

Rock Engineering in Difficult Ground Conditions – Soft Rocks and Karst

Eurock 2009

Editor

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CRC Press

Taylor & Francis Group

Boca Raton London New York Leiden

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A BALKEMA BOOK

Wavelet analysis of JRC exemplar profiles

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ABSTRACT: Exemplar JRC profiles are largely used to estimate fracture surfaces roughness on an observational basis, while its subjectivity nature has been mentioned by different people. Despite many attempts to replace this with various statistical parameters, the simplicity of JRC is the main reason for its use. In this paper the digital elevations of JRC profiles were subjected to Fourier and wavelet transforms. JRC signals energy within dominant frequency band was used to characterize surface roughness. Also, JRC profiles were decomposed into its sub-signals at different frequencies with an assigned energy level corresponding to the amount of its frequency changes, i.e. profile waviness and roughness. Comparing the results for ten profiles indicates that despite the initial intention of increasing roughness as JRC increases the order of JRC profiles changes unexpectedly; for example JRC8 is less rough than JRC6. This demonstrates the difficulty associated with using JRC to determine fracture surface roughness.

1 INTRODUCTION

The mechanical behaviour of rock fractures is complex and influenced by a great variety of factors, such as rock elastic properties, intact rock friction, material bond strength, material stiffness, presence of fluids and debris at the interfaces and surface roughness (or morphology). In this work, we study the effect of latter parameter, i.e. surface roughness and examine the difficulty associate with the use of most commonly used observational method of exemplar JRC profiles in estimating roughness of a rock fracture surface.

Most discontinuity surfaces are rough at many scales. Roughness has significant implications for estimating contact areas and modeling the hydro-mechanical response of fracture asperities under the applied external forces (i.e. normal and shear loads). In rock engineering, fracture asperity sliding, separation, shearing, wearing and breakage are kinds of failure modes in which fracture surface roughness is identified as an effective factor. Among them asperity shearing has sophisticated mechanism which has not been fully understood due to its dependency to fracture surface roughness. Numbers of empirical criteria have been developed to estimate the contacts shear strength. Empirical shear strength criterion introduced by Barton (1973) is the widely used method in which roughness of a fracture surface is estimated on an observational basis by comparing it against 10 exemplar profiles and assign a value between 1 and 20 as being the profile roughness. This parameter is called Joint Roughness Coefficient (JRC) proposed later by Barton & Choubey (1977).

To date, despite several attempts to replace JRC with other methods such as artificial neural networks (Lassard & Hadjigeorgiou 1998), multivariate statistical approach developed in Riemannian space (Rasouli 2002), statistical techniques (Unver & Unal 2004), and fractal (Kulatilake et al., 2006), the general preference in rock engineering is to use JRC for roughness determination. This is perhaps due to the simplicity of using this method.

The Fourier transform method has been used successfully in characterizing fracture surfaces morphology (Aydan et al., 1996). Later in 2001, the Fourier series function was applied to resolve the original JRC profiles. Two fracture models containing various harmonics of Fourier series function coefficients were tested to investigate the role of primary and secondary asperity in the shear behavior of fracture surface (Yang et al., 2001). They concluded that JRC is unable to describe the roughness behavior of a fracture composed of different scaled asperities. In this study, Fourier transform was applied to obtain JRC signals energy.

Wavelet technique, with its main application in electrical engineering to characterize signals and waves has been applied to other engineering disciplines mostly in mechanical engineering. Lee et al. (1998) carried out the potential application of wavelet transform to explore roughness and morphological characterisation of surface. Similarly, Josso et al. (2000) introduced a new wavelet strategy for roughness analysis. They proposed frequency normalized wavelet transform for surface roughness characterization (Josso et al., 2001). However, to the knowledge of the Authors, wavelet technique has not been used extensively in rock

fracture surface roughness characterization and the analysis of 2D profile roughness reported by Lee et al. (1998) is one of the few attempts carried out in this area.

