Probabilistic Seismic Facies: A Gaussian Mixture Model Approach- Canterbury Basin, offshore New Zealand

AASPI

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Introduction:
Visual examination of seismic facies on large 3-D seismic data sets where there is little *a priori* geological information can be time consuming and inaccurate. The process can be more semi-automated and improved through the use of unsupervised machine learning. By allowing the data to speak for themselves, features can be automatically generated. This has the obvious benefit of quicker interpretations while also highlighting features that might otherwise go unnoticed. The Gaussian Mixture Model (GMM) provides a flexible framework by which to accomplish this. A seismic attribute can be represented as a single dimension in a d-dimensional space where d is the number of attributes (Wallet et al., 2009). The d-dimensional attribute space is an appropriate space for a GMM to be applied. The objective is to generate seismic facies via an automated, soft classification scheme.

Geologic Setting:
The seismic survey is located on the Canterbury Basin, offshore New Zealand (**Figure 3**). More specifically, the area lies in the transition zone of the continental rise and continental slope. The data set contains many Cretaceous and Tertiary age paleocanyons and turbidite deposits. Sediments were deposited in a single transgressive-regressive cycle driven by tectonics (Zhao et al., 2015). The basin has been evaluated as a basin centered gas system (Cozen, 2011).

Gaussian Mixture Model (GMM):
GMM's are used to estimate probability density functions (PDF) using the weighted sums of Gaussian distributions. In this case, the GMM is being used as an unsupervised clustering algorithm. The parameters of each Gaussian, {πj, **μ**j, **C**j,}, can be estimated using maximum likelihood and an expectation-maximization algorithm (**Figure 2**) (Zhao et al., 2015). The 1-D case of the GMM can be seen in **Figure 1**.

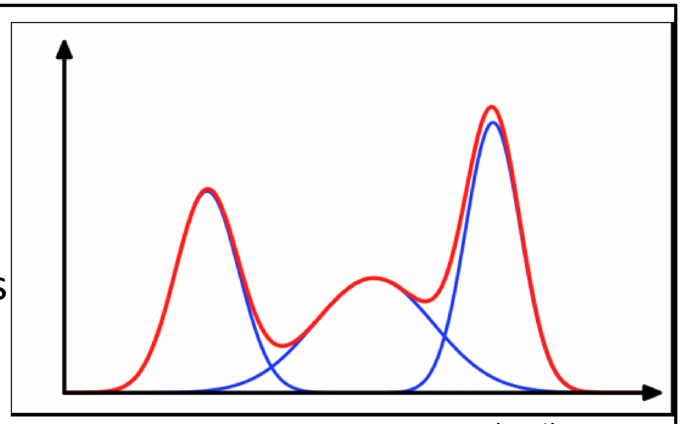


Figure 1: 1-D Gaussian Mixture (red) using three Gaussians of equal weight (blue)

$$\varphi(\mathbf{x}|\mu,\mathbf{C}) = \frac{1}{(2\pi)^{\frac{d}{2}}|\mathbf{C}|^{\frac{1}{2}}} e^{-\frac{1}{2}(\mathbf{x}-\mu)'\mathbf{C}^{-1}(\mathbf{x}-\mu)}$$

$$p(\mathbf{x}_i|\psi) = \sum_{j=1}^{k} \pi_j \varphi(\mathbf{x}|\mu,\mathbf{C}) \quad \text{where} \quad \Sigma_{j=1}^{k}\pi_j = 1$$

