Delineation of geological elements from RGB color blending of seismic attribute volumes

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Seismic data contain a vast amount of information regarding different properties of the imaged geology. Unravelling the disparate types of information to produce an accurate and detailed subsurface model is a primary purpose of seismic interpretation. To aid this task, a wide range of volumetric seismic attribute computation techniques have been developed. Seismic attributes are designed to measure, extract, or enhance specific characteristics of the data so information regarding different aspects of geology can be examined independently. However, an accurate and comprehensive interpretation can seldom be obtained from analysis of individual attributes in isolation; rather, it is necessary to consider information from different attributes simultaneously. Multiattribute analysis can be formulated as a process of examining a joint attribute space where there is often a degree of correlation between the bases.

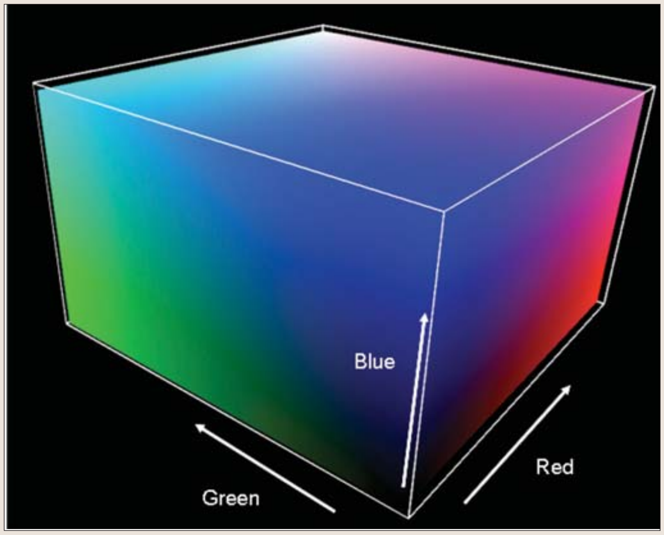


***Figure 1**. RGB color space.*

3D visualization plays an important role in this analysis and in recent years has become a core component of 3D seismic interpretation workflows. Much of the 3D seismic visualization software currently in use is based on 8-bit display technology. However, recent advances in workstation hardware capabilities allow 3D seismic visualization applications to operate in high and true color modes for realistic quantities of data. This not only facilitates real-time visualization of 16-bit seismic data on the workstation, but also has led to the introduction of more sophisticated and higher fidelity multivolume display techniques.

One such technique is volumetric co-rendering of multiple data sets using the RGB color model (Henderson et al. 2007; Stark, 2006). RGB co-rendering allows highly informative, multiattribute displays to be created that often show features with greater clarity and increased detail compared to standard displays.