In current paper we apply wavelet method to assess the subjectivity nature of using JRC profiles in roughness characterisation of fracture surfaces. To do this JRC exemplar profiles were decomposed to signals and sub-signals using wavelet technique. Each decomposed signal is assigned an energy level corresponding to the amount of its frequency levels. It was found that the major portion of energy signals is accumulated within 1% of frequency bands. Also, comparing the wavelet results for ten JRC exemplars indicates that despite the initial intention of increasing roughness as JRC increases the order of JRC profiles change unexpectedly; for example JRC8 is less rough than JRC6. This demonstrates the real difficulty associated with using JRC to determine profile roughness and why the use of JRC or any observational method is not trustworthy for roughness estimation of fracture surfaces.

2 FRACTURE SURFACE MORPHOLOGY

Joint Roughness Coefficient (JRC) developed by Barton & Choubey (1977) is perhaps the most widely used observational tool to incorporate the fracture surface roughness effect in its hydro-mechanical behaviour. It was first implemented to estimate the shear strength of rock fractures through the simple failure criterion in the form of (Barton 1973):

$$\tau = \sigma_n \tan \left(\phi_r + JRC \log_{10} \left(\frac{JCS}{\sigma_n} \right) \right) \quad (1)$$

where σ_n is the effective normal stress, ϕ_r is the residual friction angle, JCS is the joint wall compressive strength and JRC is the joint roughness coefficient (1 for the smoothest and 20 for the roughest surface).

Figure 1 shows exemplar JRC profiles with its numerical values next to it. To estimate JRC value, one needs to compare the morphology of the real fracture against these standard profiles and choose the closest one. The immediate difficulty in use of this observational method is that the morphology of 3D fracture surfaces is very complicated and the choice of direction to at which the surface is looked, at (surface roughness anisotropy) can influence the results significantly.

To investigate this difficulty in further detail, here, these profiles are analysed using the approach used in image processing, as being a robust tool in

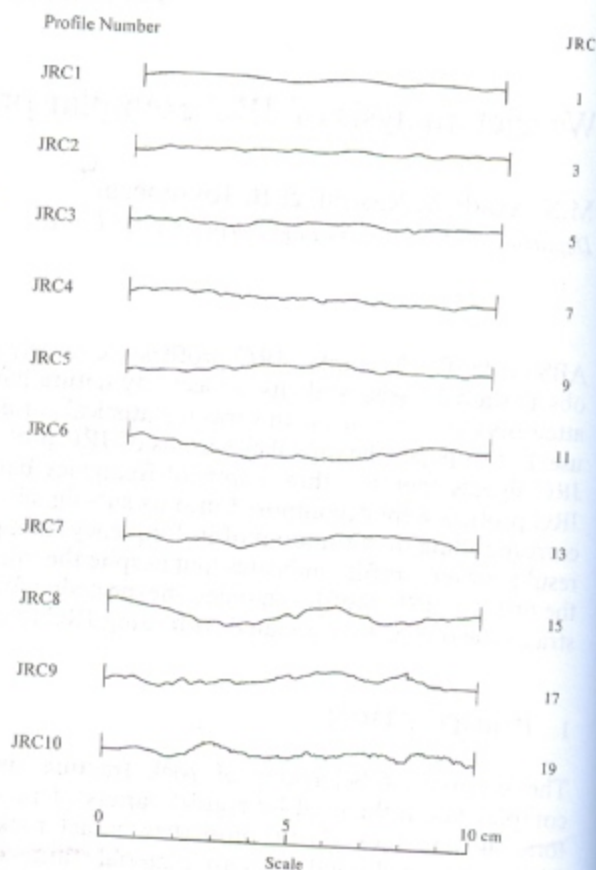


Figure 1. Exemplar JRC profiles (Hudson & Harrison 1998).

synthesizing signals to extract information regarding its variation at different frequencies (Poropat 2008). Therefore, in this study, (x,y) co-ordinates of the JRC exemplars extracted from its original profiles (Rasouli & Harrison 2001) were subjected to wavelet analysis, as one of the techniques available in signal processing. As many as 5500 points for each profile was available and used for this analysis.

One of the objectives of this study was to distinguish between waviness and roughness (i.e. first and second order variation) of each JRC profile. In a more general classification this is referred to as the roughness, the waviness and the form (British Standard Institution 1982), which represents features of the surface at three different wavelengths. Finding the optimum cut-off frequencies to separate these three wavelengths is of great concern to surface characterization.

