GENERATING TEXTURE ATTRIBUTES – PROGRAM glcm3d

Contents

Overview

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 within the space of your fingertip. In contrast, silky textures exhibit very small differences in elevation”. Seismic textures work in an analogous manner with elevation replaced by amplitude, and the probing of a finger by rectangular or elliptical analysis window oriented along the structure.

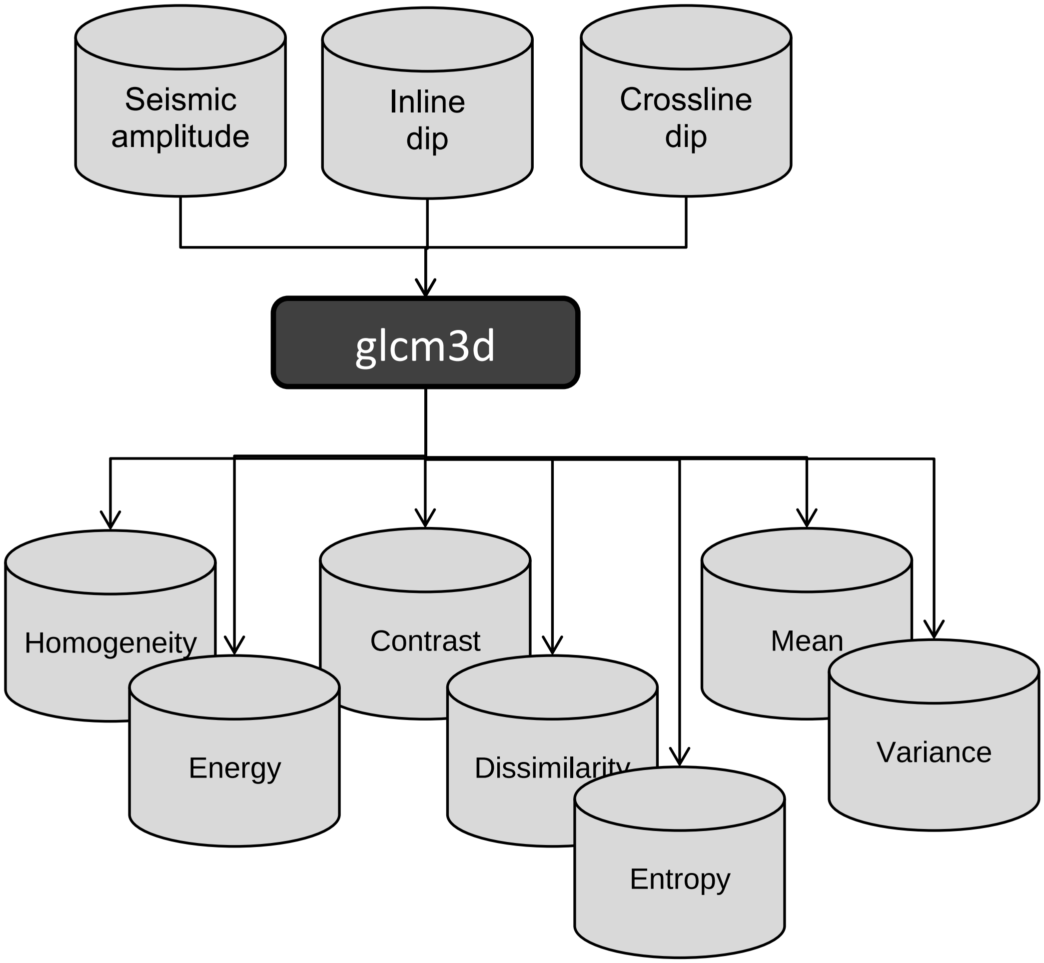
While several GLCM textures will appear to be similar to the previously-introduced edge detectors, many others are not. Texture analysis holds significant promise in computer-aided interpretation. Examples of what the future holds in store can be found in Gao (2004, 2007, 2009) and West et al. (2002). Gao has used these attributes in both human-supervised classification (visually correlating textures to well logs) and unsupervised learning (clustering the various textures using a self-organizing map algorithm in Paradigm's Stratimagic software). West et al. (2002) classified similar attributes using an interpreter-driven neural network workflow. More powerful 'latent space' clustering algorithms are on the horizon, such as the generative topological mapping (GTM) algorithm described by Roy et al. (2014).

Program **glcm3d** extracts a rectangular window of data and its Hilbert transform along dip of user-defined length, width, and height. Within this window the RMS amplitude of each time sample is calculated. The data within each one-sample thick analysis window, is then scaled to range over the integer range (number of levels) of the GLCM. 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. In this manner, the GLCM variance produces results comparable to more common similarity attributes (energy-ratio similarity, Sobel filter similarity, and so on).

Computation flow chart

The AASPI gray-level co-occurrence matrices and textures attributes are computed along structural dip. In addition to supplying the inline and crossline dip components, the user supplies the input volume to be analyzed, which may be the seismic amplitude, acoustic impedance, coherence, spectral components, or any other attribute. In general, the output attributes provide images that are somewhat fuzzy and not very useful for human interpretation. Rather, these attributes serve as input data to self-organized maps, generative topological maps, probabilistic neural networks, random forest decision trees, and other clustering algorithm.

Geometric Attributes: Computing Texture Attributes – Program **glcm3d**



Output file naming convention

Program **glcm3d** will always generate the following output files:

Output file description	File name syntax
Program log information	glcm3d_*unique_project_name_suffix*.log
Program error/completion information	glcm3d_*unique_project_name_suffix*.err

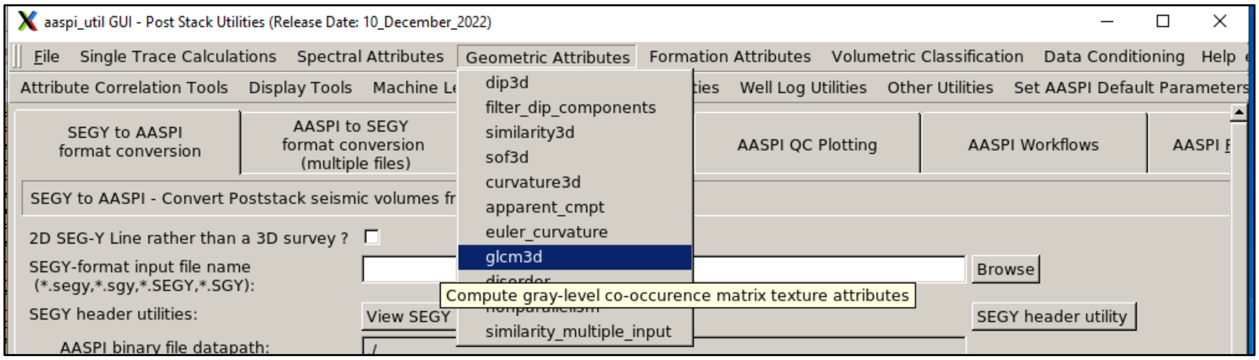
where the values in red are defined by the program GUI. The more common errors (ones we anticipated could arise) will be written to the **.err* file and be displayed in a pop-up window upon program termination. These errors, much of the input information, a description of intermediate variables, and any software trace-back errors will be contained in the **.log* file.

If selected on the GUI, program **glcm3d** will also generate the following attribute volumes (defined in the theory sections later in this document):