A multiattribute RGB image is formed by defining

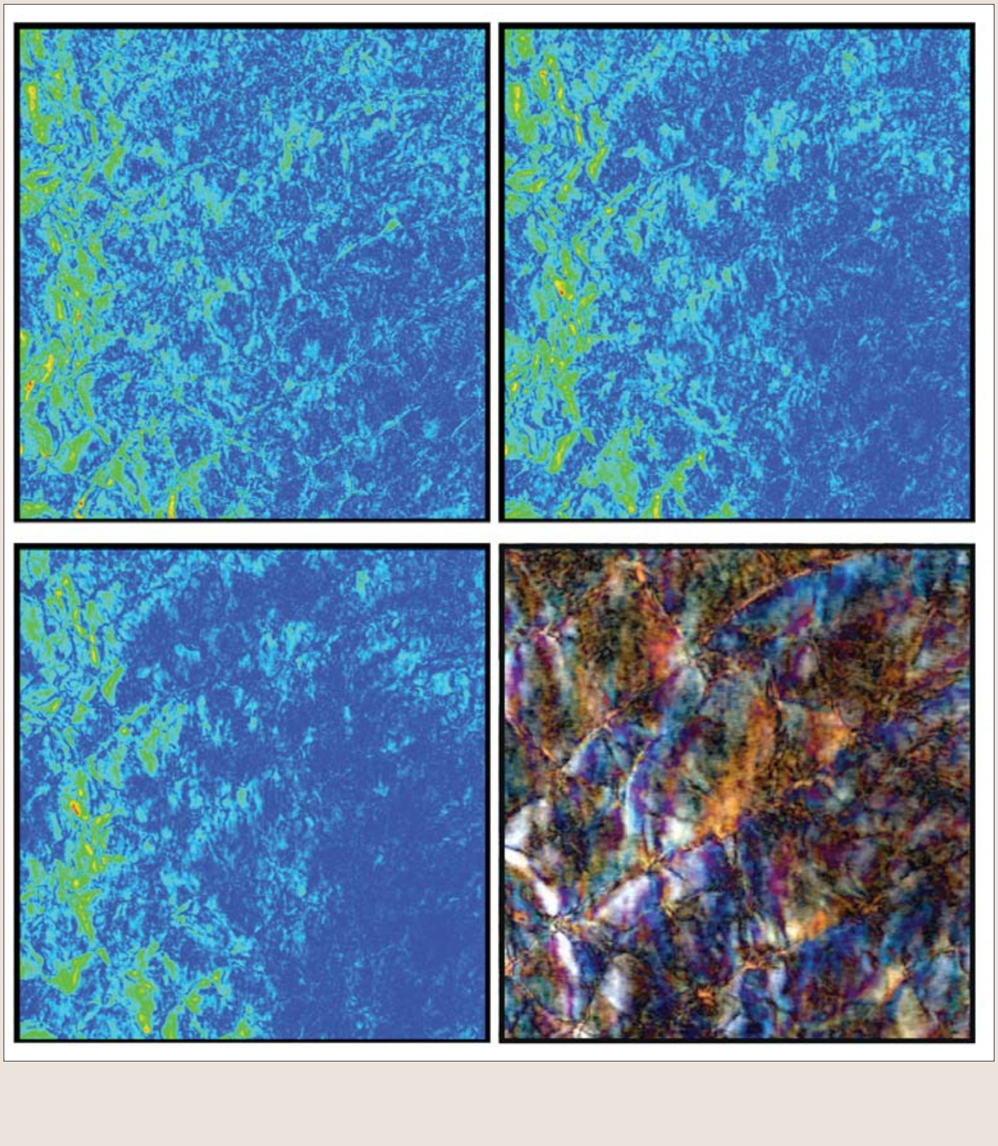


***Figure 2.** Time slices through spectral magnitude components at 24, 32, and 40 Hz and resulting RGB blend.*

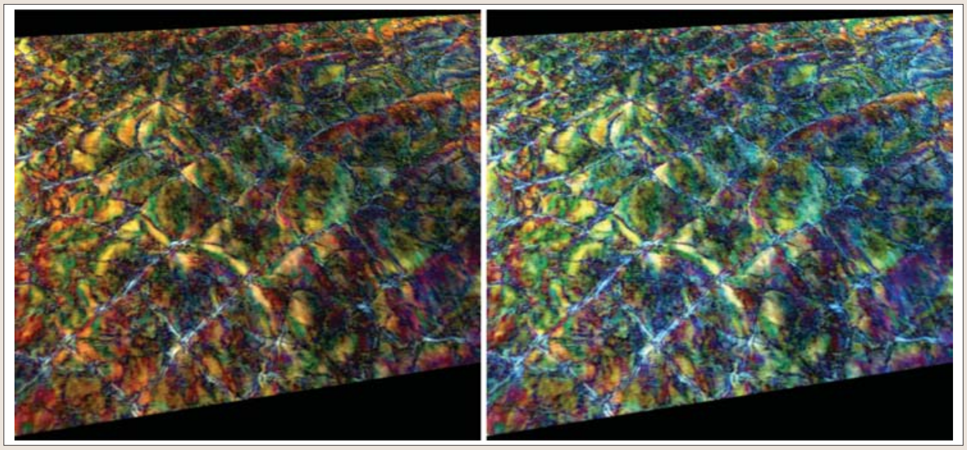


Figure 3. *RGB blends: (left) Constant scale applied to each input component. (right:) scale set to optimize each input component independently.*

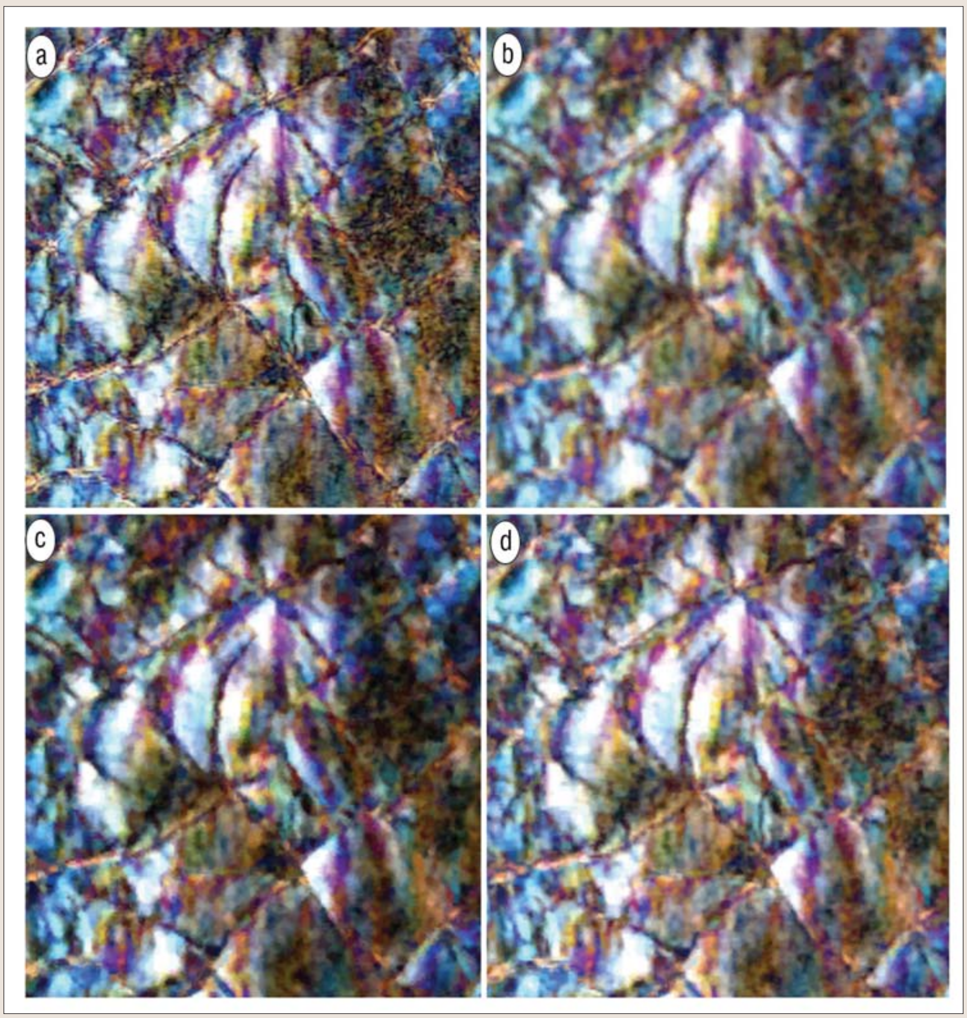


Figure 4: *Effect of noise attenuation filtering on RGB blended volumes. (a) Original data, (b) mean filter, (c) vector median filter, (d) adaptive neighborhood mean filter.*

a mapping S that assigns a color to each point in an output volume based on the values in each of the three input volumes.

$$I_{RGB}(\mathbf{x}) = S\left[I_R(\mathbf{x}), I_G(\mathbf{x}), I_B(\mathbf{x})\right] \tag{1}$$

where $\mathbf{x}=(x,y,z)$ is the position within the 3D volume. We can consider the RGB blend as utilizing a 3D color space, C_{RGB}, with the distance along the color space axes representing the relative intensity of the red, green and blue components (Figure 1). The mapping, S, defines the transformation applied to each of the three input volumes I_R, I_G and I_B to fit the input data into the 3D C_{RGB} color space.