Within the scope of this work, JRC exemplar profiles are decomposed using wavelet techniques, and for each profile high and low frequency bands are separated as being equivalent to first and second order asperities (i.e. waviness and roughness), respectively.

3 WAVELET TRANSFORM

A 1D wavelet is used for this study. Since JRC exemplar profiles represent fracture surface roughness, extracted elevations of each profile is analysed using a wavelet technique where the original profile is treated as a signal and decomposed into its sub-signals at different frequencies. A discrete wavelet transformer (*DWT*) of a signal $x(z)$ as defined below (Daubechies 1988 & Mallat 1989).

$$DWT_x^w(\tau, s) = \frac{1}{\sqrt{|s|}} \int x(z) \psi\left(\frac{z-\tau}{s}\right) dz \quad (2)$$

transforms signal $x(z)$ using mother wavelet $\psi(z)$ from distance domain (z) to translation (τ) and scale (s) domain. In equation 2, $z-\tau$ is the distance translation. The term $1/\sqrt{|s|}$ is normalization factor and removes the scale effect from wavelets with different scales. An increase in scale s (i.e. smaller frequency) corresponds to a larger window being analysed, which reduces the ability in distance resolution but increases the frequency resolution ability. Therefore by increasing the scale, smaller frequency bands are detected and efficiency resolution increases whereas this ability reduces in distance domain.

Here, a signal energy matching algorithm is used to choose the optimum mother wavelet in order to analyse the JRC exemplar profiles, where the signal is firstly transformed from distance-amplitude domain to frequency-amplitude using a Fourier transformer to detect the dominant frequencies. Then the signal is transformed using different mother wavelets.

Energy matching strategy is taken into account in which a wavelet with the highest energy matches between amounts of signal energy at the dominant frequency band (Burrus et al., 1997). In current study, this strategy was applied to choose the optimum mother wavelet. The procedure was first to define the signal energy of 10 JRC profiles within dominant frequency band using Fourier transform. Thereafter, optimum mother wavelet was found by searching the best match between JRC signals energy and standard wavelets energy (Table 2).

4 WAVELET ANALYSIS OF JRC PROFILES

In this study, we employ two parameters obtained from Fourier transform technique and wavelet decomposition analysis to study roughness of JRC profiles. These are the signal energy and the amplitude of JRC profiles within different frequency bands with the objective of discriminating the first and second order asperities, waviness and

roughness, respectively. This is explained in the following subsections.

4.1 Signal energy analysis of JRCs

Different energy levels are laid at high and low frequency bands of a signal. Fourier transform has to be utilized in order to calculate the magnitude of relative and absolute signal energy. To choose the optimum mother wavelet, Fourier transform of ten exemplar JRC profiles were acquired and frequencies with dominant energy were used for the analysis purposes. Fourier transformer transforms signals from distance domain to frequency domain. For instance, Fourier transform of profile JRC7 is given in Figure 2. It is seen that the area of effective frequency band (EFB) is extremely small. In current study, Magnitude of signal energy in EFB was considered as a main parameter to characterize roughness of JRC profiles.

It is seen that the effective frequency is limited to 2.4 Hz where maximum frequency is 204 Hz. Therefore, maximum effective frequency (i.e. particular frequency band along which the majority of signal energy takes place) in JRC profiles is 2.4 Hz. Finally, results of Fourier transform show that JRC signals energy is almost accumulated within 1% of frequency bands.

Figure 3 indicates the EFB signal energies (EFBSE) corresponding to ten JRC profiles calculated from their corresponding Fourier transform analysis. In principal, it is expected that a profile with larger EFBSE has smoother profile geometry. This logic appears to be followed for profiles

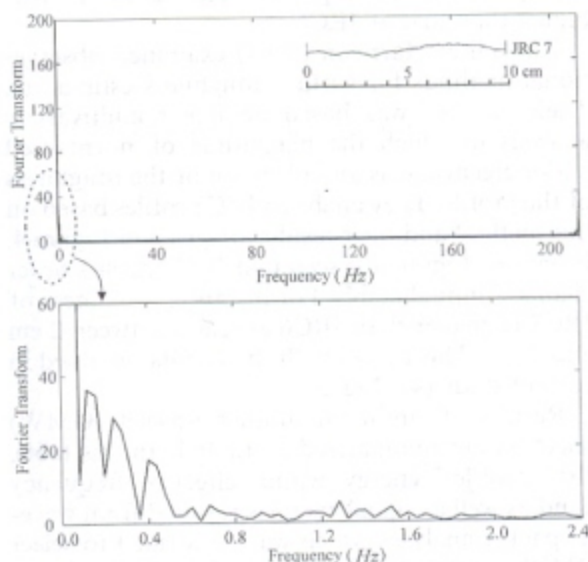


Figure 2. JRC7 Signal energy within entire (top) and 1% (bottom) of frequency band obtained from Fourier transform.