Figure 2: Mixture Model Equations

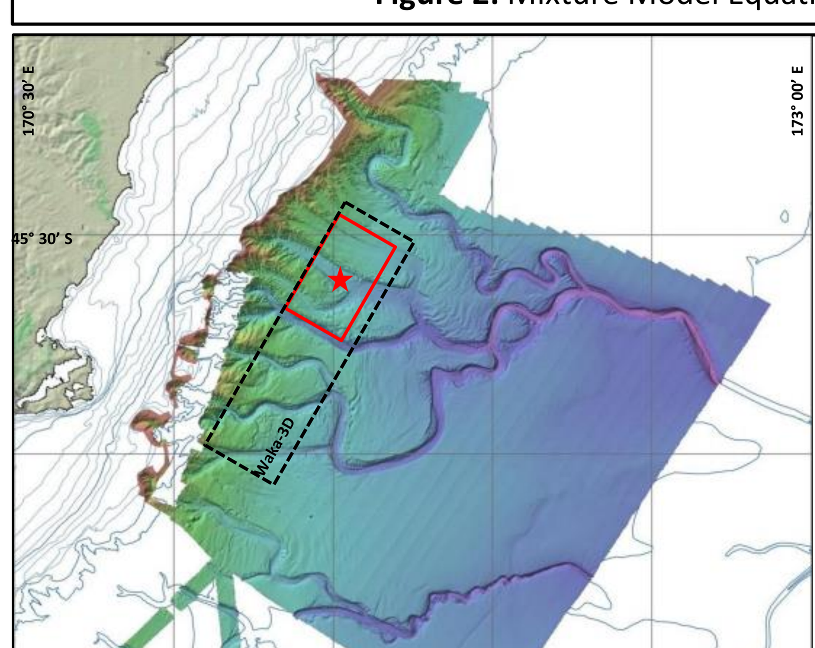
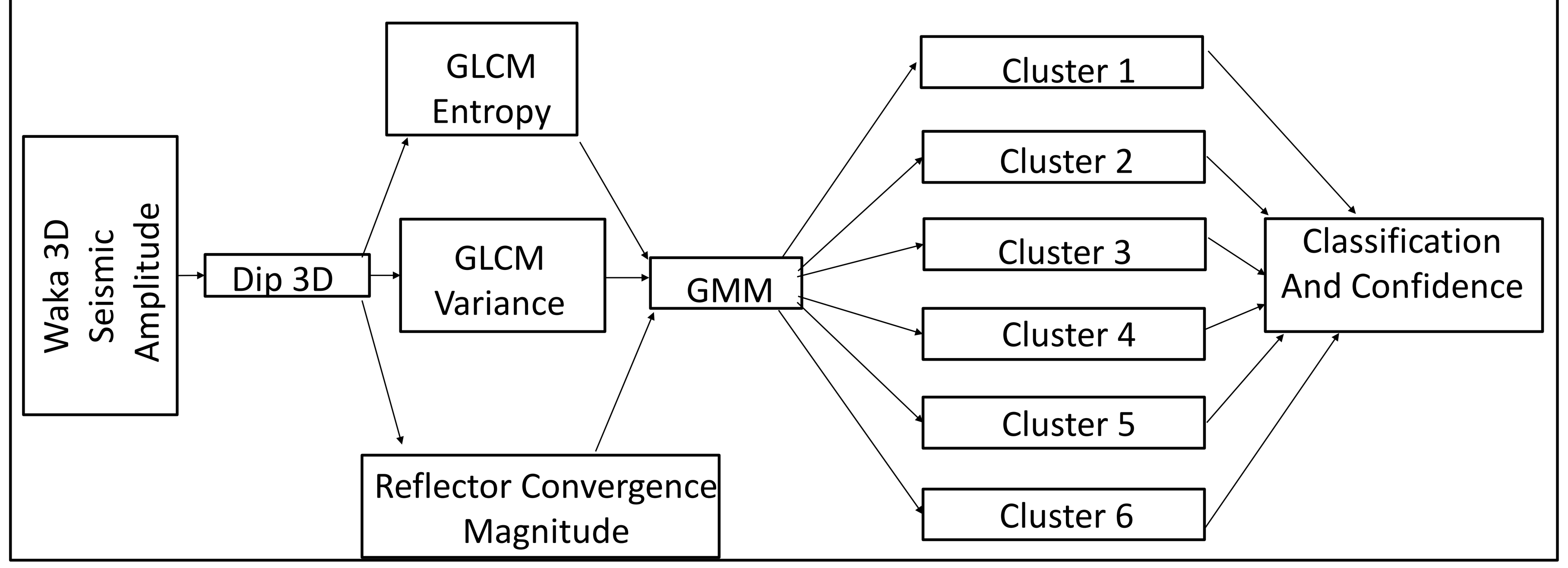


Figure 3: Aerial view of study area. (Modified from Tao et al., 2016)

Application to Waka3D: Methods
Using AASPI software, GLCM variance, GLCM entropy, and reflector convergence magnitude were generated for a picked horizon in the Waka3D volume (**Figure 4**). The three attributes were converted to z-scores, which were then used as inputs for GMM3D.

GMM3D Workflow



Application to Waka3D: Observations

Three volumes were input to the mixture model, and six clusters were found. The voxels used for training can be seen in **Figure 5**. The first cluster has low GLCM variance and reflector convergence and moderate GLCM entropy. The second cluster is similar to the first cluster except that the second cluster has higher GLCM variance. Clusters three and four both have large variability in GLCM variance and entropy. Furthermore, clusters three and four have large determinants, indicating that their distribution in attribute space is quite vast. The fifth and sixth clusters have very small model weights (3.91% and 1.85% respectively) and don't appear on the optimal classification map.

