

## 2D SEISMIC FACIES ANALYSIS – PROGRAM

### **pca\_waveform\_classification**

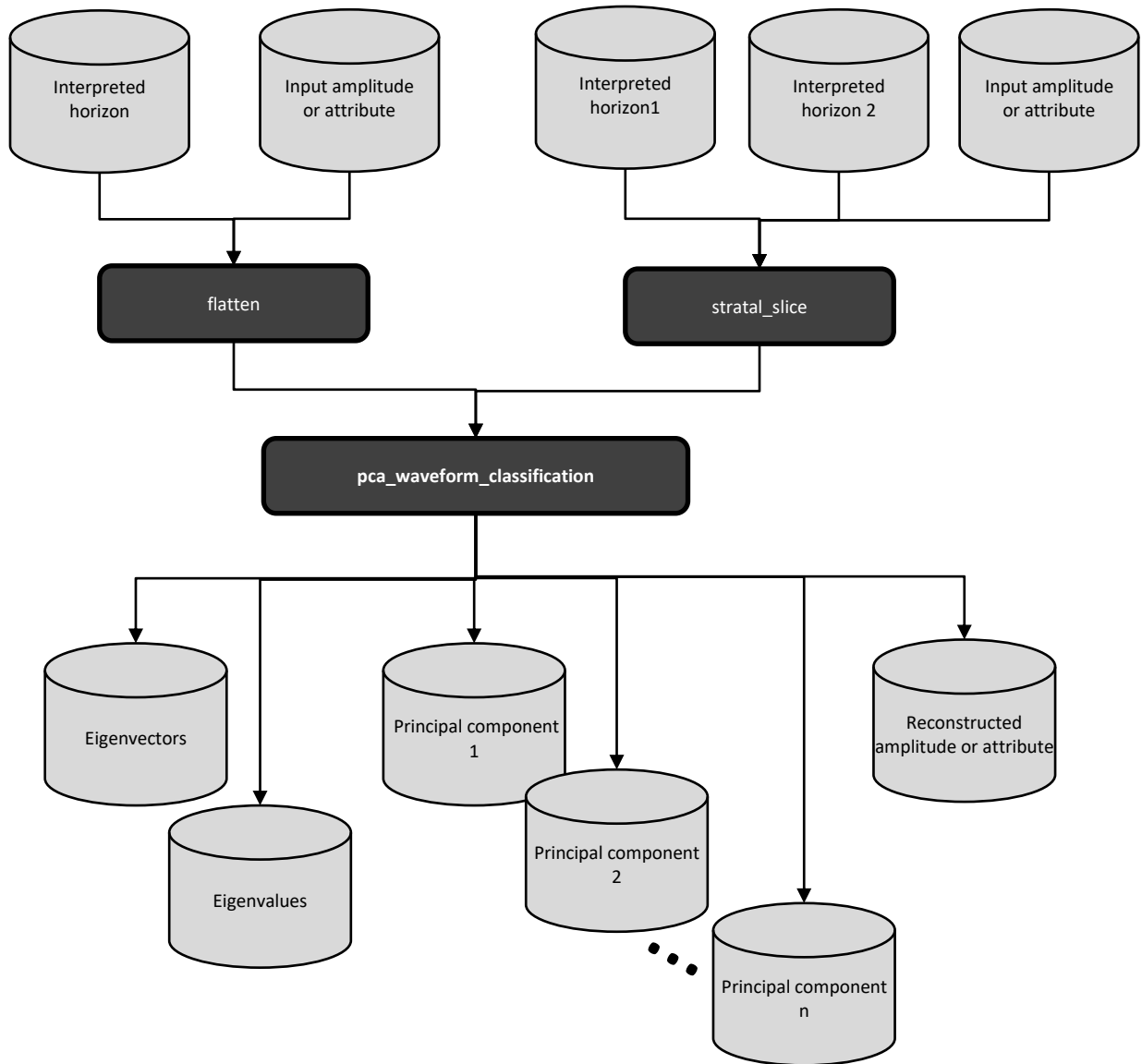
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#### **Computation flow chart**

Principal component analysis is one of the simplest means reducing redundant high dimensional data to a much lower dimensional space. While useful, one should recognize that the meaning of principal components is mathematical rather than physical. Program **pca\_waveform\_classification** reads in a window of seismic amplitude, impedances, Poisson's ratio, or other attribute and outputs a suite of principal component slices. For facies analysis the input data should either be flattened or stratal-sliced along previously interpreted geologic horizons.