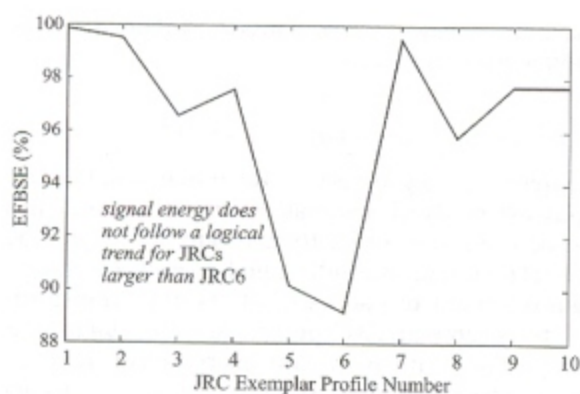


Figure 3. EFBSE of JRC exemplar profiles.

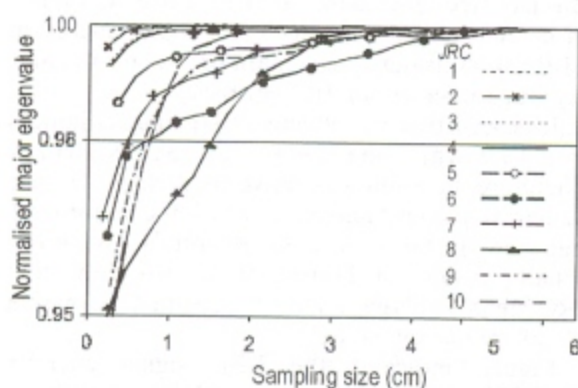


Figure 4. Multivariate analysis of JRC profiles' roughness (Rasouli & Harrison 2001).

between JRC1 and JRC6, but unexpectedly becomes invalid for profiles greater than this, for example EFBSE for profile JRC7 is about 10% higher than that of JRC6.

Rasouli & Harrison (2001) examined observational methods for surface roughness estimation. Their analysis was based on linear multivariate analysis in which the magnitude of normalised major eigenvalue is an indication of the roughness of the profile. They analysed JRC profiles based on this method and their results are given in Figure 4. From this Figure it is seen that JRC profile's order changes unpredictably. For instance, roughness of JRC8 is greater than JRC6 at scales between 2 cm and 4 cm. This agrees with the results obtained in current study (see Fig. 3).

Results of optimum mother wavelet (OMW) selection are summarized in Table 1. In this table, JRC profiles' energy within effective frequency band as well as signal energies resulted from wavelet packet analyses which was performed to select OMW is presented. It is noted that the results of Fourier transform represent the low variability in JRC profiles amplitudes. This quantity will be used later to separate roughness from waviness.

Table 1. JRC signals energy and optimum mother wavelets.

| Character | EFBSE % | OMW | OMWE % |
|-----------|---------|-----------------|--------|
| JRC1 | 99.84 | <i>rbio</i> 3.3 | 99.84 |
| JRC2 | 99.52 | <i>rbio</i> 3.3 | 99.78 |
| JRC3 | 99.59 | <i>rbio</i> 3.1 | 96.60 |
| JRC4 | 99.58 | <i>rbio</i> 3.3 | 97.78 |
| JRC5 | 90.16 | <i>rbio</i> 3.3 | 97.56 |
| JRC6 | 89.12 | <i>bior</i> 3.7 | 98.96 |
| JRC7 | 99.46 | <i>bior</i> 3.1 | 99.83 |
| JRC8 | 95.79 | <i>rbio</i> 3.3 | 98.94 |
| JRC9 | 97.71 | <i>rbio</i> 3.3 | 98.22 |
| JRC10 | 97.71 | <i>rbio</i> 3.1 | 96.37 |