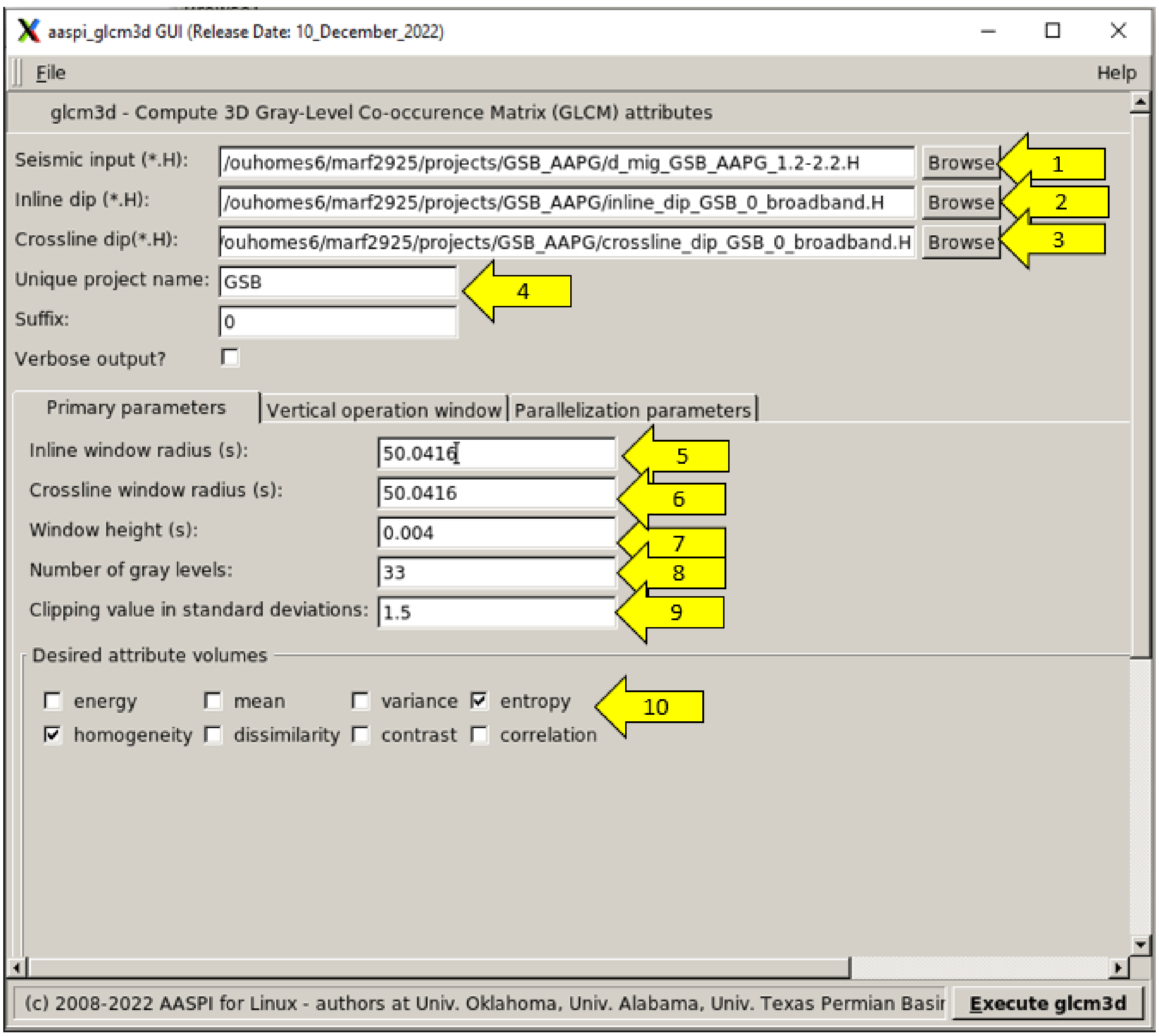
Output file description	File name syntax
GLCM entropy	glcm_entropy_*unique_project_name_suffix*.H
GLCM energy	glcm_energy_*unique_project_name_suffix*.H
GLCM homogeneity	glcm_homogeneity_*unique_project_name_suffix*.H
GLCM contrast	glcm_contrast_*unique_project_name_suffix*.H
GLCM dissimilarity	glcm_dissimilarity_*unique_project_name_suffix*.H
GLCM variance	glcm_variance_*unique_project_name_suffix*.H
GLCM correlation	glcm_correlation_*unique_project_name_suffix*.H
GLCM mean	glcm_mean_*unique_project_name_suffix*.H

Invoking the glcm3d GUI:

To begin, select program **glcm3d** option under the *Geometric Attributes* tab:



The following GUI should appear:



For our example we have (1) entered the 3D seismic file, the (2) inline dip file, and the (3) crossline dip file. For the running window analysis, the default (5) inline and (6) crossline window radius is set to be four times the inline and two times the crossline physical trace spacings (in this example they were *dcdp*=12.5 and *dline*=25 m). The (7) window height is also set at a default to be one sample interval of the seismic data (giving 3 samples). We (8) used 33 gray levels and (9) clip the data at each sample level at 1.5 standard deviations of the distribution. Finally, (10) we select the desired output attribute volumes. We have found entropy and homogeneity to be the most useful.

By default, our implementation of the GLCM generates a 33 by 33 matrix at every sample point, or a 1,089 increase in the data volume. To address such an explosion of data, Haralick et al. (1973) proposed fourteen statistical measurements of the GLCM; Gao (2003) added one more measurement – randomness. Each of these measures is a function of the 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 fifteen GLCM 'attributes'. These fifteen measurements can be broken into three general categories: contrast, orderliness, and statistics

Theory: The Gray Level Co-Occurrence Matrix (GLCM)

The Gray Level Co-occurrence Matrix (GLCM) is a tabulation of how often different combinations of voxel amplitude brightness values (gray levels) occur in an analysis window. Parallel to the local dip, one defines a local analysis window as done previously when constructing the covariance matrix for coherence computation. GLCM requires converting the seismic data from 32-bit floating point format to a user-defined number of integer gray levels. Interpreters routinely use 8 bits to represent their seismic data, which would result in a 256x256=66,536 element matrix for every voxel. Such a large matrix is both expensive to manipulate and overly sparse when constructed from a 5-trace by 5-trace by 11-sample window containing only 275 samples. For this reason, the examples in this book are all constructed using (approximately) 5-bit data, with $2L+1=33$ levels of gray, where levels -16 to -1 correspond to troughs, 0 to a zero-crossing, and +1 to +16 to peaks. For a given ($2M+1$) trace by ($2N+1$) trace sample vector oriented along dip, the contribution to the GLCM matrix, p_{kij} is

$$p_{kij} = \sum_{m=-M}^{+M} \sum_{n=-N}^{+N} \Big[\delta\left(\bar{d}_{kmn} - i\right)\delta\left(\bar{d}_{k,m,n+1} - j\right) + \delta\left(\bar{d}_{kmn} - i\right)\delta\left(\bar{d}_{k,m+1,n+1} - j\right) + \delta\left(\bar{d}_{kmn} - i\right)\delta\left(\bar{d}_{k,m+1,n} - j\right) + \delta\left(\bar{d}_{kmn} - i\right)\delta\left(\bar{d}_{k,m+1,n-1} - j\right)\Big] \quad (1)$$

where $\bar{d}_{kmn}$ indicates the integer-valued scaled seismic data along the sample vector k at x-index m, and y-index n. The values i and j range between -16 and +16 (the number of gray levels in this implementation) and the Kronecker delta function, $\delta(\xi)=1$ if $\xi=0$ and 0 otherwise. Equation 1 compares the value at ($m\Delta x$, $n\Delta x$) to its neighbors at 0°,45°,90°, and 135°. Other implementations may examine the repetition pattern at larger distances (say two or three voxels away).

Seismic samples (in a seismic trace) differ significantly from remote sensing data such as satellite images. First, we have as many as several thousand rather than one sample per (*x, y*) location. Although we wish to examine the lateral changes in geology along structural dip expressed by its reflectivity, what we measure is the reflectivity convolved with the seismic wavelet. Clearly, the reflectivity pattern aligned with a zero crossing of the seismic wavelet has a very low signal-to-noise ratio. For this reason, we need to somehow vertically "stack" the patterns at each slice to provide a more robust result. As in most other AASPI programs, we can also improve the result by stacking in the pattern of the Hilbert transform of the amplitude data as well. To combine the pattern seen in multiple sample vectors, they need to be first scaled. In the implementation used here, the sample vectors are scaled to span 1.5 standard deviations using

$$\bar{d}_{kmn} = \mathrm{CLIP}\left(\frac{L}{1.5\sigma_k + \varepsilon} d_{kmn}\right), \quad (2)$$

where

$$\sigma_k = \left\{\frac{1}{(2M+1)(2N+1)} \sum_{m=-M}^{+M} \sum_{n=-N}^{+N} \left(d_{kmn}^2\right)\right\}^{1/2} \quad (3)$$

is the RMS amplitude of the sample vector, ε is a value to avoid division by zero, and the function CLIP clips values beyond the interval ($-L$,$+L$) to the values $-L$ or $+L$.

The unnormalized GLCM matrix is then

$$P_{ij} = \frac{\sum_{k=-K}^{+K} \left[\sigma_k p_{kij}\right]}{\sum_{k=-K}^{+K} \sigma_k} \quad (4)$$

after which the values are normalized so that sum of $P_{ij}=1.0$. We repeat the process to compute the GLCM matrix for the Hilbert transform version of the data, generating P_{ij}^{H}.

Theory: The contrast group of GLCM attributes

The contrast group of GLCM attributes includes Haralick et al.'s (1973) measurements of contrast, dissimilarity and homogeneity. Their weights are related to the distance *(i-j)* from the GLCM diagonal. Since the contrast group of attributes is a function of amplitude differences *(i-j*), rather than amplitudes (*i* and *j*), they are insensitive to the mean value of the amplitude within the analysis window, and are a measure of texture independent of how strong or weak the average amplitude may be.

The GLCM contrast attribute, C_{GLCM}, is defined as

$$C_{GLCM} = \sum_{i=-L}^{+L} \sum_{j=-L}^{+L} \left(P_{ij} + P_{ij}^{\mathrm{H}} \right) (i-j)^2 \qquad (5)$$

where *L* is the number of gray levels. When the cell is on the diagonal, *i-j=0.* Since the diagonal of the GLCM represents the percentage of voxels equal to their neighbors, a zero change in contrast is given a weight of *0*. If *i* and *j* differ by *1*, there is a small contrast, and the weight is *1*. If *i* and *j* differ by *2*, the contrast weight is $2^2 = 4$. The weights continue to increase with the square of (*i-j*). Patches of data that are constant will have one value of P_{kk}=0 and all other values of P_{ij}=0, resulting in a value of C_{GLCM}=0.0.
The GLCM dissimilarity attribute, D_{GLCM}, is defined as

$$D_{GLCM} = \sum_{i=-L}^{+L} \sum_{j=-L}^{+L} \left(P_{ij} + P_{ij}^{\mathrm{H}} \right) \left| i-j \right|$$

(6)

where the weights |*i-j*| are the L^1 rather than the L^2 norm used in the contrast attribute. Because of this construct, D_{GLCM} will be less sensitive to outliers than C_{GLCM}. Like the contrast attribute, patches of data that are constant will have a value of D_{GLCM}=0.0.
The GLCM homogeneity attribute, H_{GLCM}, is given by:

$$H_{GLCM} = \sum_{i=-L}^{+L} \sum_{j=-L}^{+L} \frac{\left(P_{ij} + P_{ij}^{\mathrm{H}} \right)}{1+(i-j)^2} \qquad (7)$$

where the weights are now inversely proportional to the square of the distance away from the diagonal. Patches of data that are constant will have a single component P_{kk}=1, with all other elements of the matrix P_{ij}=0, resulting in a value of H_{GLCM}*=1.0*. Patterns that are smooth with *i≈j will have a value of* H_{GLCM} close to 1. Patches of data that are chaotic will have multiple data values where $(i-j)^2$ is large, resulting in smaller values of H_{GLCM}, in the limit approaching 0.