Color-based co-rendering techniques work well when the individual data sources are naturally correlated to some degree, such as is found with multispectral satellite imagery or fMRI data in medical imaging. In seismic attribute applications, RGB blending has been most commonly applied to co-render the outputs of spectral decomposition analyses (Figure 2). In general, highly informative RGB blends can be generated from spectral decomposition magnitude response data using a simple linear transformation for the mapping function, the main purpose of which is range compression. Typically, seismic attribute data are computed at 16-bit integer, 32-bit integer or floating-point precision. To map this into a 24-bit RGB color space requires that each input be compressed and quantized to at most eight bits.

Generally, with spectral decomposition magnitude response data, S defines a linear mapping function and the user must choose whether to scale all three inputs equally or whether to utilize the maximum available dynamic range of each individual component. This can lead to substantial changes in the appearance of the generated RGB image (Figure 3), as the former will preserve the relationship between absolute values in each component, while the latter masks this relationship. Clearly this must be taken into account when "interpreting" RGB blended volumes.

The power of RGB blends as an intuitive visualization tool is readily apparent. The richness of structure and relative ease by which objects can be visually separated is very compelling, and the next natural step in an interpretation workflow is to extract these structures as geobodies. Extracting accurate geological information from such a multiattribute data space means addressing the issues of color-noise suppression and color volume based object delineation. We also note that small variations in data values in each input volume can result in large differences in color value in the final RGB image due to the color quantization process. Subsequent processing of RGB images should therefore be based on the full precision data in each color component after transformation but before quantization for visualization purposes.

Analysis of RGB images is as affected by noise as is analysis of any other type of image and noise attenuation can have a significant impact on the ability to delineate objects from RGB blended images. There are a wide variety of noise cancellation schemes that can be applied to seismic attribute data in order to improve the signal-to-noise ratio and enhance structures within the image. In general the most useful results are generated by edge-preserving filtering techniques such as adaptive median filtering and anisotropic diffusion. Conceptually, traditional "scalar" algorithms can be readily applied to denoise individual components within an RGB image by treating each component independently.

The simplest type of noise attenuation filter is an averaging process in which the value of the current point in the image is replaced by the mean value of the points within a given neighborhood. Simple linear processes like the mean readily generalize to RGB image data. Considering application of a mean filter with a 3D neighborhood of K points, R_{xyz}, to an RGB image, the resulting local average RGB value is given by $\bar{I}_{RGB}$:

$$\bar{I}_{RGB}(\mathbf{x}) = \frac{1}{K}\sum_{\mathbf{x}\in R_{xyz}} I_{RGB}(\mathbf{x}) \tag{2}$$

which can readily be expressed as:

$$\bar{I}_{RGB}(\mathbf{x}) = \begin{bmatrix} \frac{1}{K}\sum_{\mathbf{x}\in R_{xyz}} I_R(\mathbf{x}) \\ \frac{1}{K}\sum_{\mathbf{x}\in R_{xyz}} I_G(\mathbf{x}) \\ \frac{1}{K}\sum_{\mathbf{x}\in R_{xyz}} I_B(\mathbf{x}) \end{bmatrix} \tag{3}$$

where I_R, I_G, and I_B indicate the intensity of the red, green, and blue color components. The mean filter is a special case of color image filtering as it can be achieved both by applying the filter to each color component separately or as an operator, which is applied to the RGB vector representation (Figure 4).

A recognized drawback of any mean filtering is attenuation of the high spatial frequency content of the image irrespective of whether the high spatial frequencies are due to noise or provide information.

To avoid this problem, a number of edge-preserving noise attenuation techniques have been developed for single component image filtering (e.g. median, Kuwahara, and anisotropic diffusion filters). Unlike a mean filter, these edge-preserving noise attenuation techniques cannot be applied to the RGB color components independently. As an example we can consider the operation of median filtering. A median filter works by selecting the middle value when the data within a user defined neighborhood are ordered from smallest to largest. If we just select the median red value, the median green value and the median blue value independently then we are likely to end up with a color that is not in the original RGB blend. This violates an important statistical property of the median filter and the resulting color may be poorly representative of the colors within the examined neighborhood. The effect may also be detrimental as local attribute maxima in each component can shift independently (Koschan and Abidi, 2001). Visually this can affect the spatial alignment of features, for example taking edge structures out of alignment.

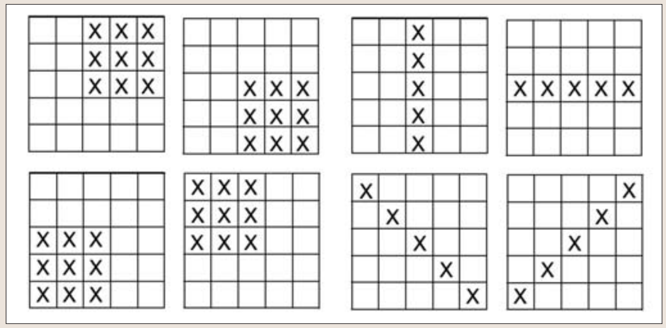


Figure 5. Examples of possible quadrant masks for ANM RGB noise filtering. 2D masks are shown for ease of illustration; in practice 3D masks are applied.

To implement a true RGB median filter, it is necessary to introduce the mathematical concept of rank within the 3D color space. A popular solution to this problem is through the use of vector order statistics to produce a so-called reduced ordering scheme (Koschan and Abidi, 2005; Weickert and Brox, 2002; Vertan et al., 1996; Nikolaidis and Pitas, 1996). This leads to a definition of the vector median filter (VMF). The VMF considers an RGB value as a multivariate term, $\boldsymbol{c} = (I_R, I_G, I_B)$, where I_R, I_G and I_B are random variables. If $\boldsymbol{c}_i$ $\boldsymbol{i} = 1,2,...,N$ is an observation of $\boldsymbol{c}$ within a given neighborhood, R_{xyz}. The following distance metric can be computed:

$$d_i = \sum_{k=1}^{N} \left\| \mathbf{c}_i - \mathbf{c}_k \right\| \tag{4}$$

where $\|\cdot\|$ represents the vector norm. The metric values, d_i, are sorted into ascending order and the same order is associated with the observed values, $\boldsymbol{c}_i$. The vector corresponding to the lowest metric value is the vector with the minimum distance to all other vectors in the set and is taken as the median vector.

Although the VMF is a widely used technique in color image processing, there is little to indicate there is an accepted best approach, and the performance of color smoothing operators including the VMF are highly dependent on image content and the type of noise degradation that has occurred.