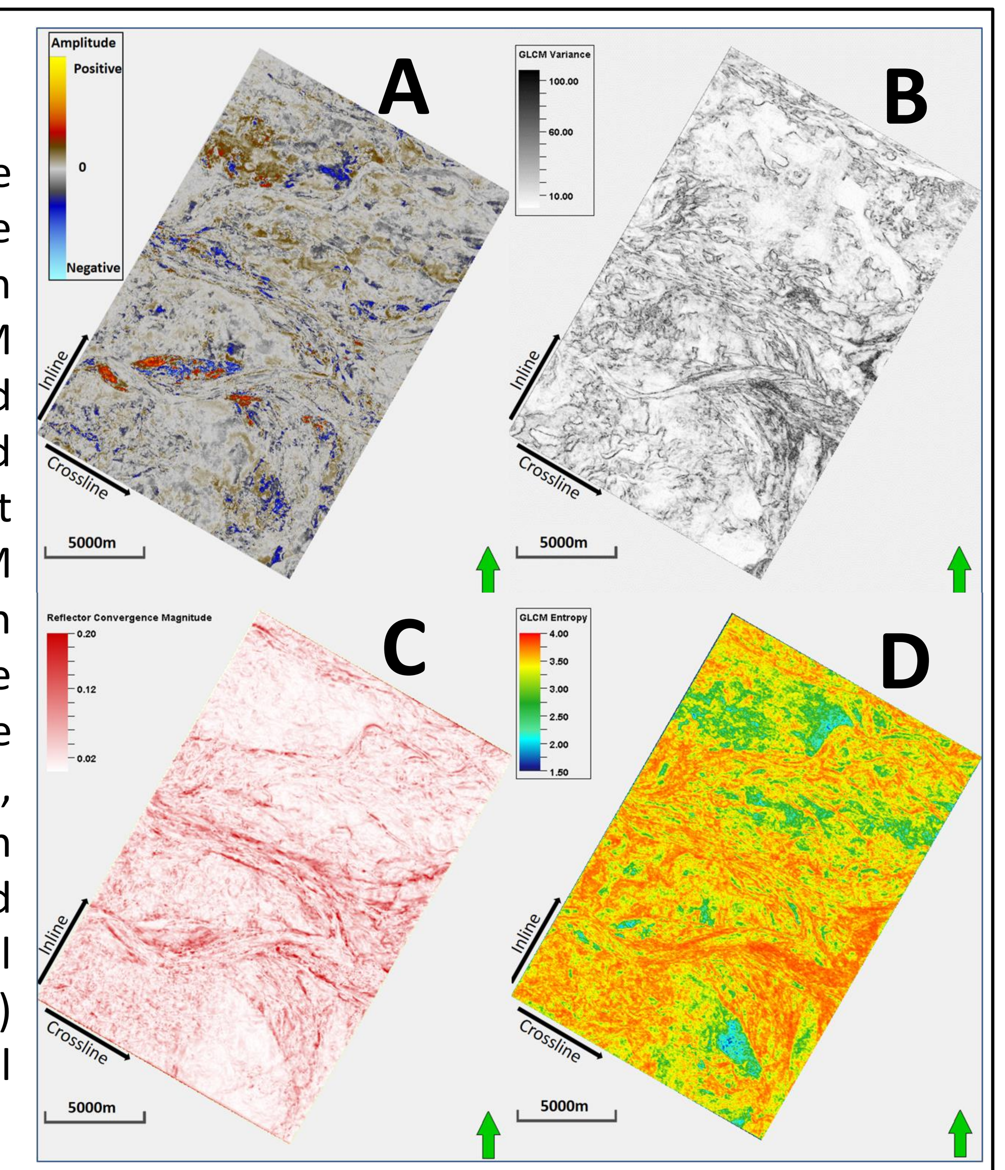


Figure 4: Horizon slices of **A)** seismic amplitude **B)** GLCM variance **C)** reflector convergence magnitude **D)** GLCM entropy