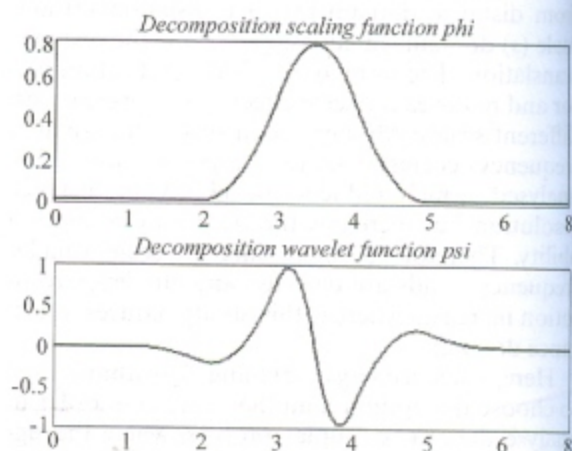


Figure 5. Wavelet (top) and scaling (bottom) functions of mother wavelet *rbio* 3.3.

Table 1 indicates that mother wavelet *rbio* 3.3 is the optimum mother wavelet for signal decomposition of 6 JRC profiles. Therefore this function is to be used if a unique OMW is required. Decomposed scaling and wavelet functions of optimum mother wavelet *rbio* 3.3 are given in Figure 5.

Later in section 4.2, amplitude of decomposed JRC signals is used as a key parameter to reclassify JRC exemplar profiles in terms of their roughness and waviness. Magnitude of this parameter is a function of chosen optimum mother wavelet. Therefore, mother wavelet *rbio* 3.3 was used in this work as an optimum mother wavelet.

4.2 Amplitude analysis of JRCs

Patton (1966) recognized that the behavior of rock fractures is controlled preliminary by the second order asperities (roughness) during small displacements and the first order asperity governs the shearing behavior for large displacements (e.g. in faults). So it is necessary to distinguish between

waviness and roughness components in each JRC profile, in order to assess their effect on hydromechanical behaviour of rock fractures (Yang et al., 2001). To do so, here amplitude analyses of JRC profiles were carried out using wavelet decomposition technique.

Figures 6 and 7 show the approximation a_4 and the details d_4 of exemplar JRC profiles, respectively in which mother wavelet *rbio* 3.3 has been utilized for wavelet decomposition up to level 4. It should be noted that details d_1 , d_2 , and d_3 were identified as white noises, due to the lack of sampling points and therefore will not be included in the analyses. Hence, only d_4 and a_4 are taken into account as effective frequency bands for the analysis of JRC profiles. Amplitude parameters characterize the surface based on the vertical deviations of the profile asperity from the mean line. Maximum vertical deviations from mean line were obtained from both a_4 and d_4 wavelet signals to assess the order of JRC exemplar profiles.

In addition to signal energy, the amplitude deviation can be used as a second parameter to characterise profile roughness in a_4 and d_4 frequency bands. In figure 8, maximum amplitude deviation is given in both a_4 and d_4 frequency bands

which show JRC profiles waviness and roughness, respectively.

It is expected that the profile roughness increases as the amplitude deviation becomes larger. This appears to be the case for profiles between JRC1 and JRC6, but unexpectedly becomes invalid for profiles JRC7, JRC9, and JRC10. For example amplitude deviation of profile JRC7 is smaller than that of JRC6 (Fig. 8). It is noted that the results exhibit almost similar trend in JRCs order in both wavelet decomposition and Fourier transform analyses (see Fig. 3). Dashed line in Figure 8