Initial results from applying the VMF to the RGB-blended results of seismic spectral decomposition show advantages and disadvantages of the technique. Figure 4c shows the result of applying the VMF with the same spatial analysis window as the mean filter applied in Figure 4b. In this example, the result is visibly less blurred than that produced by the mean filter; however, some distortion is apparent. Color variations in some regions appear to have coalesced into structures of similar hue, which do not appear to honor structures in the original blend. Around many fault type features, the depth of intensity variation has been reduced leading to a loss of detail. Conversely, where faults appear to be expressed by a significant change in hue across the fault, the features are preserved well as the hue change boundary remains quite stable.

The VMF is a direct extension of the median filter concept and we should expect it to work well in situations where an image neighborhood consists of a single cluster of values. In such cases the median vector is a good representation and robust to outliers as it will be at the center of that cluster of vectors. The initial results seem to support this.

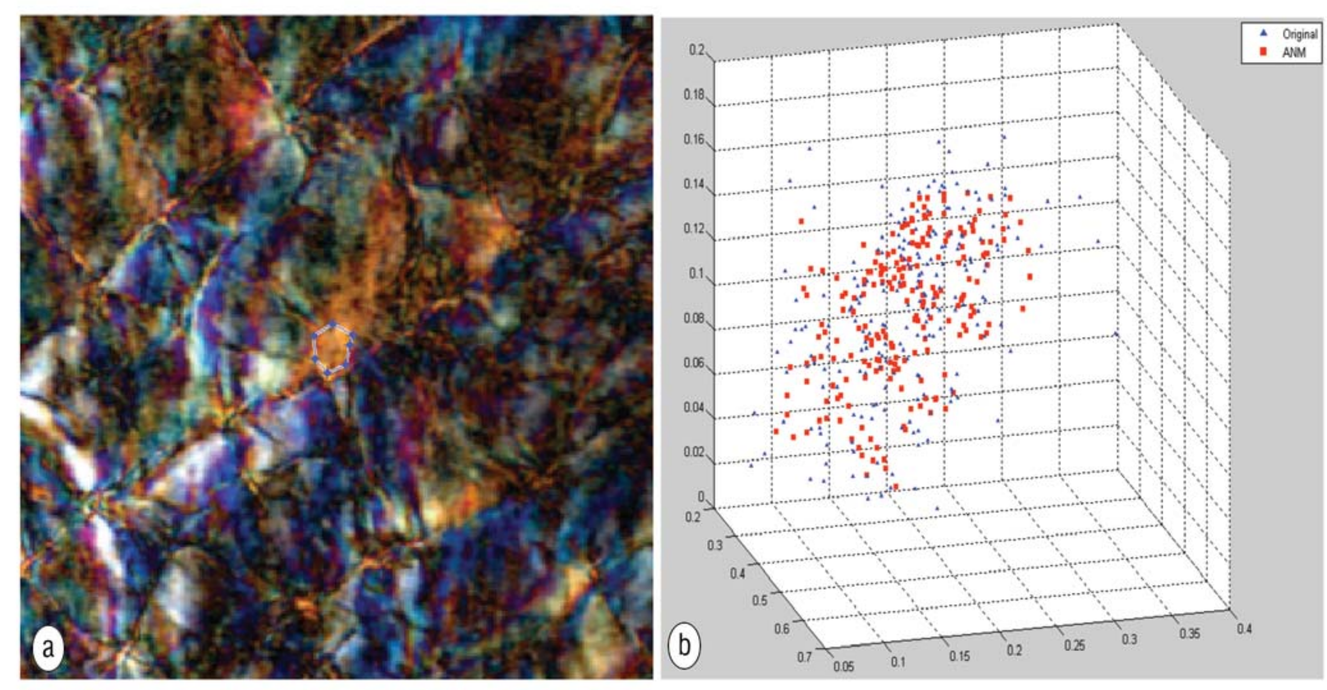


Figure 6. *Distribution of color values within a neighborhood covering a region of relatively uniform color. (a) RGB image and region of interest defined by the blue and white polygon. (b) 3D crossplot showing the distribution of values within the RGB color space: (blue) prenoise filtering, (red) postnoise filtering.*