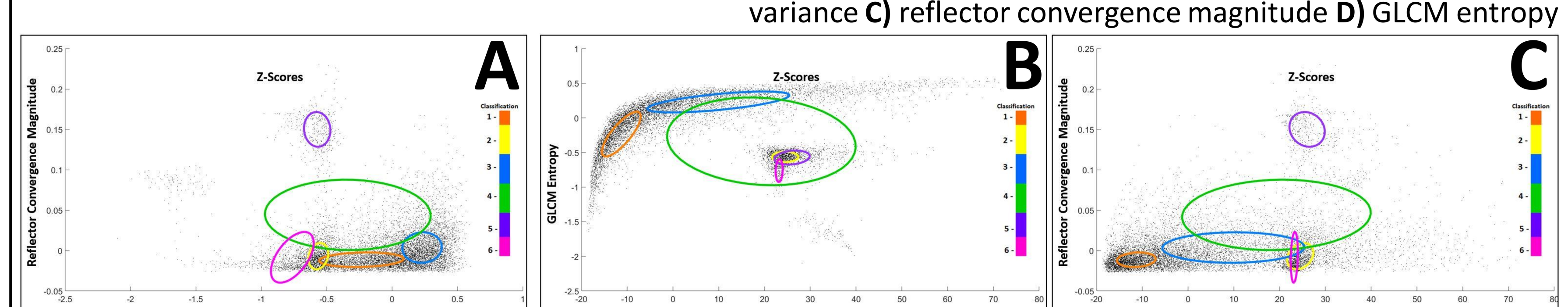


Figure 5: Training data with Gaussian clusters in color **A)** GLCM entropy vs reflector convergence magnitude **B)** GLCM variance vs GLCM entropy **C)** GLCM variance vs reflector convergence magnitude

Application to Waka3D: Interpretation
The results of the Gaussian mixture model is in **Table** 1. Each voxel can be assigned to cluster via a soft classification. Summing all those probabilities generates model confidence (**Figure 6A**), which seems to correlate to geological features. High model confidence is interpreted as modeling complexities well, while poor confidence is indicative of oversimplification. The seismic attribute response of deep water deposits has been summarized by Roy (2013) (**Table 2**). The first two clusters are likely sand, but cluster one should be considered to have more shale content due to its higher GLCM variance. Clusters three and four can both interpreted to be shale. GMM3D provides a convenient framework for multiattribute analysis.

Mixture Model Parameters					
Cluster	π(%)	$\mu(GLCM\ variance)$ $\mu\left(\begin{matrix}GLCM\\ entropy\end{matrix}\right)$ $\mu(Reflector\ convergence)$	C		
1.	37.8%	-11.3 -0.253 -0.113	17.9 1.08 0.00488	1.08 0.104 $3.86E-4$	0.004.88 $3.86E-4$ $8.12E-5$
2.	12.8%	24.5 -0.564 -0.00687	8.18 1.08 0.0126	$5.07E-4$ 0.00574 $3.86E-4$	0.0126 $3.86E-4$ $2.64E-4$
3.	35.9%	9.9 0.229 -0.00376	241 1.5 0.00979	1.5 0.028 $1.06E-4$	0.00979 $1.06E-4$ $3.56E-4$
4.	7.80%	19.3 -0.339 -0.0442	425 -1.49 0.0605	-1.49 0.402 $-6.03E-4$	-0.0605 $-6.03E-4$ 0.0019
5.	3.91%	26.0 -0.573 0.15	14.9 -0.0763 -0.0113	0.0763 -0.0102 $-1.24E-4$	-0.0113 $-1.24E-4$ -0.0043
6.	1.85%	23.2 -0.763 -0.0083	0.591 0.0131 -0.0113	0.0131 0.0268 0.00289	0.0043 0.00289 $-9.86E-4$

Table 1: Mixture model parameters

Deep Water Deposits	Seismic amplitude and pattern internal configuration	Attribute Anomalies
Mass Transport Complex (MTC)	Moderate to high amplitude, discontinuous, chaotic, hummocky, rotated blocks	High reflector convergence due to pinch out patterns and rotated blocks. High values of GLCM variance and entropy
Basin Floor Fan	High amplitude continuous, isolated or connected features within fan.	Low reflector convergence due to sub-parallel reflectors. Moderate values of GLCM variance and entropy
Marine Pelagic Shale	Moderate to low amplitude, continuous, very thin, and separated from MTC	Low reflector convergence due to sub-parallel reflectors. Moderate values of GLCM variance and entropy

Table 2: Expected attribute responses of deep water deposits (Modified from Roy, *2013*)