Theory: The orderliness group of GLCM attributes

The orderliness group of GLCM attributes includes Haralick et al.'s (1973) measurements of energy and entropy and Gao's (2003) 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, unlike the GLCM contrast attributes, which were a function of (*i-j*), the GLCM orderliness attributes are a true measurement of texture, independent of the mean amplitude in the analysis window.

The GLCM energy attribute, E_{GLCM}, is defined as

$$E_{GLCM} = \left[\sum_{i=-L}^{+L} \sum_{j=-L}^{+L} \left(P_{ij} \right)^2 \right]^{1/2} + \left[\sum_{i=-L}^{+L} \sum_{j=-L}^{+L} \left(P_{ij}^{\mathrm{H}} \right)^2 \right]^{1/2} \quad (8)$$

where the argument inside the square root can be interpreted as the second moment; high values of GLCM energy occur when the amplitude values are nearly constant, with all of the energy concentrated in one element of P_{kk}. For seismic interpreters, the name 'energy' leads to considerable confusion, since 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. Indeed, a patch of data that is identically zero will have E_{GLCM}=1.For this reason, it is good practice to always explicitly denote this attribute as GLCM energy rather than simply energy.

The GLCM entropy attribute, S_{GLCM}, measures the disorderliness (or roughness) rather than the orderliness (or smoothness) of the patch of seismic amplitude values and is defined as

$$S_{\mathrm{GLCM}} = -\sum_{i=-L}^{+L} \sum_{j=-L}^{+L} \left[P_{ij} \left(\ln P_{ij} \right) + P_{ij}^{\mathrm{H}} \left(\ln P_{ij}^{\mathrm{H}} \right) \right]. \quad (9)$$

In this definition, we use a negative sign because all values of $P_{ij} \leq 1$, such that $\ln(P_{ij}) \leq 0$. Minimum entropy (and maximum energy) occurs when all scaled amplitude values are equal to a constant value *k*, such that P_{kk}=1, $\ln(P_{kk})$=0 and all other values P_{ij}=0, resulting in S_{GLCM}=0. Maximum entropy occurs when all probabilities of values are equal, representing a random distribution of values. In this case, $P_{ij}=1/(2L+1)^2$, or $S_{\mathrm{GLCM}}=\ln[(1/2L+1)^2]$. We scale equation 2 by this maximum value such that SGLCM ranges between 0 and 1. Because seismic data are highly correlated, we rarely approach this upper limit.

Theory: The statistics group of GLCM attributes

The statistics group of GLCM attributes includes Haralick et al.'s (1973) measurements of mean, variance and correlation. The GLCM mean attribute, μ_{GLCM}, is a scaled sum of the normalized probability P_{ij} of a given sample having the value *i:*

$$\mu_{GLCM} = \sum_{i=-L}^{+L} \sum_{j=-L}^{+L} jP_{ij} , \quad \text{and} \tag{10a}$$

$$\mu_{\mathrm{GLCM}}^{\mathrm{H}} = \sum_{i=-L}^{+L} \sum_{j=-L}^{+L} jP_{ij}^{\mathrm{H}} . \tag{10b}$$

The GLCM variance attribute, V_{GLCM}, defined as,

$$V_{GLCM} = \sum_{i=-L}^{+L} \sum_{j=-L}^{+L} \left[P_{ij} \left(i - \mu_{GLCM} \right)^2 + P_{ij}^{\mathrm{H}} \left(i - \mu_{\mathrm{GLCM}}^{\mathrm{H}} \right)^2 \right] \tag{11}$$

is similar to the conventional definition of variance found in statistics books. Unfortunately, the GLCM variance attribute can be confused with the trace similarity variance attribute defined by Pepper and Bejarano (2005). The latter is computed using only the data (and not its Hilbert transform) and is normalized by the energy of the seismic amplitudes within the analysis window and variance is closely related, if not identical, to semblance-based coherence. The GLCM variance attribute will often look similar to the GLCM contrast attribute defined earlier. Because the coefficients $(i\text{-}j)^2$ for the GLCM contrast are similar to the coefficients $(i\text{-}\mu_{GLCM})^2$ about the mean for the GLCM variance, these two attributes may produce similar images.

Finally, the GLCM correlation attribute, *R*, is defined as,

$$R_{GLCM} = \frac{1}{V_{\mathrm{GLCM}}} \sum_{i=-L}^{+L} \sum_{j=-L}^{+L} \left[P_{ij} \left(i - \mu_{GLCM} \right) \left(j - \mu_{\mathrm{GLCM}} \right) + P_{ij}^{\mathrm{H}} \left(i - \mu_{\mathrm{GLCM}}^{\mathrm{H}} \right) \left(j - \mu_{\mathrm{GLCM}}^{\mathrm{H}} \right) \right] . \tag{12}$$

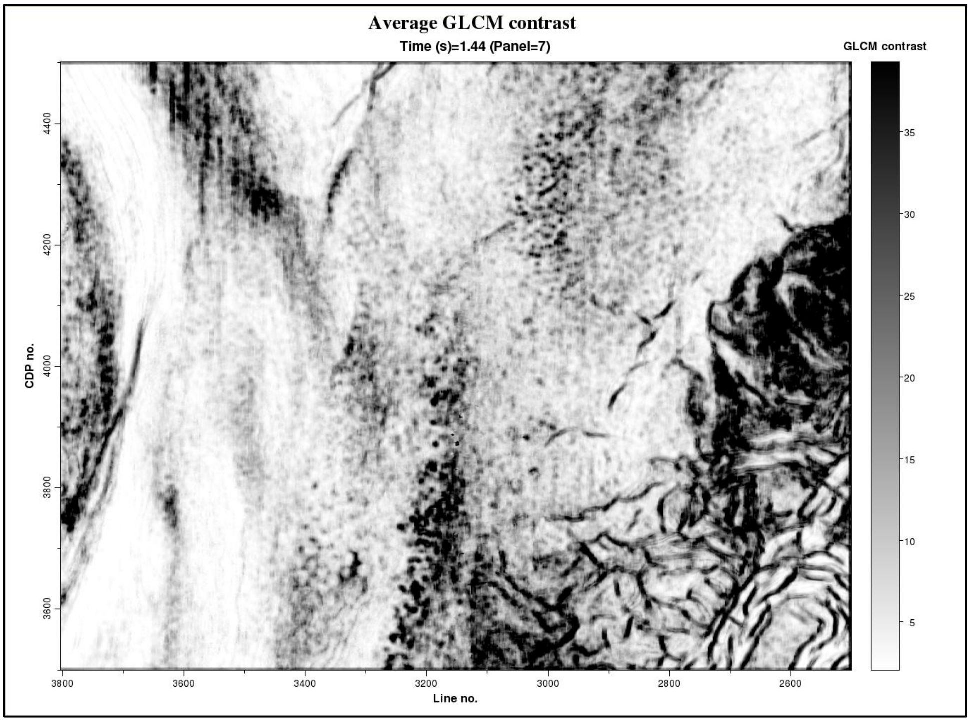
The name "correlation" and many published articles suggest that the GLCM correlation attribute indicates how correlated neighboring voxels are to each other. This is not the case for the end member when all samples are the same and shows how repetitive a pattern is within the analysis window, with a value of $R=0.0$ being totally uncorrelated, and a value of $R_{GLCM}=1.0$ totally correlated.