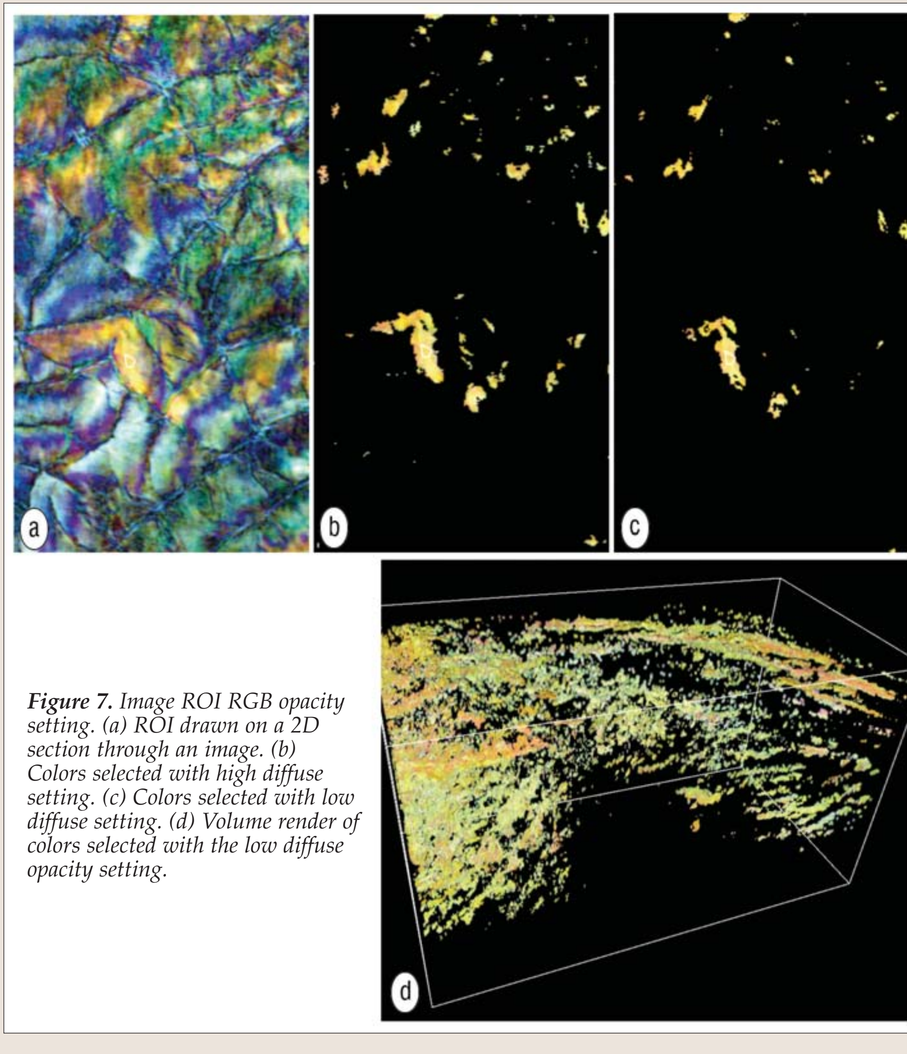


Figure 7. *Image ROI RGB opacity setting. (a) ROI drawn on a 2D section through an image. (b) Colors selected with high diffuse setting. (c) Colors selected with low diffuse setting. (d) Volume render of colors selected with the low diffuse opacity setting.*

In cases where vector distributions are bimodal or multimodal we would not expect the VMF to perform well. Clearly, any RGB noise attenuation filter needs to consider how the values in neighboring spatial locations are clustered within the 3D RGB space.

An alternative RGB-based, edge-preserving noise attenuation filter can be defined by considering the compactness of the clusters and how it varies within different quadrants of the 3D neighborhood being examined. Using this approach, we can define an adaptive neighborhood mean (ANM) filter. The ANM filter provides several options for defining the manner in which the neighborhood is divided into quadrants (Figure 5). To preserve lineations—for example, faults—it may be appropriate to divide the neighborhood into planes of varying orientation. To preserve the boundary between regions of bulk difference in data values, it may be appropriate to use quadrants that divide the neighborhood into a number of 3D blocks.

The operation of the ANM filter is as follows: The center in RGB space of the cluster of points from an individual quadrant is given by $[\overline{I}_R(x,y,z), \overline{I}_G(x,y,z), \overline{I}_B(x,y,z)]$ where $\overline{I}$ is the average value of each color

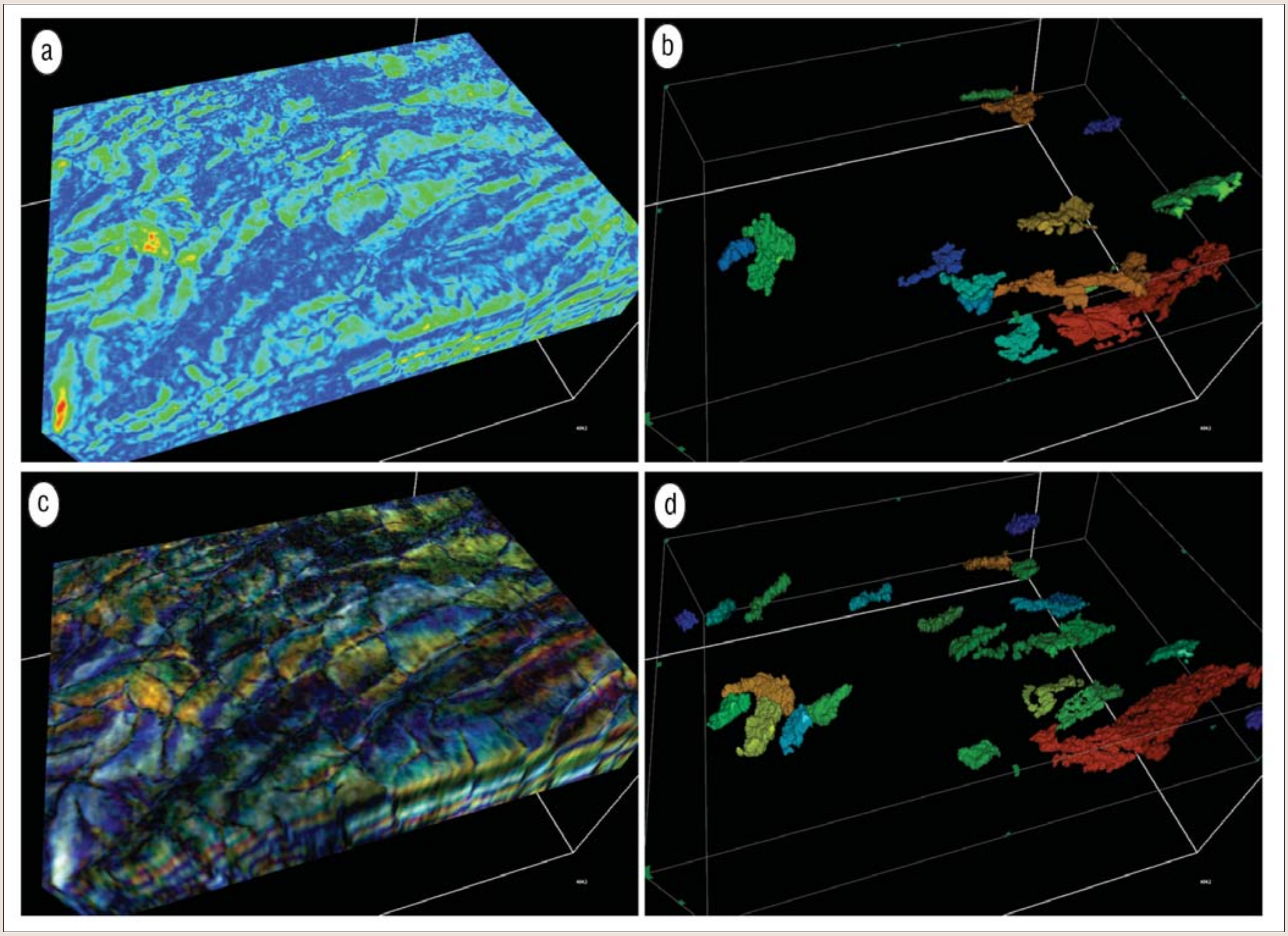


Figure 8. Comparison of conventional and RGB-based body delineation results. (a) Instantaneous envelope volume, (b) bodies detected based on an envelope threshold aimed at differentiating the different responses within the western section of the data set, (c) RGB blend of the response at three different frequencies for the same data set, and (d) bodies detected using the RGB ROI opacity technique.

taken over the points in the quadrant. Cluster compactness is defined as the average distance, D, in RGB space between each point within a quadrant and the cluster center:

$$D = \frac{\left[\sum\sqrt{\left(I_R - \bar{I}_R\right)^2 + \left(I_G - \bar{I}_G\right)^2 + \left(I_B - \bar{I}_B\right)^2}\right]}{n} \tag{5}$$

where the sum is over the n points within each quadrant.