# Formation Attributes: Program `pca_waveform_classification`



### Theory: Covariance matrices, eigenvectors, eigenvalues, and principal components

The covariance matrix,  $\mathbf{C}$ , is constructed by comparing each sample vector  $d(t,x,y)$  to itself and all its neighbors. As an example, consider a suite of  $N$  phantom horizon slices through an  $M$ -trace seismic amplitude volume. We begin by defining the mean,  $\mu_k$  for each slice:

$$\mu_n = \frac{1}{N} \sum_{m=1}^M d(t_n, x_m, y_m). \quad (1)$$

The covariance matrix is then defined as

$$C_{kn} = \frac{1}{M} \sum_{m=1}^M [d(t_n, x_m, y_m) - \mu_n][d(t_k, x_m, y_m) - \mu_k], \quad (2)$$

which is simply an  $N$  by  $N$  matrix of auto-correlation (if  $k=n$ ) and cross-correlation (if  $k \neq n$ ) coefficients of phantom horizon slices. This covariance matrix measures lateral similarities and dissimilarities (or patterns) amongst the seismic wavelets.

Any symmetric  $N$  by  $N$  matrix can be decomposed into  $N$  eigenvalue-eigenvector pairs,  $\lambda_n$ , and  $\mathbf{v}_n$  that satisfy

$$\mathbf{C}\mathbf{v}_n = \lambda_n \mathbf{v}_n, \quad (3)$$

where  $n$  varies between 1 and  $N$ . By construction, the first eigenvector  $\mathbf{v}_1$  is the vector (waveform) of unit length that best represents the energy of all vectors  $d_{nm}$ . If we cross-correlate this eigenvector with each trace, we obtain the first principal component:

$$p_{k1} = \sum_{n=1}^N d(t_n, x_m, y_m) v_{n1}. \quad (4)$$

Subtracting the data represented by the first principal component gives a residual

$$\tilde{d}_{nm} = d_{nm} - p_{n1}. \quad (5)$$

Physically, the second eigenvector  $\mathbf{v}_2$  is the vector (waveform) of unit length that best represents the energy of all the residual vectors. The corresponding principal component is

$$p_{k2} = \sum_{n=1}^N d(t_n, x_m, y_m) v_{n2}, \quad (6)$$

and so on for all  $N$  components. While the eigenvectors are orthogonal,

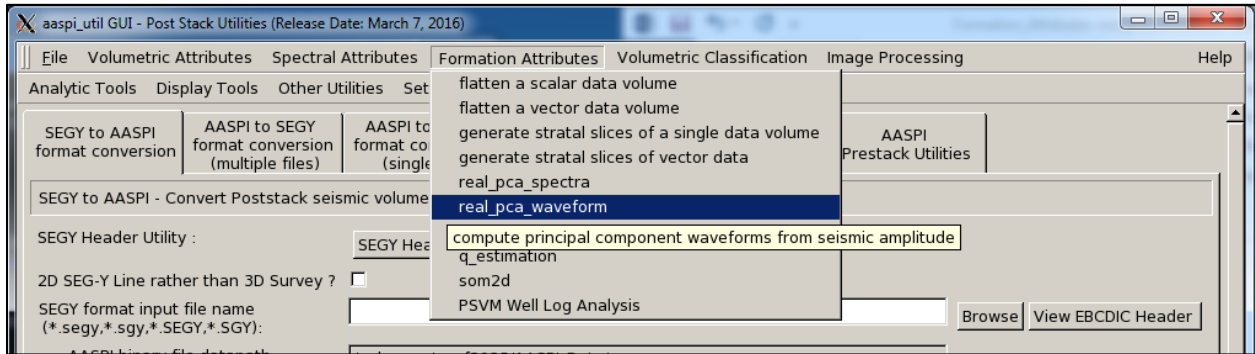
$$\mathbf{v}_i \cdot \mathbf{v}_j = \delta_{ij}, \quad (7)$$

the principal components are not.

