Seismic texture analysis for reservoir prediction and characterization

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A plethora of seismic attributes are currently in use for reservoir prediction and characterization. Some are useful in understanding subsurface stratigraphy (like channels) while others are useful for structural interpretation (anticlines, faults/fractures etc). Volumetric computation of seismic attributes is helpful to interpreters for 3D seismic visualization and interpretation. In addition to the time of a seismic reflection (resulting in a time-structure map), the more commonly used seismic attributes are rms amplitude, frequency, coherence, AVO, and impedance. These attributes are based on clearly established morphological or petrophysical models with some attributes sensitive to rock types, some to fluid saturation, some to porosity and some to minor faults or fractures within the reservoir. Our case study of a diagenetically altered Mississippian limestone resulting in complex paleo topography defies simple analysis. Even with adequate well control and good ties to 3D seismic data, uncertainty in the attribute expression of different reservoir architecture may result in the failure to identify sweet spots for drilling.

In Tertiary basins, wells drilled on the basis of direct hydrocarbon indicators such as bright spots sometimes turn out to be dry or uneconomic, as a small amount of gas present in a reservoir could produce amplitudes similar to a reservoir saturated with gas. Furthermore, bright spot and AVO technology is more difficult to apply to more indurated Paleozoic rocks, and to carbonate rocks in general. In this paper, we use gray-level co-occurrence matrix (GLCM) texture analysis to correctly predict and characterize the reservoir parameters. We generate volumetric texture attributes and study the rock types by evaluating the response of reservoir to nonreservoir facies with respect to fluid saturation in a development field. We suggest that texture analysis can be utilized as an interpretation tool by geoscientists during exploration and exploitation stages of a field.

Seismic texture analysis

Haralick et al. (1973) introduced the concept of texture analysis for image processing. GLCM texture analysis is routinely used in remote sensing applications of urban planning and agriculture. Hall-Beyer (2007) defines texture as "an everyday term relating to touch that includes such concepts as rough, silky, and bumpy. When a texture is rough to the touch, the surface exhibits sharp differences in elevation." Seismic textures work in an analogous manner with elevation replaced by amplitude, and the probing finger by a rectangular or elliptical analysis window oriented along the structure. Love and Simaan (1984) were among the first to apply texture analysis to seismic data. Gao (1999a, 1999b, 2003) and West et al. (2002) used statistical measures of the gray-level co-occurrence matrices (GLCMs) to extract patterns of common seismic signal character which can be related to the geologic environment in which their constituents were deposited. These textures were combined and analyzed using unsupervised self-organizing maps and supervised learning neural networks, respectively.

Seismic texture attributes are statistical measures of amplitude (or other attributes) extracted along a dipping horizon. While the internal architecture of geologic elements may fall below seismic vertical resolution, lateral variation within these elements may give rise to a distinct texture that can be detected and recognized. Skilled interpreters can often recognize turbidites, mass transport complexes, dewatering features, carbonate build-ups and diagenetic alteration by their appearance, or texture, on time slices. GLCM quantitatively measures these textures by tabulating how often different combinations of voxel amplitude brightness values (gray levels) occur within an analysis window. Our method differs from others in that it employs structure-oriented computation and can therefore be applied to 3D seismic volumes. Given that the seismic wavelet modulates the reflection coefficients and hence the subsurface lithology, we feel that measures such as spectral decomposition do an excellent job of measuring amplitude variability normal to the locally dipping plane. Parallel to the local dip, we define a local analysis window. We reformat the data from 32-bit floating point format to a user-defined number of integer gray levels. If we choose the number of gray levels to be 65, then levels 1–32 would correspond to troughs, 33 to a zero-crossing, and levels 34–65 to peaks. We can compute the GLCM matrix, **P**, within a $(2m_x + 1)$ by $(2m_y + 1)$ window:

$$P_{ij} = \sum_{p=-m_x}^{+m_x} \sum_{q=-m_y}^{+m_y} \delta(d_{p,q} - i)\delta(d_{p+\Delta p,q+\Delta q} - j) \qquad (1)$$

where $d_{p,q}$ and $d_{p+\Delta p,q+\Delta q}$ are the integer-valued scaled seismic data at the (p,q) and $(p + \Delta p, q + \Delta q)$ CDP locations and the delta function, $\delta(\xi) = 1$ if $\xi = 0$ and 0 otherwise.