The RGB value assigned to the output image is the center of the most compact cluster. The ANM filter shows significantly better edge preserving properties than the standard mean filter, does not produce the distortion seen with the VMF (Figure 5) and is computationally simple to apply. One of the primary benefits of noise filtering is that it tends to result in an increase in compactness of the color values that represent a particular object (Figure 6) simplifying geobody delineation in the next stage of the RGB analysis workflow.

Although, features may be clearly visible in multiattribute blended color displays extracting those features as geobodies is nontrivial. Two classes of problem are addressed here: (1) delineation of objects defined by a set of color values and (2) delineation of objects defined by changes in color values. Solutions to the first class of problem are required to delineate objects that are laterally extensive, for example, potential reservoir geobodies. The second class of problem has been investigated with the primary aim of fault delineation.

When the objects of interest are represented by a set of discrete color values then it is possible to apply a combination of thresholding and connectivity analysis techniques as are commonly used in single attribute geobody delineation. The output of this type of technique is a volume in which all connected voxels having values within a given range are assigned a unique label. This technique can be implemented in a way that allows direct visual feedback using opacity based volume rendering. In such implementations the opacity curve settings are used to define the threshold(s) applied to select the voxels relating to the feature of interest. When attempting to apply such a visual feedback link to RGB images there is the challenge of defining a 1D opacity function based on the content of the 3D color space. In addition, as illustrated in Figure 6, it is usually necessary to select multiple regions within the 3D color space as the colors defining a particular object do not necessarily form a contiguous set.

To avoid the difficulties of drawing or selecting colors of interest from the 3D RGB space (Figure 1), a data-driven approach is adopted. The colors that define a feature of interest are selected by interacting directly with the RGB image. A polygon that encompasses only those colors representative of the object of interest is drawn on a 2D section of the

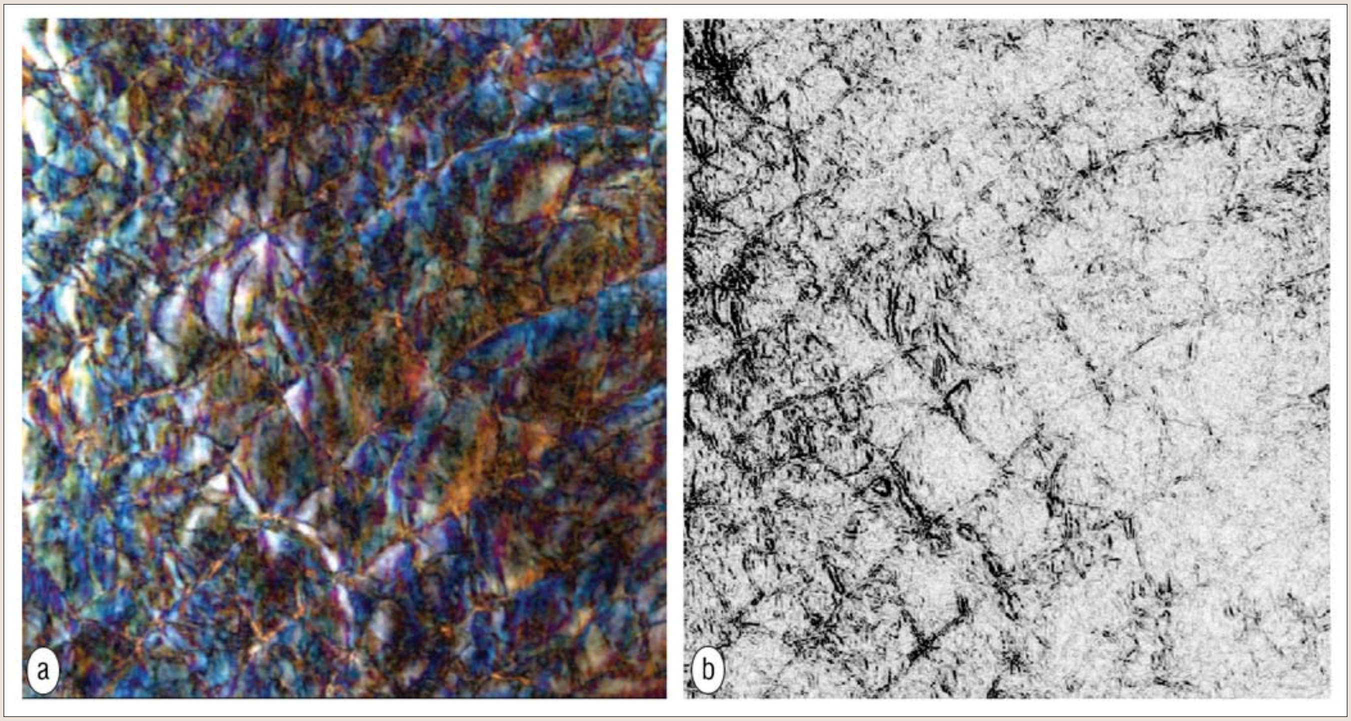


Figure 9. (a) Time slice from an RGB blend. (b) Faults highlighted using a color canny edge detection filter.

