TEXTURE ANALYSIS AND SEGMENTATION OF SEISMIC IMAGES

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ABSTRACT

A new method is presented in the texture analysis and segmentation of geophysical images. It is based on the detection of the seismic horizons and on the calculation of their features (e.g. length, average reflection strength, signature). These features represent the texture of the seismic image. The horizons are clustered into classes according one or a multitude of their features. Each cluster represents a distinct texture characteristic of the seismic image. After this initial clustering, the points of each horizon are used as seeds for geophysical image segmentation. All pixels in the seismic image are clustered in those classes, according to their geometric proximity to points lying on classified horizons. Thus the entire seismic image is classified according to different seismic texture patterns. Two new methods are presented for pixel clustering according to the their geometric proximity to reference points. The first one is based on Voronoi tesselation and on mathematical morphology. The second one is based on a "radiation" model for region growing.

1. INTRODUCTION

In oil and gas prospecting, geophysisists are confronted with the problem of estimating earth subsurface to depths up to 6000 meters. Reflection seismology is a widely used method to construct an accurate profile of the subsurface geology. Seismic energy from an explosion or other artificial seismic source on the earth surface propagates downward through rock layers. If acoustic impedance variations between different layers of geologic strata exist, reflection of some of the seismic energy from the rock layer interfaces occurs and is detected at the surface receivers. A number of such receivers, called *geophones*, is located on or near earth surface. Seismic trace the output of a geophone/hydrophone. A seismic section is composed of many seismic traces. Seismic traces are usually very noisy. Therefore, they are processed extensively before being used for the interpretation of the earth subsurface. Such processing techniques are stacking, velocity filtering, deconvolution and migration [1]. The processed seismic sections provide a fairly accurate image of subsurface geology. The next step in oil prospecting is to interpret the seismic sections. Seismic interpretation [1] generally assumes that:

1. Coherent events seen on seismic records or on processed seismic sections are reflections from acoustic impedance contrasts in the earth.
2. Seismic detail (waveshape, amplitude etc) is related to geological detail, that is to stratigraphy and the nature of the interstitial fluids.

An interpreter generally starts with the most obvious feature, usually the strongest reflection event or the event which possesses the most distinctive character and follows this event as long as it remains reliable. After following reflective horizons, the interpreter tries to identify fairly large-scale features of the depositional structure of sedimentary rocks and the major deformations which has affected such rocks. These structures can be broadly classified as being either faulting or folding. Such interesting structures are faults, anticlines, saltdomes, unconformities etc [1]. This step is called *structural interpretation*. The second step seismic interpretation is *seismic stratigraphy*. Parts of a sedimentary sequence can be distinguished from others according to general seismic appearance. The following seismic data (i.e seismic facies elements) should be taken into consideration during stratigraphic interpretation:

reflection amplitude, dominant frequency, interval velocity, reflection configuration, reflection continuity, the geometry of the seismic facies unit, abundance of reflections, presence of diffractions.

They contain information about type of stratification, lithology, depositional process and environment etc. For example, reflection free configuration is characteristic of reefs. Parallel configuration is naturally the most widespread configuration in sedimentary rocks. Convergent one may be caused either by pinching out or by differential compaction. Cross-bedding is characteristic of psammites and a diagnostic criterion for sandy rocks (sands, sandstones etc.). Sigmoid and oblique configurations occur in connection with progradational patterns on the shelf margin. Chaotic reflection configuration is characteristic of diapiric cores whose internal structure is very complex.

The interpretation of seismic sections has not been automated because of the heavy amount of knowledge involved in the decision making process. The human brain is an exceptionally good pattern recognizer and in general has not yet been surpassed by any computer. However, there exist some reasons for using computerized methods in assisting the interpreter. Such reasons are speed, consistency and concrete specification of decision making criteria. There have been several efforts to use image and signal processing techniques in seismic interpretation. Some techniques are concentrated on the automatic horizon picking [8,11]. Parametric description of seismic reflection signatures and the use of fuzzy set theory in seismic interpretation are described in [11,12]. A knowledge-based approach to geophysical interpretation is described in [13]. The use of the texture in seismic image segmentation is described in [9,13]. The local texture of a seismic image is described in terms of templates. Such templates characterizing different textures are derived. A least squares approach is used for template matching at each pixel of the seismic image. The result of the template matching is used for the segmentation of the seismic image. Another approach for texture description is the use of the run length at each image pixel [9]. Pixels in regions having elongated characteristics (e.g. long parallel horizons) tend to have longer run lengths than the pixels belonging to regions of chaotic reflections. Thus seismic image segmentation in terms of the horizon length can be achieved.