To illustrate GLCM process, we first set our quantization level to vary between 1 and 9, where values of 1–4 correspond to troughs, 5 to a zero crossing, and 6–9 to peaks (Figure 1) in order to generate and display a small (9 by 9) GLCM matrix. For flat to moderately dipping horizons, vertically adjacent samples carry much the same information about the geology, and are correlated by convolution of the seismic wavelet with the reflectivity. This redundancy suggests that we can stack our GLCM statistical measures to obtain a more robust result. Our implementation extracts a rectangular window of data and its Hilbert transform along dip of a user-defined length, width, and height. Within this window, the rms am-

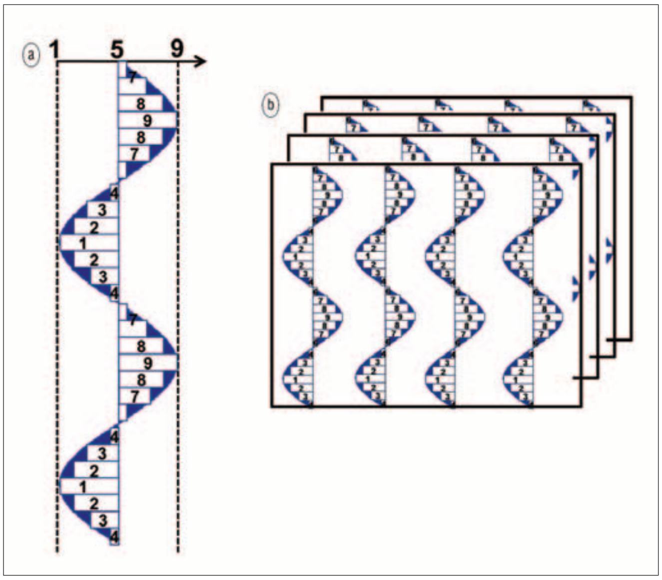

Figure 1. (a) Seismic trace representation using nine gray levels. (b) A cubic texel.

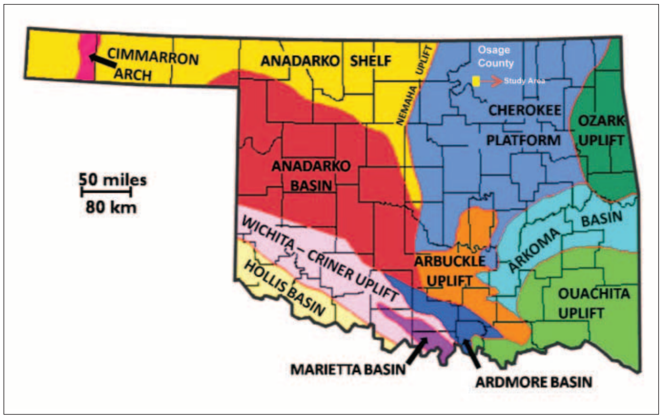

Figure 2. Map showing the geological provinces of Oklahoma. e study area is in Osage County, the Cherokee Platform, northeast Oklahoma. (Modi ed after Northcutt and Campbell, 1995.)

plitude of each time sample is calculated. The data within the analysis window are then scaled so that the data quantization levels ranging between 1 and 65 span two standard deviations of the input seismic amplitude data. The GLCM statistical measures (attributes) are calculated at each sample within the analysis window for both the data and its Hilbert transform, and then summed together using normalized weights based on the rms amplitude.

Haralick et al. (1973) proposed 14 statistical measurements of the GLCM; Gao (2003) added one more measurement, randomness. Each measure is a function of the co-occurrence probability, P_{ij}, (the coefficients of the GLCM matrix) of a given gray-level relationship to the amplitude values (i and j) or differences (i-j), resulting in a total of 15 GLCM attributes. These 15 measurements can be broken into three general categories: contrast, orderliness, and statistics.