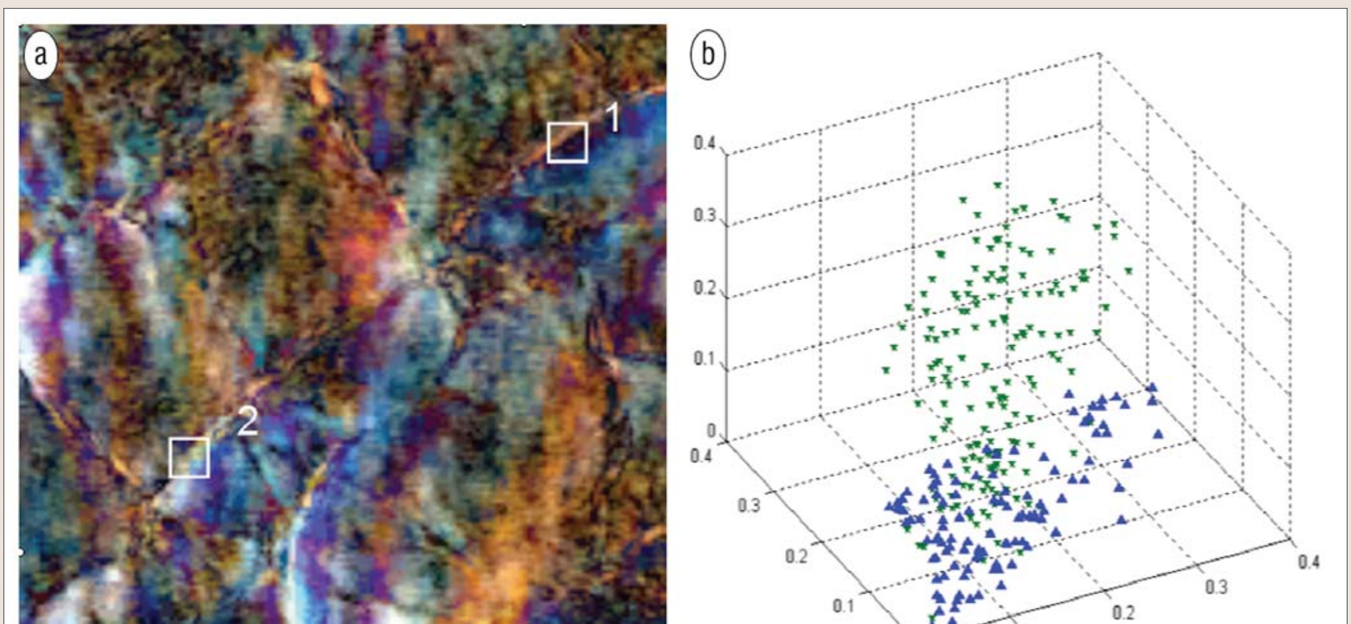
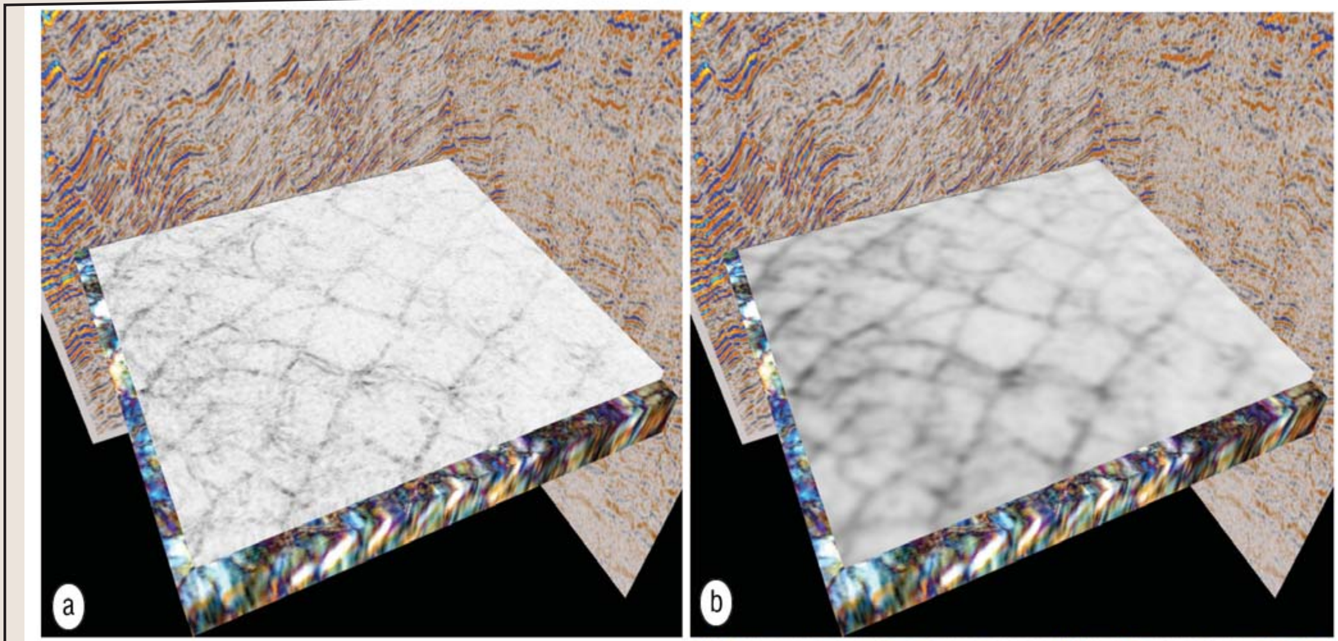


***Figure 10.** Distribution of color values defining faults within an RGB blend. (a) RGB image showing two different fault signatures. (b) 3D crossplot showing the distribution of values within the RGB color space relating to fault region 1 (blue) and fault region 2 (green).*

RGB volume (Figure 7a). An opacity value of 100% is then assigned to all the colors within the region of interest, and an opacity value of 0% is assigned to all other colors.

The opacity setting must take account of variations in color within the feature of interest. Subtle differences in color can be difficult to discern by eye, particularly if comparing areas that are not adjacent. To take this into account, without the constraint of having to define a polygon that exactly defines the extent of the object of interest, a diffusivity parameter is used. The diffusivity parameter defines a distance in the 3D color space, and all colors within this distance of those within the user-drawn region of interest (ROI) are included in the clustering (or segmentation). This provides ample control over the data selection (Figure 7b and 7c). Once the appropriate polygon and diffusivity values have been set, they are used to define an opacity curve for volume rendering the RGB volume data (Figure 7d).