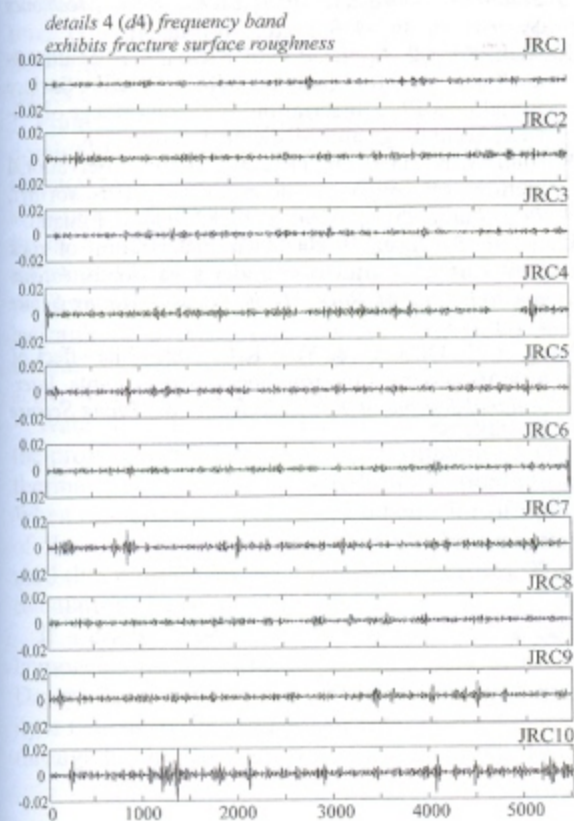


Figure 6. Approximation (a_4) frequency band of JRC profiles.

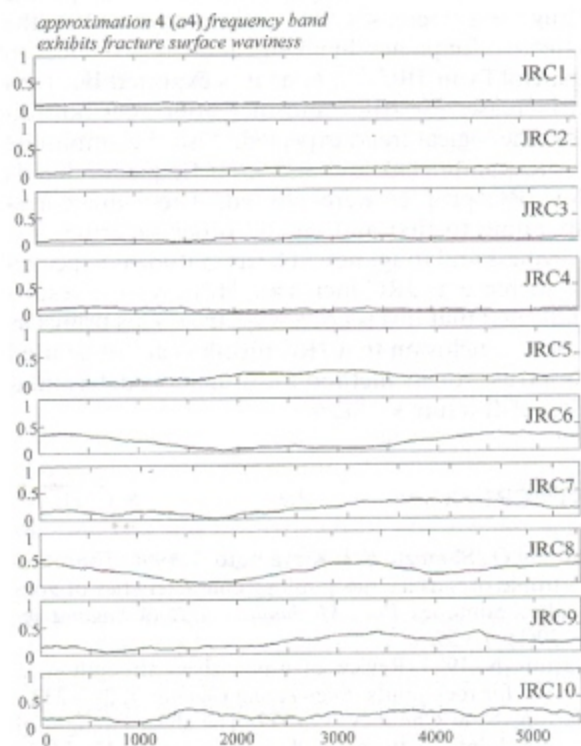


Figure 7. Details (d_4) frequency band of JRC profiles.

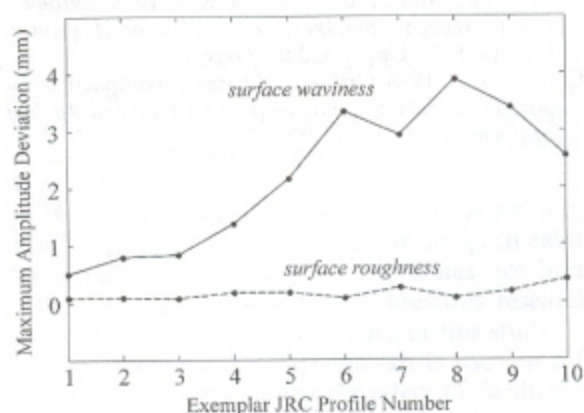


Figure 8. First and second order asperities in JRCs.

corresponds to surface roughness where amplitude deviation is extremely small comparing to the solid line which corresponds to surface waviness, as expected.

5 CONCLUSION

In this study JRC exemplar profiles were subjected to Fourier and wavelet transforms. In this method, each profile is treated as a signal and was decomposed into its different frequency bands each associated with a level of energy. In general, the energy level within LFB is expected to reduce as profile roughness increases. The results show that the effective frequency band signal energy, reduces in general from JRC1 to 6, as it is expected but then it increases for JRC7 and thereafter does not follow the logical trend expected. Also the amplitude corresponding to low and high frequency bands for JRC profiles were plotted. These are corresponding to first and second order asperities, i.e. waviness and roughness. The amplitude is expected to increase as JRC increases. However the results indicated that this is not always true. This brings us to the conclusion that JRC profiles cannot be used as a trustworthy method for roughness determination of fracture surfaces.

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