The contrast group of GLCM attributes includes Haralick et al.'s measurements of contrast, dissimilarity, and homogeneity. Their weights are related to the distance (i-j) from the GLCM diagonal. Because the contrast group of attributes is a function of amplitude differences (i-j), rather than amplitudes (i and j), it is insensitive to the mean value of the amplitude within the analysis window, and is a measure of texture, independent of how strong or weak the average amplitude may be. GLCM contrast is weighted by the square of the gray-level differences whereas the dissimilarity is weighted by the absolute value of the gray-level differences. While calculating the homogeneity, the weights are inversely proportional to the square of the distance away from the diagonal.

The orderliness group of GLCM attributes includes Haralick et al.'s measurements of energy and entropy and Gao's measure of randomness. The orderliness group includes measurements of how smoothly varying the voxel values or seismic amplitudes are within a window and is a function only of the GLCM matrix values, P_{ij}, and not of the amplitude values themselves (i and j). Thus, like the GLCM contrast attributes which are a function of (i-j), the GLCM orderliness attributes are a true measurement of texture, independent of the mean amplitude in the analysis window. High values of energy occur when the amplitude values in a window vary smoothly. For seismic interpreters, the word "energy" leads to considerable confusion, because the GLCM energy attribute has absolutely nothing to do with the value of seismic amplitude, but rather with a measure of the change in seismic amplitude. The GLCM entropy attribute, S, measures the disorderliness (or roughness) rather than the orderliness (or smoothness) of the patch of seismic amplitude values; maximum entropy occurs when all probabilities of values are equal and therefore result in a random distribution of values.

The statistics group of GLCM attributes includes Haralick et al.'s measurements of mean, variance, and correlation. Of all 15 texture attributes, we found the following three measures generate the desired discrimination without any redundancy: homogeneity, energy, and entropy. Homogeneity gives the information about the overall smoothness of an image and is useful for quantifying reflection continuity. Energy which measures textural uniformity in an image is low when all elements in the GLCM are equal and is useful for highlighting geometry and continuity. Entropy which measures disorder or complexity of an image is large for images that are texturally not uniform.

Case study

The study area, in Osage County in northeastern Oklahoma, is bounded by the Ozark uplift to the east, the Nemaha uplift to the west, the Kansas state boundary to the north, and the Arkansas River to the southwest. This county is part of the gently west-southwest sloping stable shelf also known as Cherokee platform, which extends into the Anadarko and Arkoma basins from the Ozark uplift (Figure 2). Angelo et al. (2009) used GLCM attributes in a qualitative (unsupervised) analysis of a different survey in the same area using self-organizing maps. This paper builds on their effort by quantifying the GLCM attribute expression to well control in an active field currently undergoing drilling and production. The field is producing from both the Redfork sandstone and the