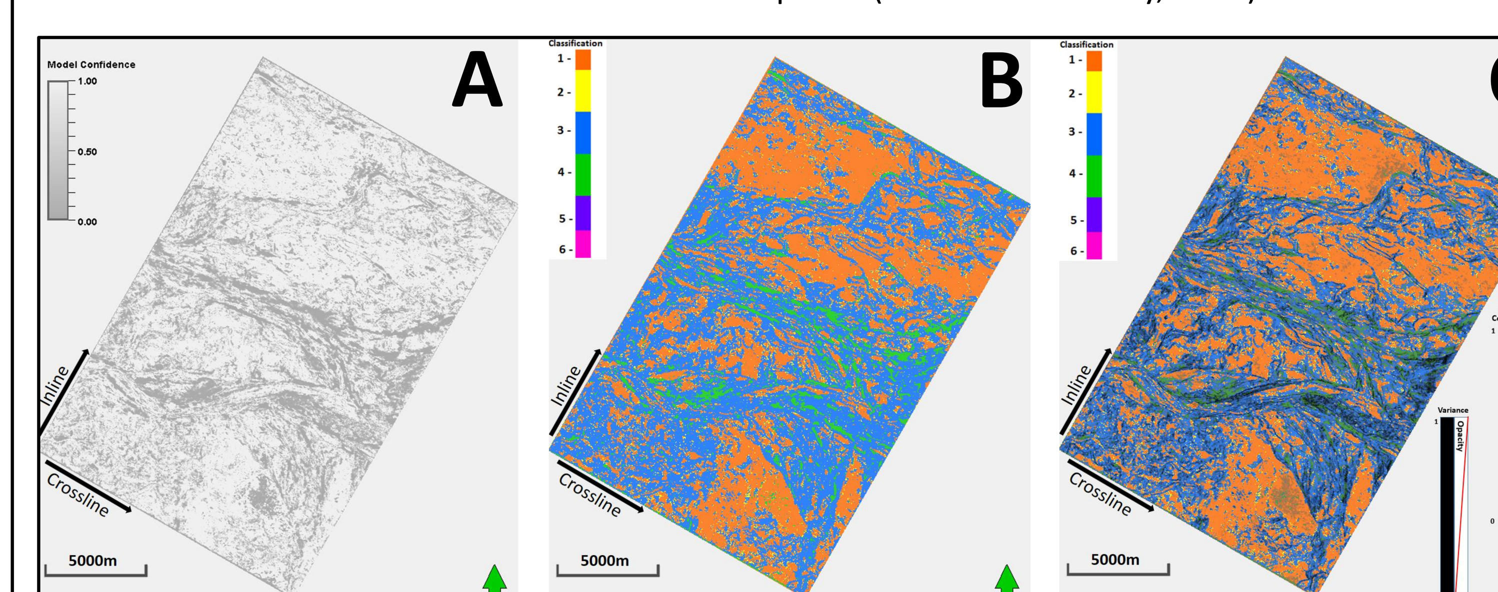


Figure 6: Gaussian mixture model **A)** mixture model confidence **B)** optimal classification **C)** model confidence co-rendered with optimal classification overlaid by variance

References

Lubo, D., V. Jayaram, K. J. Marfurt., 2014, Statistical Characterization and Geological Correlation of Wells Using Automatic Learning Gaussian Mixture Models: Unconventional Resources Technology Conference, p. 1-6.
Roy, A., 2013, Latent Space Classification of Seismic Facies. Ph.D. Dissertation, University of Oklahoma
Vlassis, N., A. Likas, 2002, A greedy EM for Gaussian mixture learning: Neural Processing Letters, v. 15, p. 77-87.
Wallet, B.C., M. C. de Matos, J.T. Kwiatowski, and Y. Suarez, 2009, Latent space modeling of seismic data: An overview: The Leading Edge, 28, p. 1454-1459.
Zhao, T., V. Jayaram, A. Roy, K. Marfurt, 2015, A Comparison of classification techniques for seismic facies recognition: Interpretation, 3(4), p. SAE29-SAE58.
Zhao, T., J. Zhang, F. Li, K. J. Marfurt, 2016, Characterizing a turbidite system in Canterbury Basin, New Zealand using seismic attributes and distance-preserving self-organizing maps: Interpretation, 4(1), p. SB79-SB89.

Acknowledgements

We would like to thank the New Zealand Petroleum and Minerals for making the Waka-3D seismic data public. We would also like to thank the sponsors of the Attribute-Assisted Seismic Processing and Interpretation (AASPI) Consortium at the University of Oklahoma. Horizon slices were generated using Petrel licenses courtesy of Schlumberger. And thanks to all our colleagues for their valuable insights.