Example 1

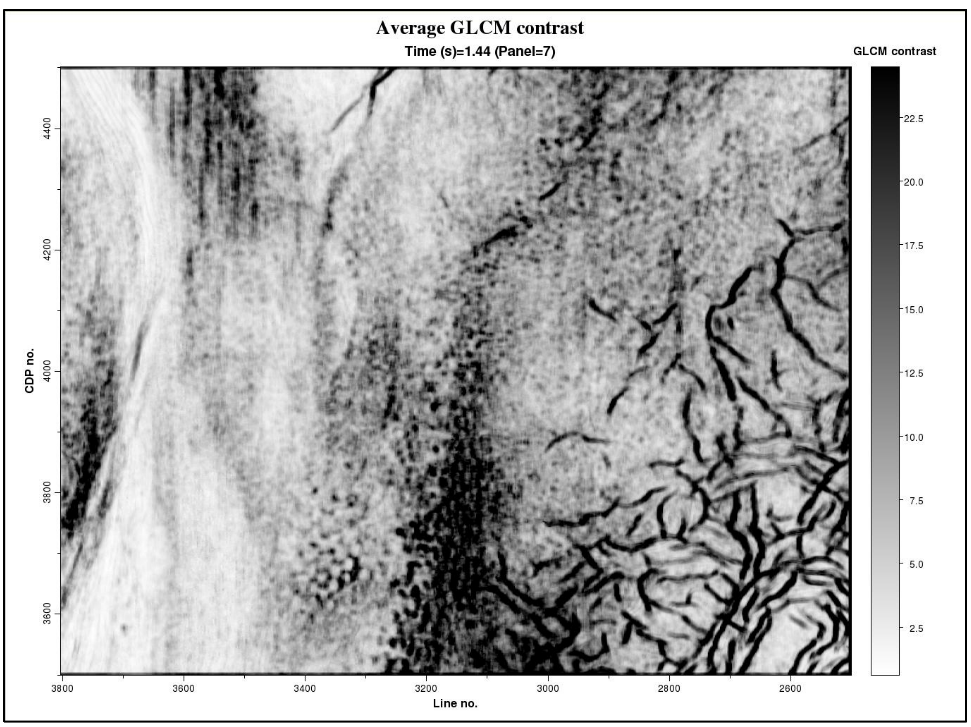
The following examples show time slices through GLCM attributes generated from a portion of the New Zealand Great South Basin survey provided to the public by New Zealand Ministry of Petroleum and Minerals. In general, these attributes are not as useful for interactive interpretation, but rather serve as input for either interactive crossplotting or machine learning based cluster analysis (as shown in Example 2).

GLCM Contrast

GLCM contrast measures how the amplitudes change laterally along structural dip. Using a window of radius 50 m by 50 m (containing 45 traces) and a vertical window of ±0.004 s (three samples) gives the following image:

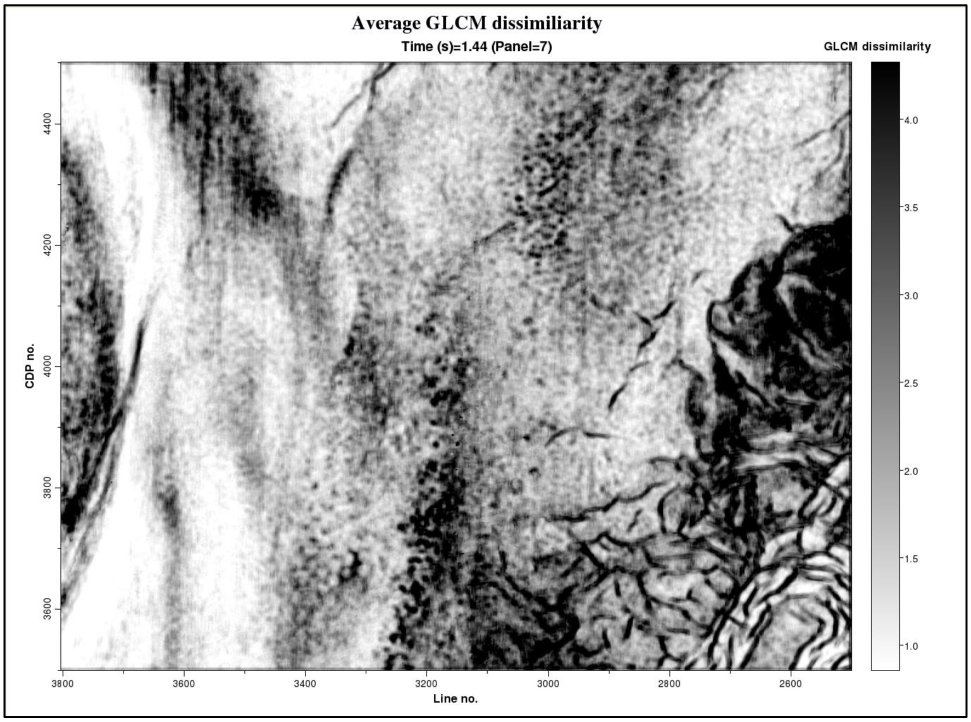


Increasing the window size to be ±0.020 s (11 samples) produces a smoother image:

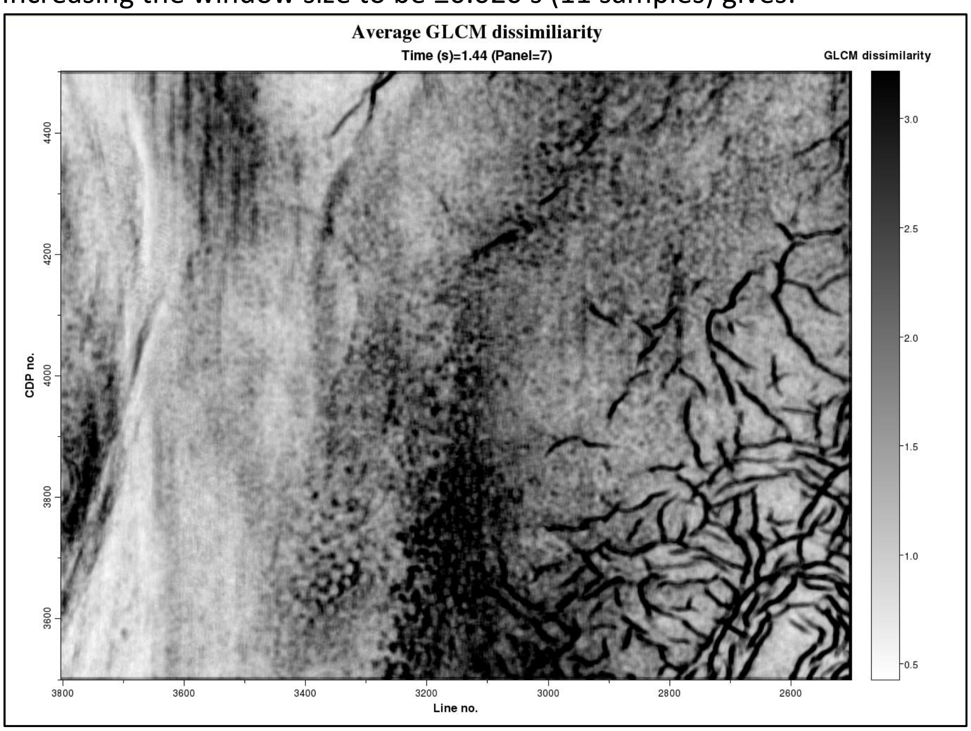


GLCM Dissimilarity

GLCM dissimilarity is like GLCM contrast and measures the lateral change in amplitude along structural dip. Using a window of radius 50 m by 50 m (containing 45 traces) and a vertical window of ±0.004 s (three samples) gives the following image:



Increasing the window size to be ±0.020 s (11 samples) gives:

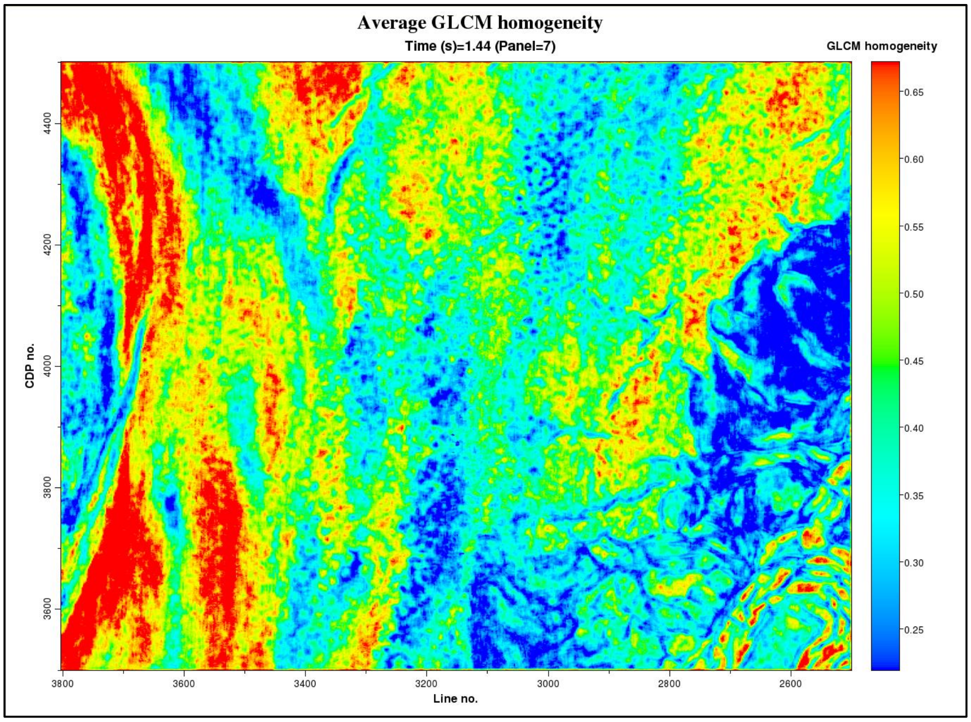


Careful examination of the equations 6 and 7 shows that the contrast is weighted by the square of the gray level differences, whereas the dissimilarity is weighed by the absolute value of the gray level differences. Because of the absolute value weighting, *D* will be less sensitive to outliers than *C*.