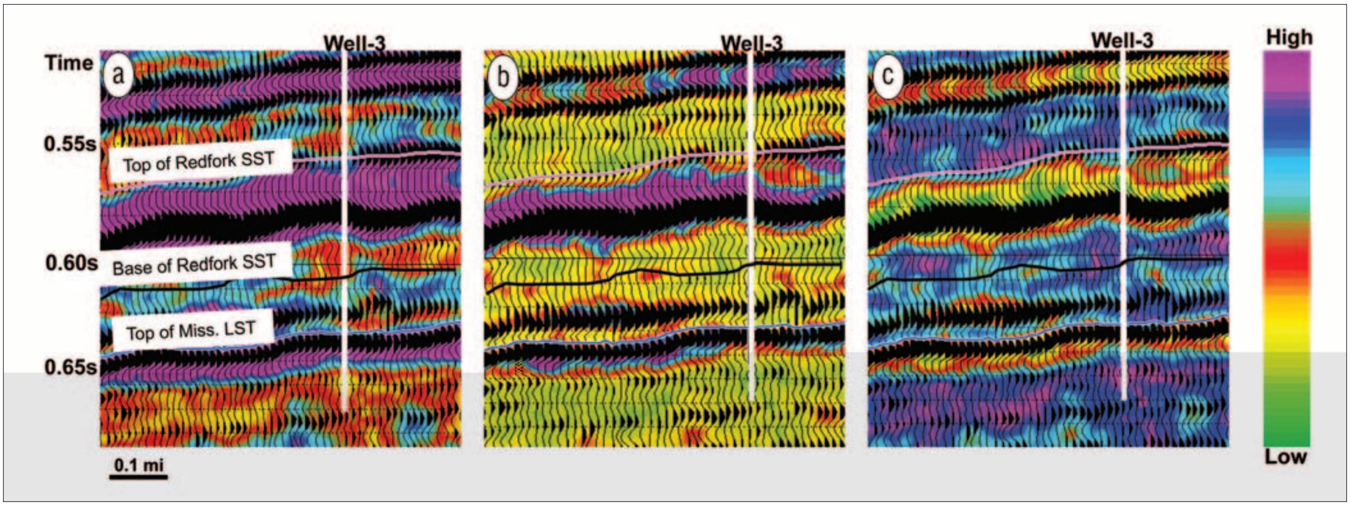

Figure 3. Seismic line passing through well 3. e color volumes represent texture attributes of (a) homogeneity, (b) energy, and (c) entropy. e texture signature within the Redfork sandstone reservoir is not uniform. e upper Redfork sandstone has high homogeneity, energy and low entropy which is a good reservoir; the lower Redfork sandstone has poor reservoir quality, re ecting low homogeneity and energy, and high entropy from the texture responses. e well tested hydrocarbons from the Mississippian limestone; the textures show high-to-medium homogeneity and energy, and medium-to-high entropy responses from the top of the limestone to TD (total depth) of the well.

Mississippian limestone. The thickness of Redfork sandstone varies between 120–150 ft in this area. The Redfork sandstone is again divided into upper and lower layers, where the upper Redfork has better porosity development than the lower Redfork. The hydrocarbon potential of the Mississippian limestone (thickness around 300 ft in the study area) is not well understood; oil was found in this formation only in well 1, and oil shows were observed in well 3. The main reasons for selecting this field for GLCM texture analysis are: it has good well control and the behavior of the reservoir and its characteristics are well established from the drilling and production testing. The objectives of this study are to be able to predict the hydrocarbon-saturated Mississippian limestone reservoir and to characterize the multilevel Redfork sandstone reservoir as it produces from different formations with different fluid saturations. This would also allow us to understand the sensitivity of GLCM texture attributes to the reservoir and nonreservoir rocks. Figure 3 shows a seismic line passing through well 3 with the GLCM texture attributes as colored volumes.