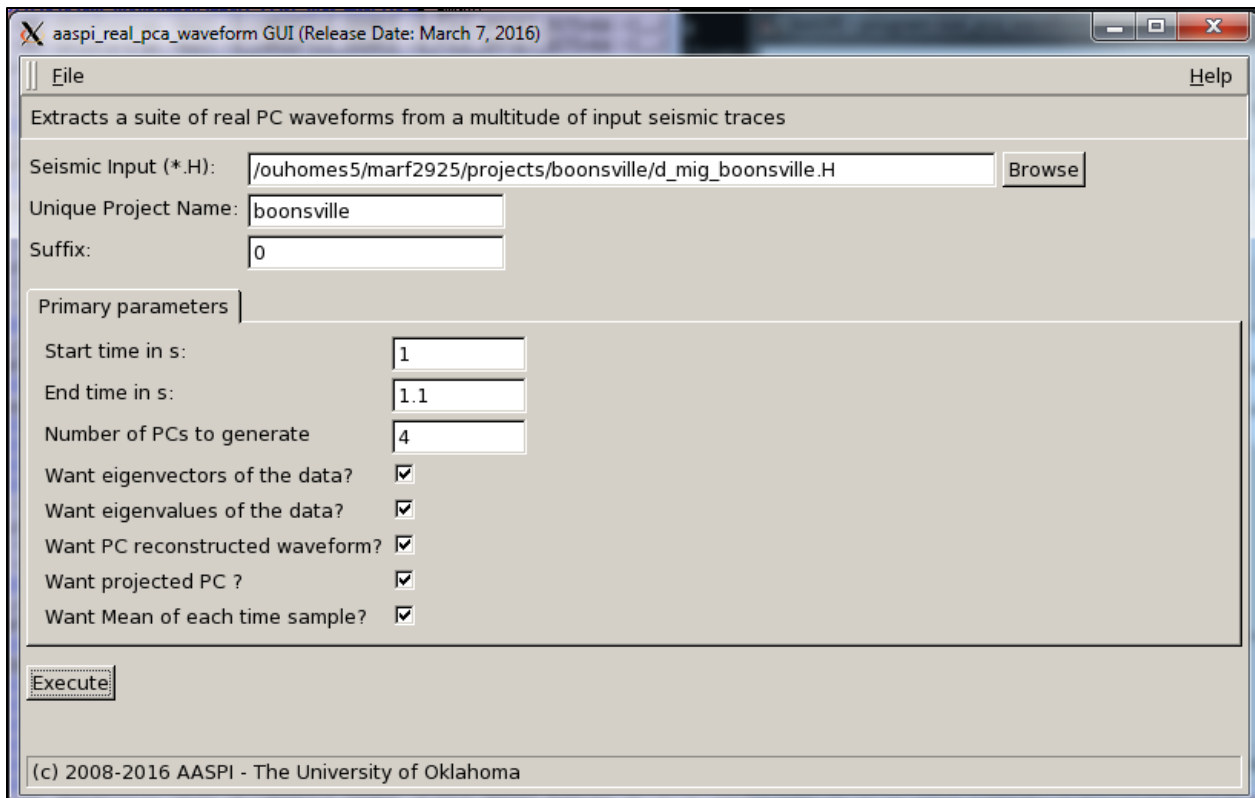
## Formation Attributes: Program **pca\_waveform\_classification**

### The **pca\_waveform\_classification** graphical user interface

This Program **2D Facies Analysis** is launched from the *Formation Attributes* in the main **aaspi\_util** GUI.



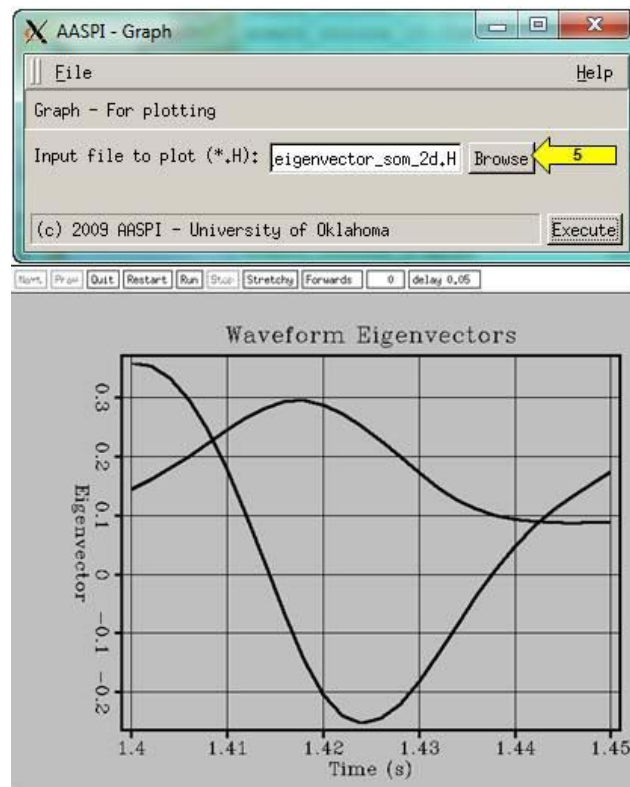
The following GUI appears:



To QC the outputs from **the pca\_waveform\_classification** program we can plot the eigenvectors, the eigenvalues and the means in the simple graph utility as shown above. The eigenvalues and the eigenvectors, which form the initial set or a priori training vectors, are shown below. The

## Formation Attributes: Program `pca_waveform_classification`

horizontal axis represents the samples of the waveform used in the analysis. The plot of the eigenvectors is the plot of the first two eigenvectors.



## Crossplotting two or three principle components in Petrel

## References