Fitting variance | Hausdorff dimension |
|---|---|---|---|---|
| Daily observation | 0.6824 | [0.6478,0.7169] | 0.6319 | 1.3176 |
| Monthly mean value | 0.9608 | [0.9018,1.0199] | 0.9839 | 1.0392 |

Table 3 Significance test results for Hurst exponent of observed displacement

| | Daily observation | | Monthly mean value | |
|---|---|---|---|---|
| | *R/S* | *E* (*R/S*) | *R/S* | *E* (*R/S*) |
| Estimated value | 0.6927 | 0.5439 | 0.5920 | 0.7229 |
| Significance test | 6.8254 | | -1.1107 | |

value of observed horizontal displacement in August 2005 is -0.1311 mm, while all observed horizontal displacement before that are less than 0 and there are the observations of horizontal displacement greater than 0 after that. That is, the observed horizontal displacement along the river of No. 4 dam section crest before the critical point is negative and the dam deformation is upstream. The observed horizontal displacement along the river of No. 4 dam section crest after the critical point is positive and the dam deformation is downstream. Finally the observations of horizontal displacement are possibly positive and negative and the general changing trend is stationary.

(3) It can be seen from the comparative analysis between daily observations and their monthly mean values, that the dam deformation process can be depicted finely with the daily observations, however the slight hysteresis quality exists. The direction of continuous dam deformation can be determined precisely with the monthly mean values of observed displacements. Although the reaction on small circular in a cycle is not obvious, the monthly mean values can reflect well the general trend of dam deformation.

(4) The follows can be seen from Fig. 5. The change rates for some *V* statistics are faster than the change rate of *N*, namely the graph is upward-sloping and the process is sustainable. The change rates for some *V* statistics are slower than the change rate of *N*, namely the graph is downward-sloping and the process is unsustainable. The graph is upward-sloping after that and tends to be stable finally with little change. Therefore, the long-range correlations of displacement time series at different times are different. Hereby, the *R/S* models can be built according to the data before and after the critical point respectively. Then the models are substituted into Eq. (13) to calculate the corresponding Hurst exponents which can be used to reveal the trend of dam deformation.

The least square method is adopted to calculate the Hurst exponent for the whole process and the significance test of *R/S* analysis is implemented. The trend segments are selected to make a comparative calculation. The calculated results are listed in Tables 1-3. In Table 2, which lists the calculated results on Hurst exponent for the trend segments, the trend segment for the daily observation consists of 876 data selected between the first critical point and the second critical point, and the trend segment for the monthly mean value consists of the 22 months data selected before the critical point.

It can be seen from Table 1 and Table 2 that the Hurst exponents of daily observation are rather closed and without big difference, but the Hurst exponents of monthly mean value change greatly. It indicates that the selected trend segments of monthly mean value are not representative and cannot reflect the characteristics on whole time series. The Hurst exponents of daily observation and monthly mean value are both larger than 0.5. Above phenomenon illustrates that the dam displacement series has the significant long range dependence, namely it is a sequence with the persistent and term trend enhanced.

The follows can be seen from Table 3. The statistic $t$ receives the hypothesis test in the interval [-1.645, 1.645], namely the sequence is regarded as a random walk. So the daily observation with long series can be a biased random walk with the persistence and memory effect. The monthly mean value with short series is in an interval, so the results of $H$ are characterized by no significance and bigger fluctuation and indistinctive long memory.

## 5. Conclusions

Under the interaction of dam body, dam foundation and external environment, the dam structural behavior presents the obvious nonlinear space-time characteristics. It is difficult to describe and diagnose the dam structural behavior only using the methods of linear science. The rescaled range analysis method is introduced to analyze the fractal feature on the prototypical observation series of dam structural behavior in this study. The approach identifying the fractal feature on observed dam structural behavior is presented. The formation mechanism on fractal characteristics of observed dam structural behavior is analyzed preliminarily.

- It is indicated in this study that the prototypical observation series of dam structural behavior has obvious fractal features and typical long-range correlations.
- When the rescaled range analysis method is used to analyze the fractal feature on the prototypical observation series of dam structural behavior, it is not necessary to assume the distribution characteristics of *R/S* measured time series. The stability of *R/S* analysis results is not affected by the distribution characteristics of time series. It has important significance for analyzing the long-range effect of observed dam structural behavior, revealing the changing law and determining the persistent measurement of dam structural behavior.
- The application example illustrates that the long-range correlation exists in the prototypical observation series of dam structural behavior. However some problems need to be studied in the future with the more perfect fractal methods. For example, it needs be determined how long the long-range correlation can keep in the long observation time. It needs be revealed what the characteristics of observed data are in each cycle period. The more reasonable evidence can be provided for evaluating the dam structural behavior by solving above problems.

## Acknowledgments

This research has been partially supported by National Natural Science Foundation of China (SN: 51579083, 41323001, 51139001, 51479054), Jiangsu Natural Science Foundation (SN:

BK2012036), the Doctoral Program of Higher Education of China (SN: 20130094110010), Open Foundation of State Key Laboratory of Hydrology-Water Resources and Hydraulic Engineering (SN: 20145027612), the Fundamental Research Funds for the Central Universities (SN: 2015B25414), a Project Funded by the Priority Academic Program Development of Jiangsu Higher Education Institutions (SN: 3014-SYS1401). The authors thank the reviewers for useful comments and suggestions that helped to improve the paper.

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