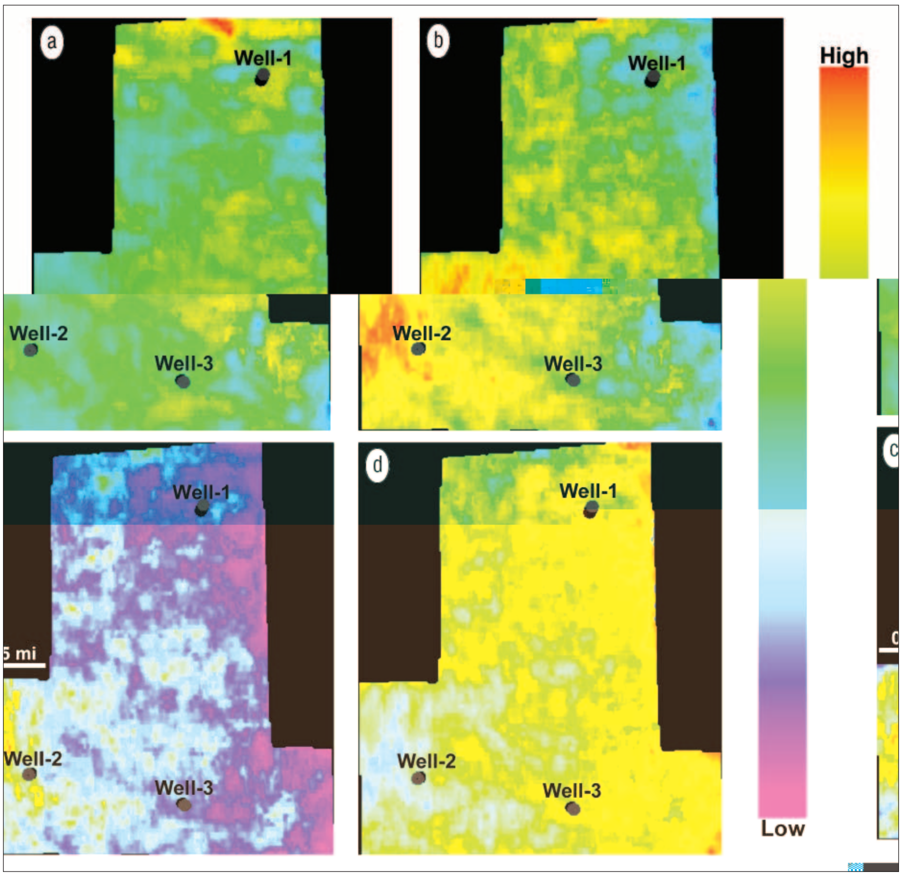

Figure 4. e rms values extracted between the top of Redfork and the bottom of the Redfork sandstone reservoir for (a) seismic amplitude, (b) homogeneity, (c) energy, and (d) entropy. Well 2 (a good gas producer) has high homogeneity and energy, and low entropy around the well. Well 3, an oil producer after fracturing, has medium homogeneity and energy, and medium-to-high entropy. Well 1, dry from the Redfork sandstone, has low homogeneity and energy, and high entropy. Based on the texture responses, the area around well 2 is proposed for further development of the Redfork sandstone reservoir.

Characterization of the Redfork sandstone

Figure 4 shows the rms values of seis-

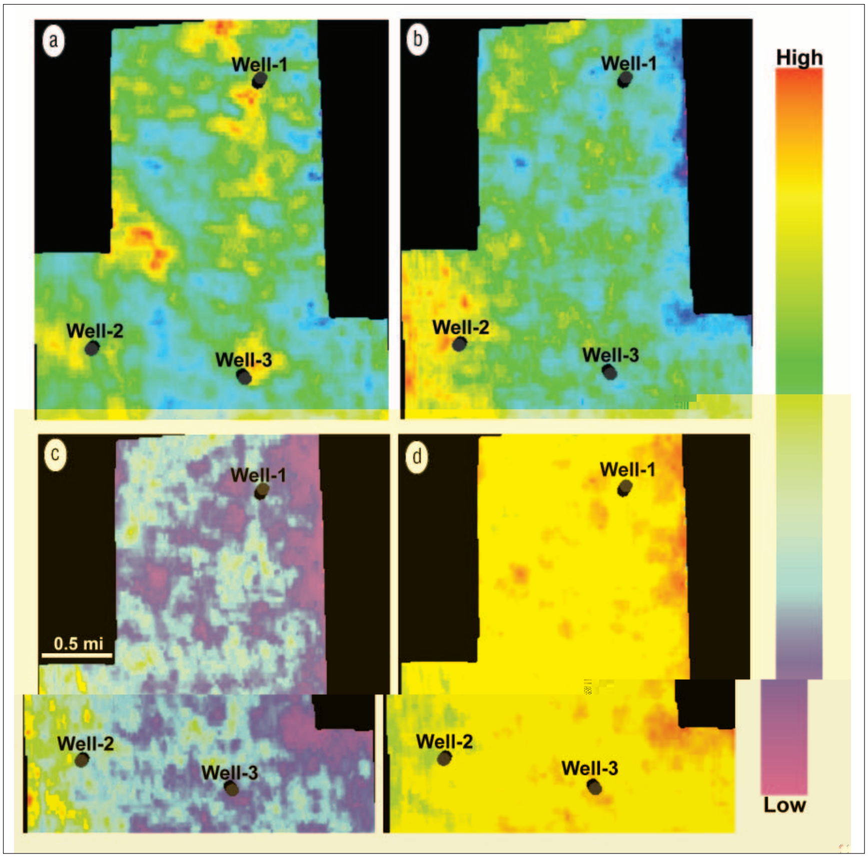

Figure 5. *e rms values extracted between top of Mississippian limestone to 30 ms below the top of Mississippian limestone reservoir for (a) seismic amplitude, (b) homogeneity, (c) energy, and (d) entropy. Wells 1 and 3, which showed hydrocarbons during testing, have low-to-medium homogeneity and energy, and high entropy, indicating highly diagenetically altered limestones with better secondary porosity. Well 2, with high homogeneity and energy, and medium entropy, did not show hydrocarbons during testing. e rms seismic amplitude map does not yield information about the presence of hydrocarbons. It is proposed from our study that the areas with low-to-medium homogeneity and energy, and high entropy are better choices for further drilling to estimate the hydrocarbon potential of the limestone reservoir.*