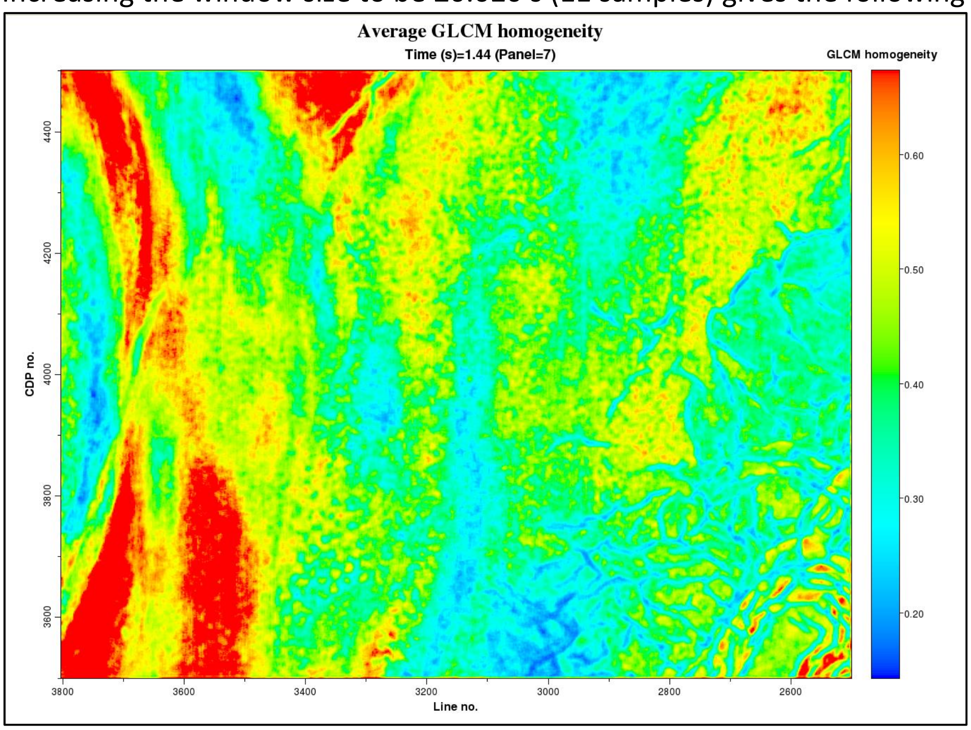
Note that the GCLM contrast and GCLM dissimilarity produce results similar to the coherence family of attributes. Not surprisingly, the GLCM variance examples shown later will be nearly identical to semblance similarity with a change in polarity and a scaling factor.

GLCM Homogeneity

Homogeneity is a measure of how smoothly the amplitudes vary along structural dip. Using a window of radius 50 m by 50 m (containing 45 traces) and a vertical window of ±0.004 s (three samples) gives the following image:

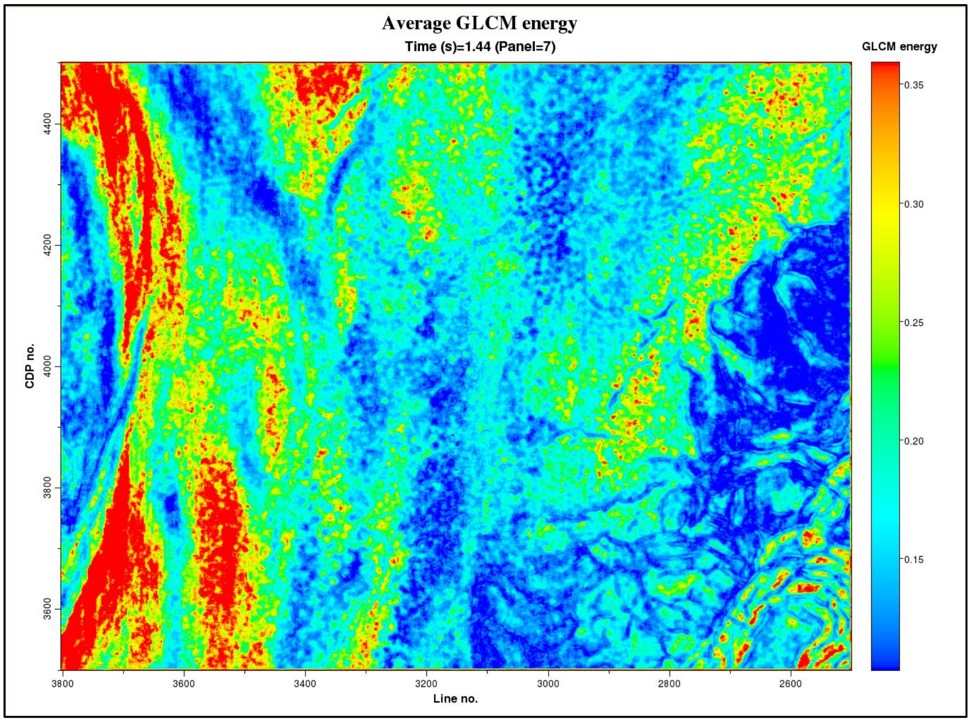


Increasing the window size to be ±0.020 s (11 samples) gives the following (smoother) image:

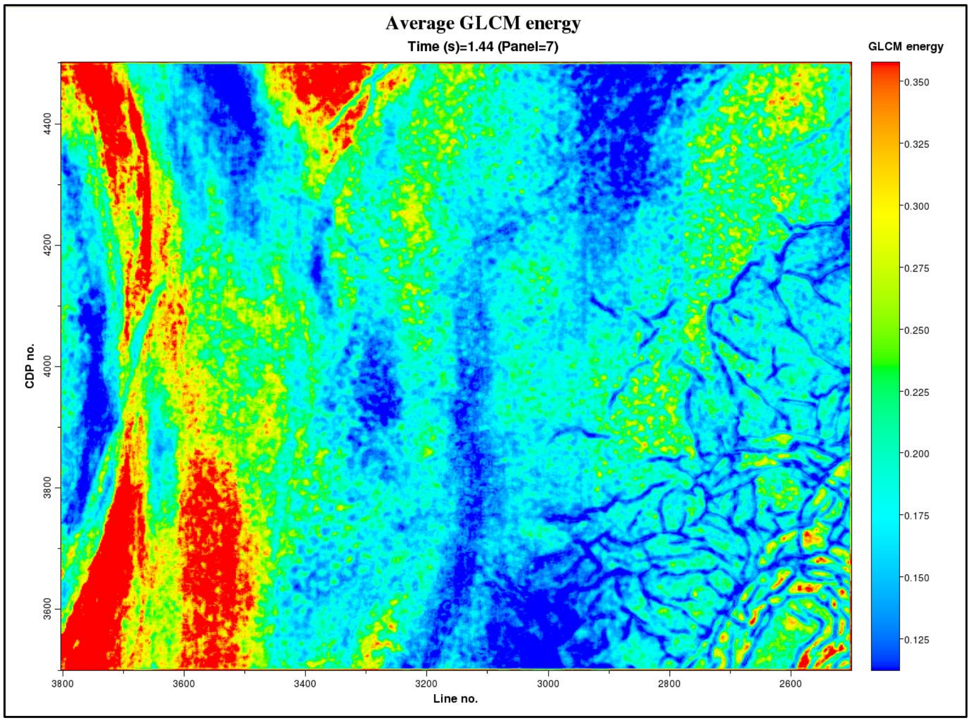


GLCM Energy

The GLCM energy is *not* a measure of the strength of the amplitude, but rather how constant it behaves laterally along structural dip. If each voxel at a given level in the analysis window is the same (even 0!) the "energy" of the GLCM given by equation 8 will be high. Using a window of radius 50 m by 50 m (containing 45 traces) and a vertical window of ±0.004 s (three samples) gives the following image:

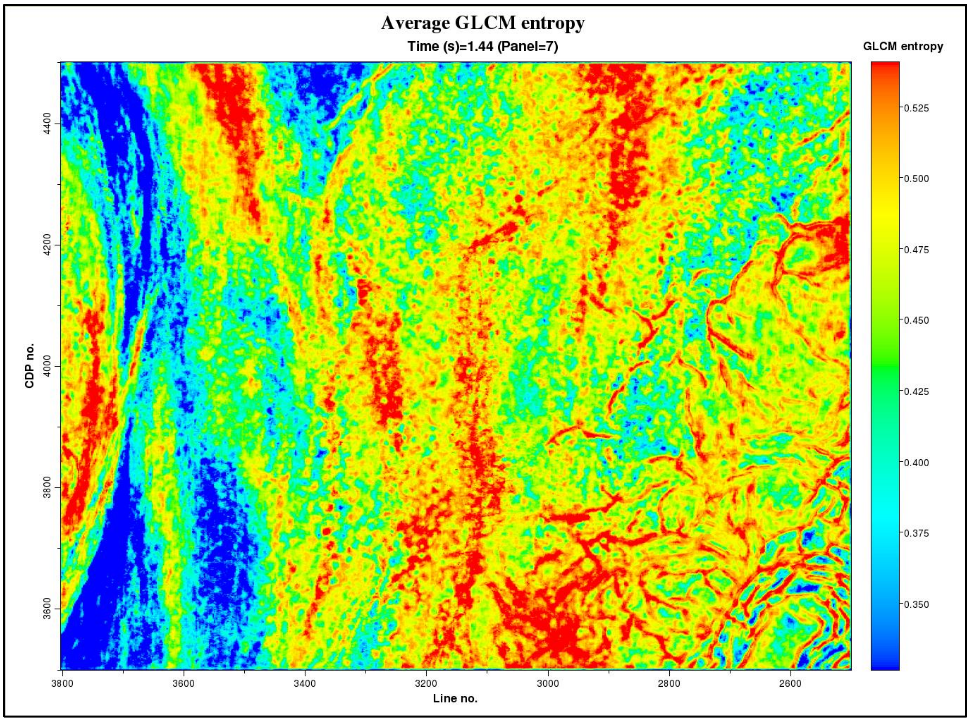


Increasing the window size to be ±0.020 s (11 samples) gives the following (smoother) image:

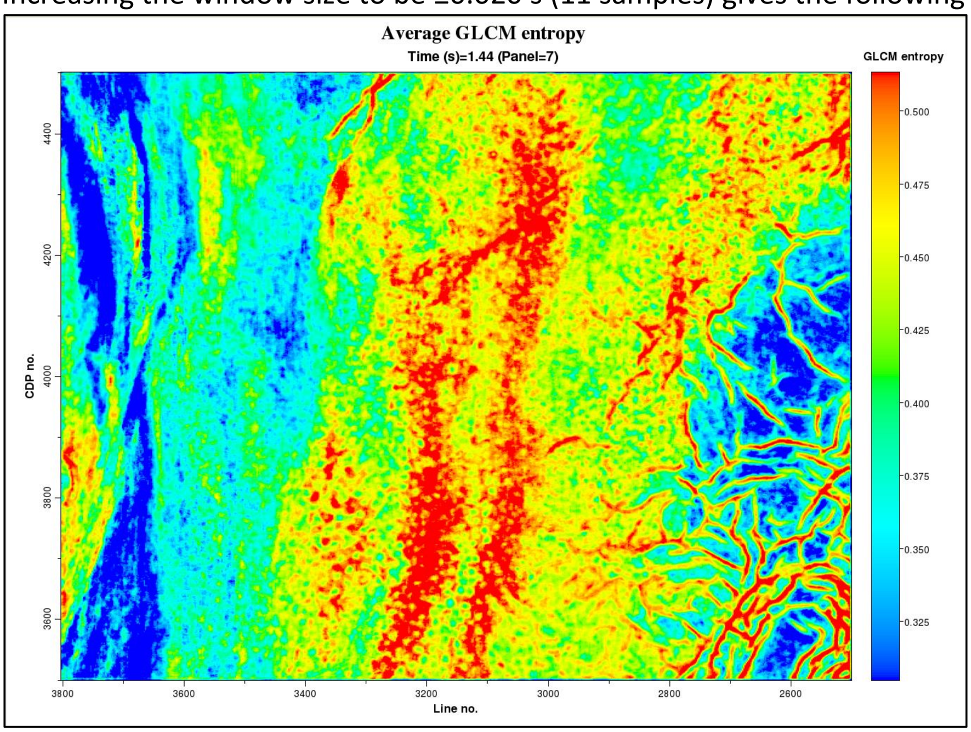


GLCM Entropy

The GLCM entropy is a measure of how random the amplitude varies along structural dip and is often numerically inversely correlated to GLCM homogeneity. Using a window of radius 50 m by 50 m (containing 45 traces) and a vertical window of ±0.004 s (three samples) gives the following image:

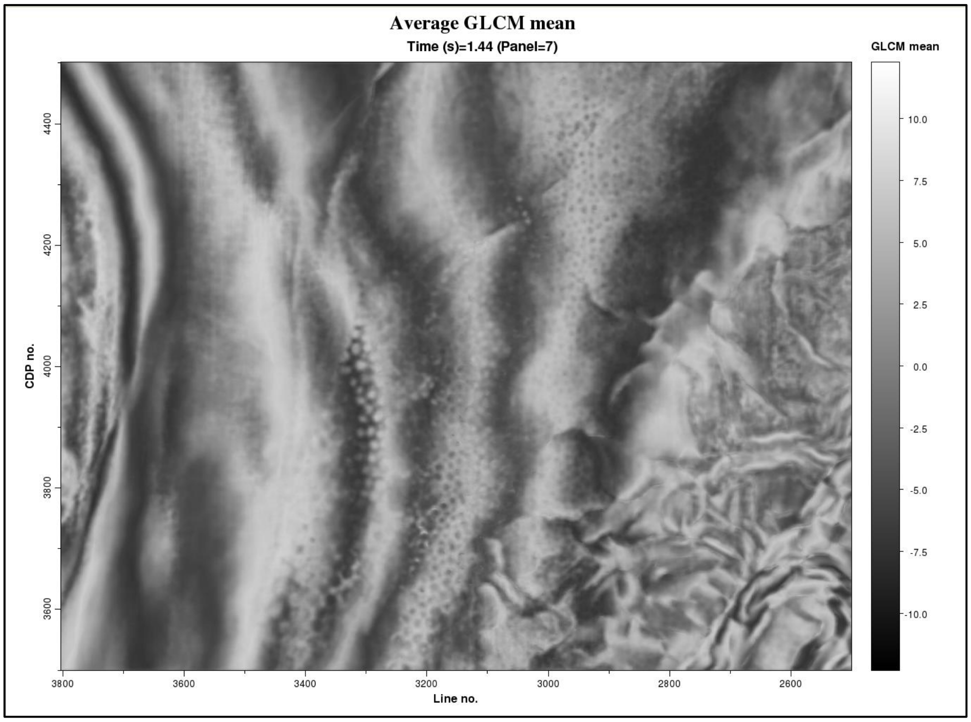


Increasing the window size to be ±0.020 s (11 samples) gives the following (smoother) image:

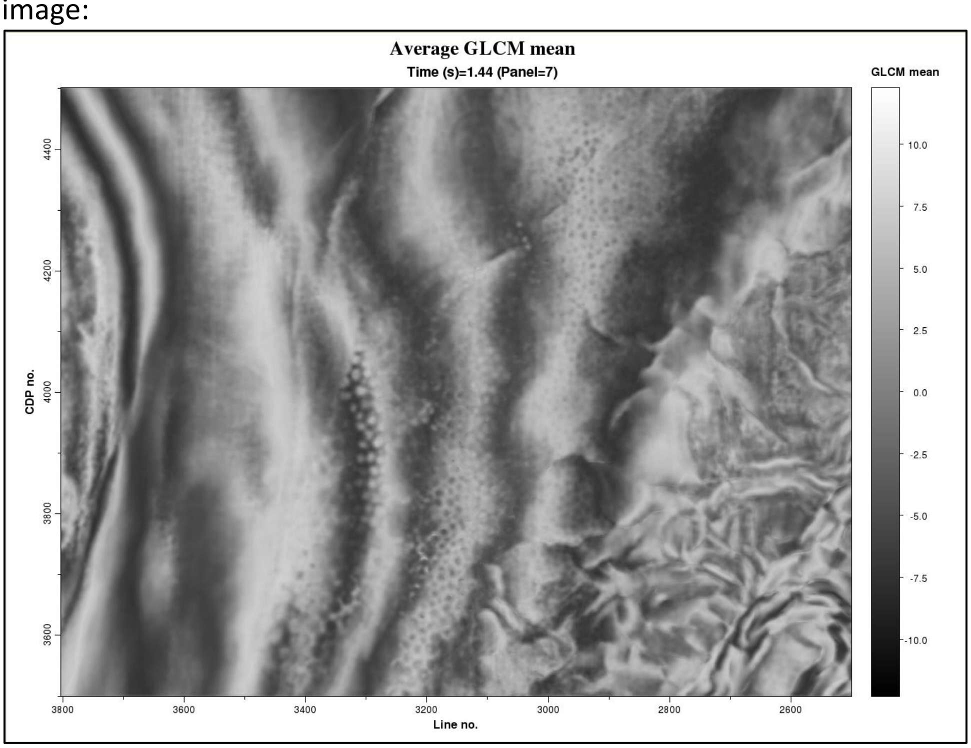


GLCM Mean

The GLCM mean is simply the mean of the scaled data along structural dip, and in general has little value in either interactive interpretation or in machine learning cluster analysis. Using a window of radius 50 m by 50 m (containing 45 traces) and a vertical window of ±0.004 s (three samples) gives the following image:

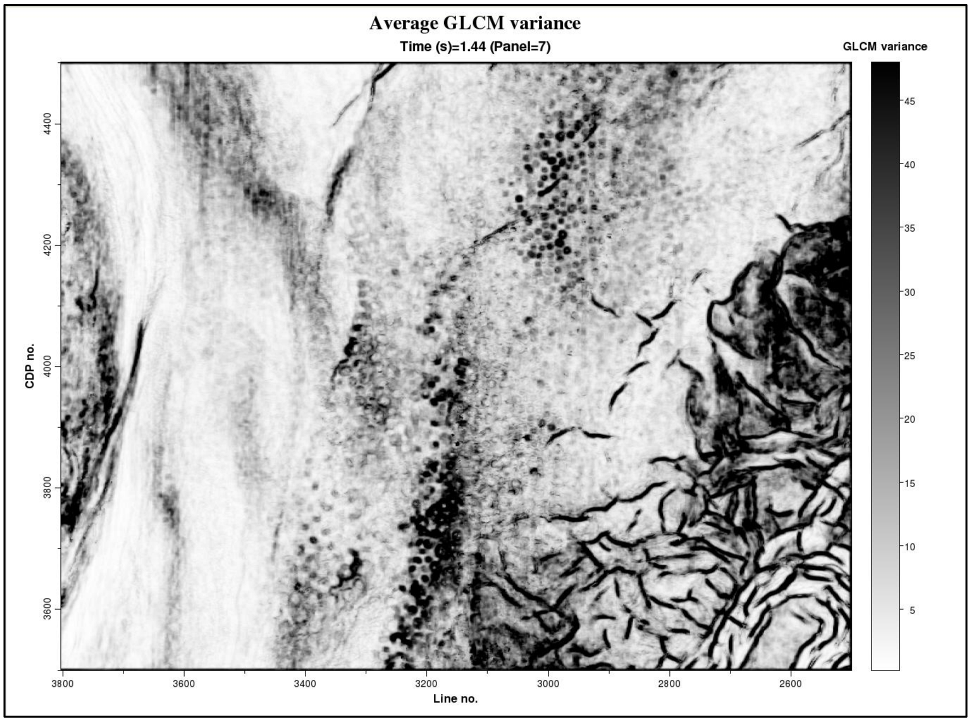


Increasing the window size to be ±0.020 s (11 samples) low-pass filters the data and gives this image:

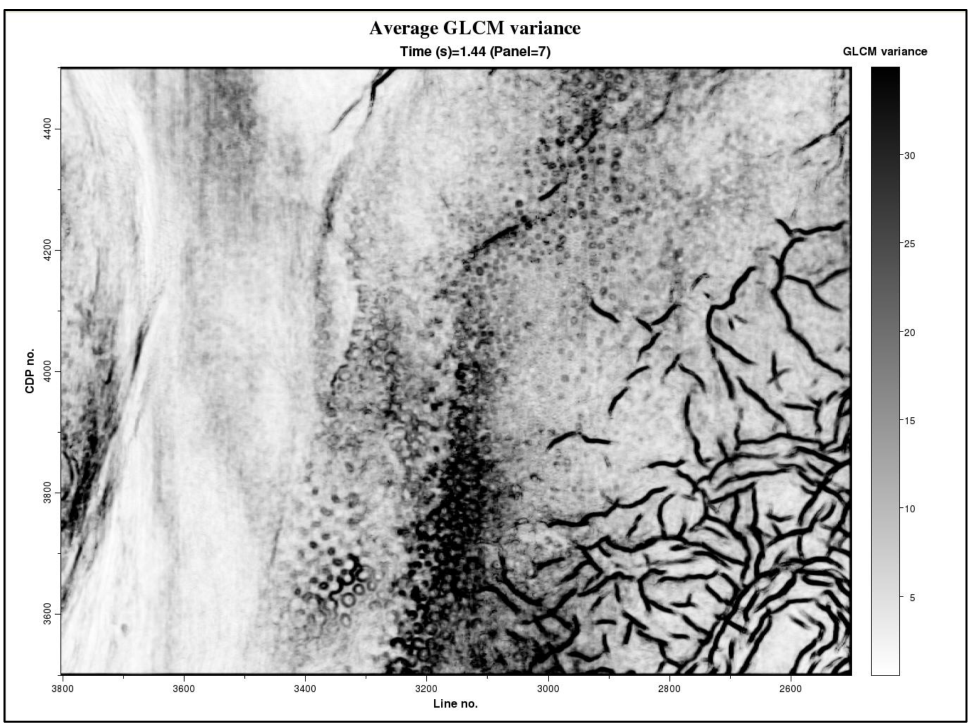


GLCM Variance

The GLCM variance is a scaled value of semblance-based similarity generated by program **similarity3d** and provides almost no additional interpretational value. Using a window of radius 50 m by 50 m (containing 45 traces) and a vertical window of ±0.004 s (three samples) gives the following image:

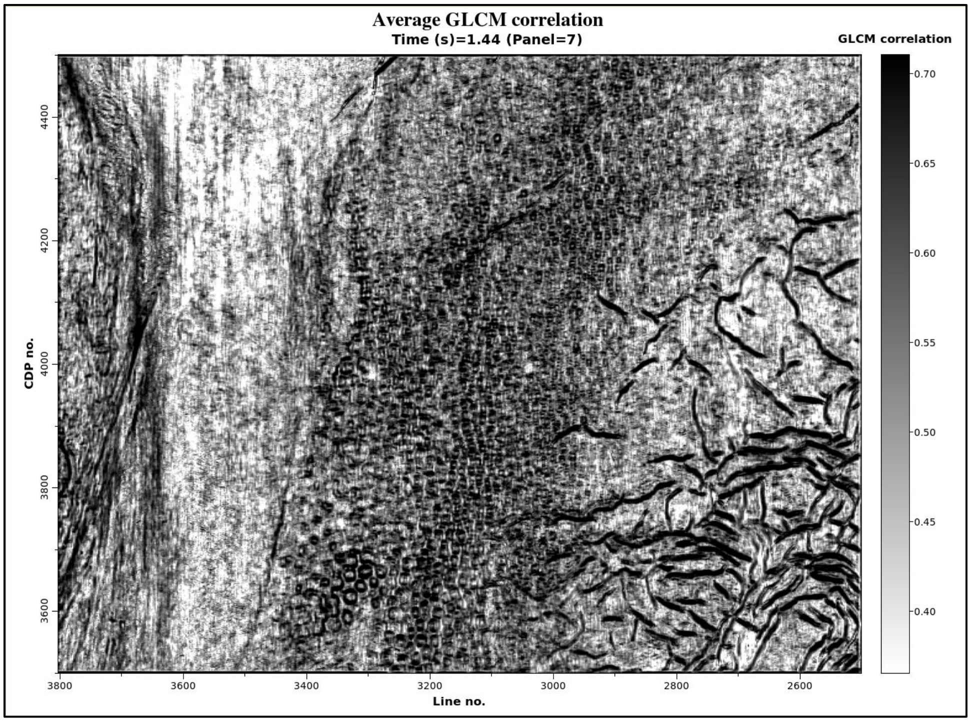


Increasing the window size to be ±0.020 s (11 samples) gives this image:

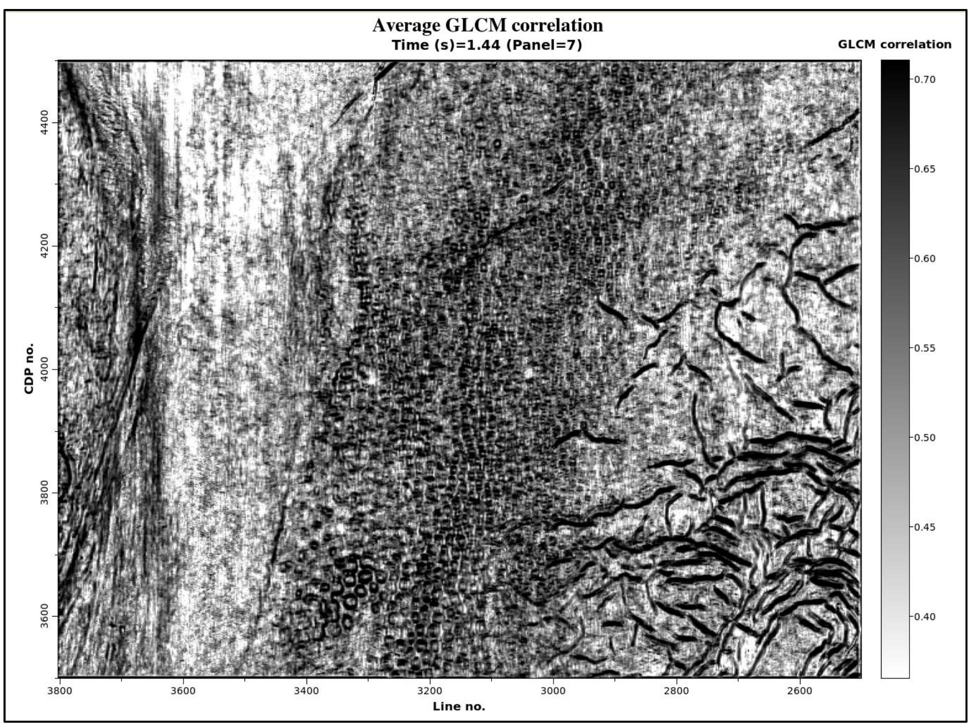


GLCM Correlation

Although often described as a measure of how similar neighboring voxels are on a satellite or aerial image, this is not the case for seismic data. Indeed, if the amplitude within an analysis window is nearly the same (nearly equal to the mean) the correlation is low, whereas where it differs, it is high. Using a window of radius 50 m by 50 m (containing 45 traces) and a vertical window of ±0.004 s (three samples) gives the following image:



Increasing the window size to be ±0.020 s (11 samples) gives this image:



Comparing the GLCM correlation to coherence (such as computed in program similarity3d), we note that equation 12 is similar to the covariance matrix:

$$\sum_{i=1}^{J}\sum_{j=1}^{J}\left[\left(d_i-\mu\right)\left(d_j-\mu\right)+\left(d_i^{\mathrm{H}}-\mu^{\mathrm{H}}\right)\left(d_j^{\mathrm{H}}-\mu^{\mathrm{H}}\right)\right]$$

Theory: Relationship of GLCM correlation to the covariance matrix

Like GLCM energy, the GLCM correlation attribute name can be quite confusing to most seismic interpreters. Examining the results of the example above shows that areas that are very similar (exhibit high similarity or coherence) whereas areas that are dissimilar, such as fault that exhibit low similarity or coherence exhibit a high correlation. To better understand just what the GLCM correlation is measuring, let's reexamine the covariance matrix **C** for *R* traces at a single slice along structural dip described in the documentation for program **similarity3d**

$$C_{rs}\equiv\left(d_r-\mu\right)\left(d_s-\mu\right). \qquad (13)$$

where for simplicity we have not included the contribution of the Hilbert transform and where we usually set the value of μ=0 for seismic amplitude data having a zero mean. The scaling in equation 2 simply gives a scaled version of equation 13. Normalizing by the energy of traces, we can write the variance of the unscaled data as

$$V_{\mathrm{similarity}}=\frac{\sum_{r=1}^{R}\left(d_r-\mu\right)^2}{\sum_{r=1}^{R}\left(d_r\right)^2}=\frac{\sum_{r=1}^{R}\left(d_r\right)^2-R\mu^2}{\sum_{r=1}^{R}\left(d_r\right)^2} \qquad (14)$$

where the term after the second equals sign is often called the fast implementation of variance. This fast implementation can result in round-off errors so should be used with care. We can write the semblance-based similarity in two ways. The traditional way is to write

$$S_{\mathrm{similarity}}=\frac{\left(\sum_{r=1}^{R}d_r\right)^2}{R\sum_{r=1}^{R}\left(d_r\right)^2}=\frac{R\mu^2}{\sum_{r=1}^{R}\left(d_r\right)^2}\equiv 1-V_{\mathrm{similarity}} \qquad (15)$$

which shows the direct mapping of semblance-based similarity to variance-based similarity. The second way is to compute the outer product with a vector **u**

$$S_{\mathrm{similarity}}=\frac{\sum_{r=1}^{R}\left(u_r\sum_{s=1}^{R}C_{rs}u_s\right)}{\sum_{r=1}^{R}\left(d_r\right)^2}\text{, where} \qquad (16a)$$

$$u_r=\frac{1}{R^{1/2}}\quad \text{for all r=1, 2, …, R.} \qquad (16b)$$

Returning to equation 12, we now see that the unnormalized version of GLCM correlation would be

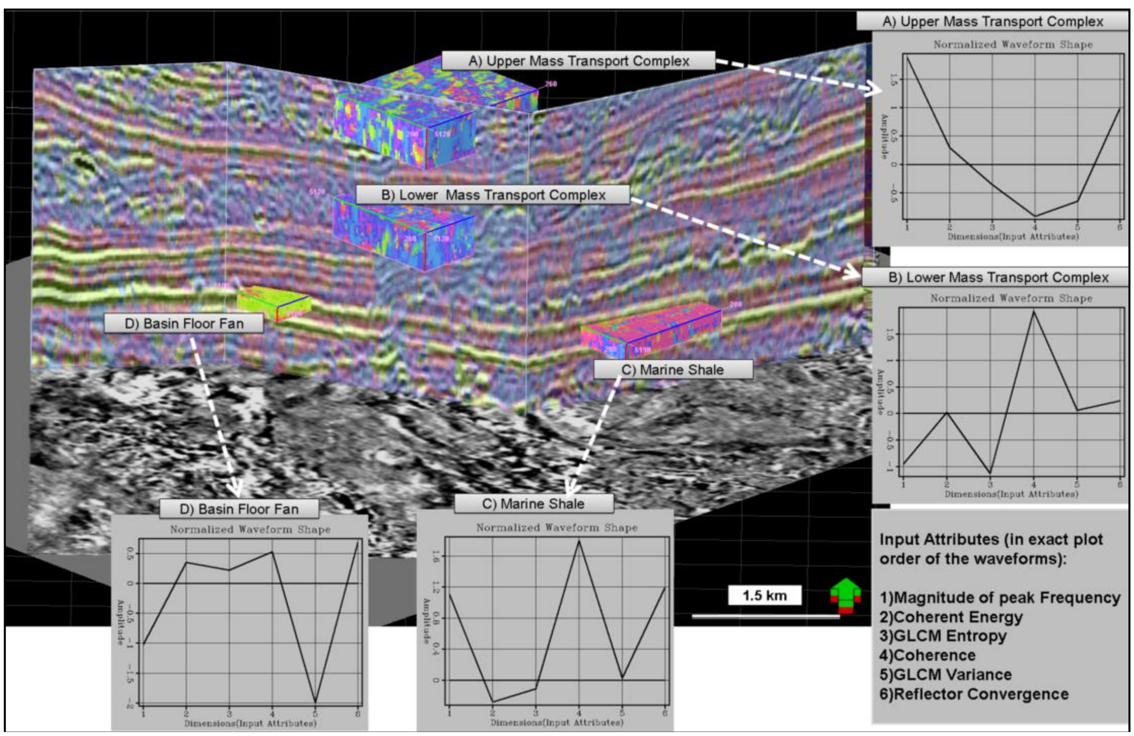
$$\tilde{R}_{\mathrm{GLCM}}=\frac{\sum_{r=1}^{R}\left(\sum_{s=1}^{R}C_{rs}\right)}{\sum_{r=1}^{R}\left(d_r\right)^2}. \qquad (17)$$

which sums all of the elements of the covariance matrix and gives a result that is nothing like semblance- or variance-based similarity.

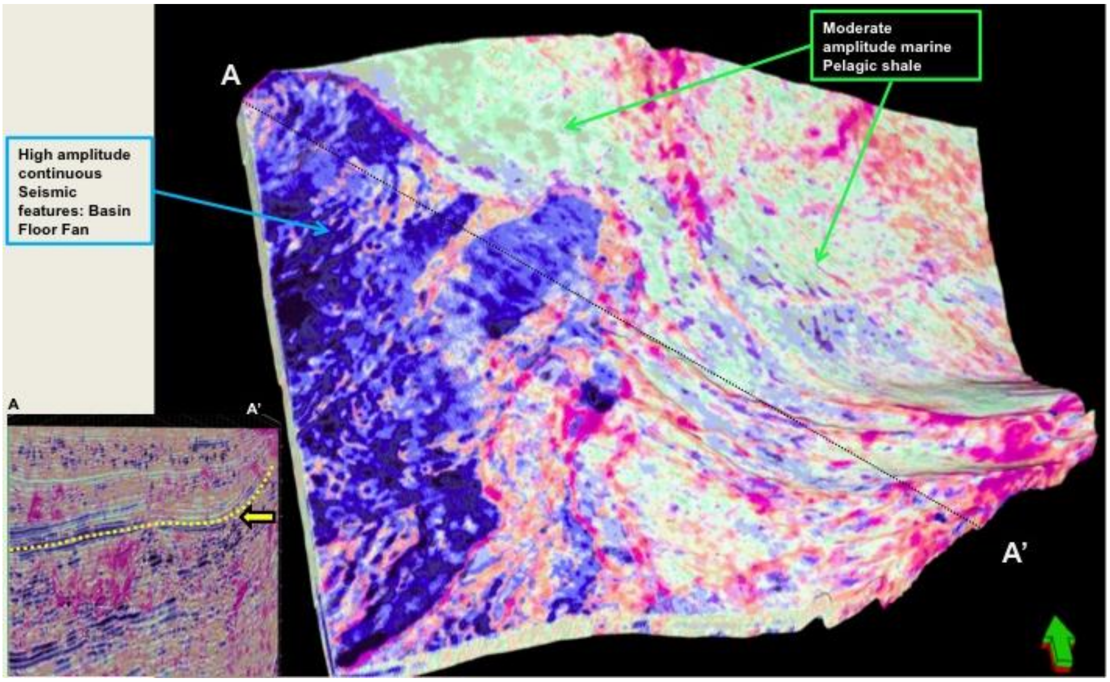
Example 2

By themselves, texture attributes are not as useful as the 'geometric attributes' that measure distinct, easily-understood geomorphology components such as edges, folds, and discrete changes in amplitude. Textures are most commonly used as input to either a supervised or unsupervised classification system. An excellent example of combining GLCM texture attributes and supervised classification using neural networks can be found in Ruffo et al. (2007), Gao (2004, 2007, 2009, 2011) shows many examples of unsupervised classification of GLCM texture attributes using self-organizing maps and a posteriori supervision using well control and geologic deposition models.

Matos et al. (2011) and Yenugu (2010) and Roy et al. (2011) also use SOM to cluster GLCM texture attributes. Here we display the results from Roy et al. (2011) that used texture attributes GLCM entropy and GLCM variance as input to program som3d.



There are some other unsupervised clustering examples considering different combinations of GLCM as input. In the following example GLCM dissimilarity and GLCM homogeneity are two of the five input to the multi-attribute clustering program. The **som3d** program is discussed in a later section of this documentation.



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