Having determined from the volume-rendered RGB image that the objects of interest have been identified, the opacity settings can be used to drive a segmentation and



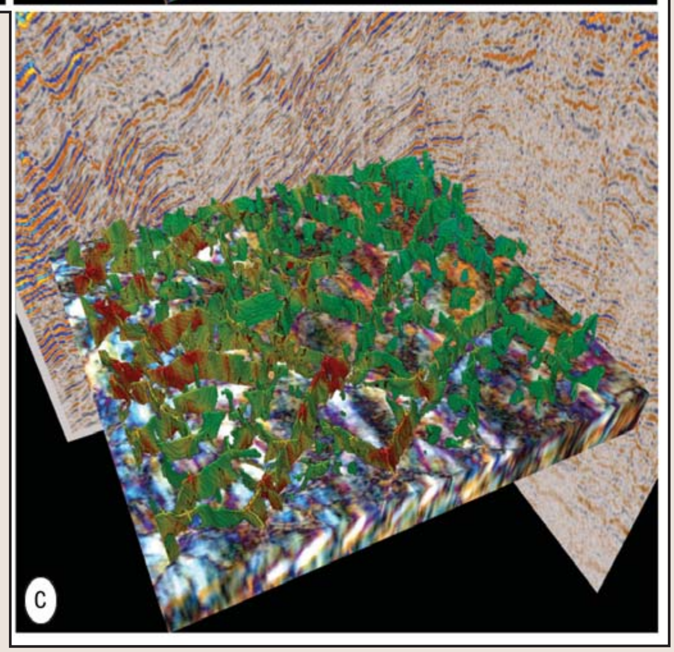


Figure 11. RGB based fault delineation. (a) Raw RGB fault attribute, (b) RGB fault attribute following structurally oriented ridge enhancement and smoothing, (c) fault network detected from the RGB blended spectral decomposition volume.

connectivity analysis process to generate a set of geobodies (Figure 8). Many features imaged in seismic data are differentiated from adjacent structures only by subtle differences in response that may not be represented adequately in a single attribute. By providing an intuitive method for simultaneously allowing geobody delineation to be driven by three attributes, the volumetric RGB-based approach can allow the differentiation of objects that are difficult to discern and/or disconnect based on a single attribute.

RGB co-rendering of volumetric spectral decomposition results often highlights faults extremely well. Faults in an RGB blend are generally apparent due to changes in both color and intensity. On a visual inspection of an RGB blend, the eye picks up lineations whose signature can vary widely. A number of techniques are available for detecting edges in color images, including the color Canny operator (Koschan and Abidi, 2005). Generally, these color-edge detectors are based on evaluating a color gradient from an analysis of the 3D color space. Unfortunately, they perform poorly for fault detection from RGB blends, as they do not respond well to ridges and do not provide clear differentiation between diffuse color changes that represent a fault boundary and the variations in color that can occur in an individual fault block (Figure 9).

One approach for detecting faults from RGB blends is to look at the distribution of color values in a small neighborhood surrounding a fault (Figure 10). The distributions encompass a much broader section of the RGB color space than areas associated with laterally extensive regions (Figure 6). Fault detection can therefore be approached by estimating how well clustered the RGB values are in a neighborhood surrounding each point in the data. This can be computed in a manner analogous to that used for estimating the compactness of RGB clusters in the ANM noise attenuation filter (Equation 2), but taking the maximum rather than the average value of the distance between the current point and its neighbors, i.e.

$$D_f = \max_{ijk}\left[\sqrt{\begin{array}{c}\left(I_R\left(i,j,k\right)-I_R\right)^2 + \\ \left(I_G\left(i,j,k\right)-I_G\right)^2+\left(I_B(i,j,k\right)-I_B{}^2\end{array}}\right] \qquad (6)$$

where i, j, and k vary from -(N-1)/2 to (N-1)/2 and N is the size of the neighborhood.

The cluster distance computation is based on a 3 × 3 × 1 neighborhood, which gives a high resolution but noisy result. However, the distance computation is fast and reduces fault delineation to the more conventional single attribute image processing problem of detection of ridges/planes within a noise-limited system. This is approached through using a combination of smoothing and orientation-sensitive ridge enhancement filters to highlight lineations of points associated with high values of D_f (Figures 11a and b). The ridge-enhancement filters reduce noise, which increases contrast and defines the scale of connectivity both laterally and vertically. Having improved the signal-to-noise ratio and enhanced the connectivity, a ridge-detection algorithm is applied to extract the 3D fault network as a set of geobodies (Figure 11c).

Definition of 3D objects from volumetric RGB displays is an important task in developing a complete workflow for analysis of multiattribute blended displays. An optimal workflow will provide access to a combination of noise attenuation geobody delineation techniques. The geobody delineation techniques in particular will need a high degree of flexibility if they are to cope with the varied expression that objects have in RGB displays.

The techniques described in this paper are an important step in providing the ability to extract geological elements from multiattribute, blended seismic attribute displays, and represent first steps in developing a comprehensive color image analysis workflow for seismic interpretation. Work is ongoing to develop techniques that are objective and intuitive but more fully utilize the information from the RGB color space representation of the attribute data.

Suggested reading. "Automated delineation of geological elements from 3D seismic data through analysis of multicomponent, volumetric spectral decomposition data" by Henderson et al. (*First Break*, 2007). "Visualization techniques for enhancing stratigraphic inferences from 3D seismic data volumes" by Stark, (*First Break*, 2006). "Diffusion and regularization of vector- and matrix-valued images" by Weickert and Brox (*Contemporary Mathematics*, 2002.) "Multicomponent L-filters based on reduced ordering" by Nikolaidis and Pitas (*IEEE Transactions on Circuits and Systems for Video Technology*, 1996). "A comparision of median filter techniques for noise removal in color images" by Koschan and Abidi (Proceedings of the 7th German Workshop on Color Image Processing, 2001) "Detection and classification of edges in color images: A review of vector valued techniques" by Koschan and Abidi (*IEEE Signal Processing*, 2005). "A review of nonlinear diffusion filtering and scale-space theory in computer vision" by Weickert (Lecture notes in computer science, 1997) "Median-filtering techniques for vector valued signals" by Vertan et al. (Proceedings of the International Conference on Image Processing, 1996). TLE

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