mic amplitude, and the seismic texture attributes, namely homogeneity, energy, and entropy extracted between top and bottom of the Redfork sandstone reservoir. From the well logs and production, it is evident that well 1 does not have good Redfork sandstone reservoir, well 2 is a gas producer, and well 3 has tight sandstone that started producing only after fracturing. The rms seismic amplitude map (Figure 4a) does not corroborate the reservoir performance. The homogeneity and energy attribute maps (Figure 4b and 4c) show high homogeneity and energy around well 2 and medium values of homogeneity and energy around well 3; the area around well 1 shows low homogeneity and energy. The GLCM entropy map (Figure 4d) shows high entropy for well 1, low entropy around well 2, and medium-to-high entropy around well 3. From the interpretation of GLCM maps, well 2 which is a gas producer from Redfork sandstone has high energy and homogeneity and low entropy, well 3 which is an oil producer after fracturing has medium homogeneity and energy and entropy, and well 1 (not a producer from the Redfork sandstone) has low homogeneity and energy and high entropy. Gao made an empirical observation based on his analysis that gas sands exhibit high energy, high homogeneity, and low entropy. In our study area also, the GLCM texture attributes have clearly brought out the distinction between reservoir and nonreservoir development of facies within the same deposition of sandstone. We tentatively conclude that the area around well 2 is the best place for further drilling in the study area.

Prediction of Mississippian limestone hydrocarbon potential

Gao (1999a, 2003) and West et al. (2002) applied seismic texture analysis to clastic sediments. Chopra and Alexeev (2006) studied the reservoir behavior from texture analysis for the clastic reservoirs of Alberta, Canada. Not much has been published on using seismic texture analysis to characterize or predict the reservoir behavior of limestones. Here, we investigated the response of seismic texture attributes to limestone reservoir from the same study area (Figure 5). Well 1 tested oil and well 3 had hydrocarbon shows from the Mississippian limestone reservoir, but well 2 had no evidence for hydrocarbons in the limestone. The objective of seismic texture analysis on this reservoir is not only to find the internal architecture but also to understand its hydrocarbon potential. Figure 5 shows the rms values of seismic amplitude, homogeneity, energy and entropy attributes extracted over a window from the top of the Mississippian limestone to 30 ms below the top of the limestone. The rms seismic amplitude in Figure 5a shows high amplitudes around the three wells, and therefore is not useful for differentiating between producing and nonproducing reservoir. The internal architecture of limestones is different from that of sandstones; limestones have high density, are more prone to diagenetic alterations, formation of vugs, and generation of secondary porosity than are sandstones. The response of texture attributes also is different from limestones than from sandstones. We anticipate that homogeneity which measures the smoothness of the internal architecture should be less for diagenetically altered limestones than for the nonaltered limestones. Energy which measures the internal geometry and continuity of rocks may be different for limestones with more vugs to less vugs which are the generators for the secondary porosity. Entropy measures the disorder within the rock elements and will be high for more highly altered limestones. Figures 5b-d show that well 2 (which does not produce from the limestone) shows high homogeneity, energy and medium entropy, while wells 1 and 3 which showed hydrocarbons presence from limestone have medium-to-low values of GLCM homogeneity and GLCM energy and high values of GLCM entropy. From this study, we observed that low-to-medium homogeneity and energy correspond to diagenetically altered limestones with better secondary porosity development. The entropy is high for these highly altered limestones. Also, the high homogeneity and energy, and medium entropy signatures of seismic texture attributes (from well 2) confirm the areas of poor limestone reservoir quality.

Conclusions

We conclude from our case study that seismic texture analysis is a useful tool in delineating hydrocarbon-bearing facies tagged by well control. Unlike attributes such as coherence and curvature that measure a distinct structural pattern in the seismic data that can be interpreted in the absence of well control, statistical GLCM attributes require significant well control to make predictions. Because of their different internal architecture, we observe that the response of seismic texture attributes for limestone reservoirs differs from that of sandstone reservoirs. More studies need to be done to better understand the response of texture attributes to internal pore structure and permeability of the reservoir rocks. TLE

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Acknowledgments: e rst two authors thank the sponsors of the Attribute Assisted Seismic Processing and Interpretation (AASPI) research consortium at the University of Oklahoma.*

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