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2. PROPOSED APPROACH

The main purpose of this paper is to develop methods for seismic image segmentation. This segmentation must be done in such a way so that it produces results which are consistent with the geophysical and geologic experience. This means that the primitive features used in the segmentation must be such so that they have correspondence with the entities used by the interpreter. Geophysical interpretation is heavily based on the seismic horizons, their characteristics, and their interrelationships, as has already been described briefly in this section. Thus we have used the seismic horizons and their features (length, signature, reflection strength, position, orientation) as our primitives for texture analysis and segmentation of seismic images. Each of those features has a value for each horizon. The frequency of appearence of a specific value of feature creates the *histogram* of this feature. The horizons can be clustered to different classes by defining thresholds on the feature histogram. Thus, by defining appropriate thresholds on the histogram of the reflection strength we can cluster the horizons to weak and strong ones. Each horizon has a position on an image. In most cases, all horizons labeled weak tend also to concentrate in the same image region(s). The same happens for horizons labeled long. This is explained by the fact that horizons having similar characteristics are created by geological formations having similar characteristics and being located in the same region(s) in the earth subsurface (e.g. reefs tend to produce very weak reflections). Thus by clustering horizons according to a specific feature we also perform clustering of the seismic image. However, this clustering is not complete. Only the image pixels corresponding to seismic horizons have been clustered. All other pixels have not been clustered yet. Those pixels can be assigned to clusters by using their geometric proximity to the seismic horizons. A similar approach can be followed, when clustering using a multitude of features is required (e.g. the seismic image regions having short and strong horizons are required). If m features are used, an m-dimensional histogram is constructed. By choosing appropriate thresholds we can cluster again the horizons into classes having similar all m features. Having performed such a horizon clustering, we can proceed to image segmentation as it has already been described for the case where one feature is used. Our approach to seismic texture description and seismic image segmentation requires the following steps:

1) Description of the seismic texture primitives in terms of horizon features.
2) Calculation of the thresholds in the horizon histograms.
3) Horizon following.
4) Calculation of the 1-d or m-d histograms of the horizon features.
5) Clustering of seismic image pixels according to their geometric proximity to seismic horizons.

Steps (1) and (2) are heavily based on experience. Therefore, they are performed by the interpreter interactively. The interpreter chooses an image region which is representative of a seismic texture and instructs the system to find the horizons in this region and calculate their features (to be described later on). Then he chooses the appropriate features and instructs the system to calculate the corresponding 1-d or m-d histograms. Based on this histogram, he chooses the appropriate thresholds and creates seismic texture description rules. Let us suppose that m features $a_1,...,a_m$ are used in the description of seismic texture. Let also $X_1,...X_K$ be K different texture clusters. A horizon h is assigned to cluster k if satisfies a decision rule of the form:

$$If\ L(P_1,P_2,...P_m)\ \ then\ h \in X_k \tag{1}$$

where L is a propositional logic formula and P_i, $i=1,..,m$ are predicates of the form:

$$P_i:\ a_i<T_i \tag{2}$$

a_i,T_i, $i=1,..,m$ are the features and their corresponding thresholds. If the selection of the horizon features is known, the choice of the optimal thresholds and of the optimal rule (1) can be done automatically by a learning procedure described in [14]. The interpreter presents to the systems regions having different textures. The system calculates the optimal thresholds $T_1,...,T_m$ which discriminate the different seismic textures. It also finds the optimal rule (1) for texture recognition. It can also reject features possessing no discriminatory power for texture description. The optimality criterion used is the minimal entropy.

3. HORIZON PICKING AND HORIZON FEATURE CALCULATION

A seismic horizon is described as a list of the following form:

```
struct linepoint{
        int dtime;   /* two way travel time */
        int trace;   /* tracenumber */
        unsigned long marker;
                /* feature assigned to every node */
        struct linepoint *nextpoint;
                /* pointer to next node */
        };
```

Information about local horizon features (e.g. local reflection strength, local signature, local orientation) at each horizon point are stored at the each node of the horizon. Global information about the horizon (e.g. average reflection strength, reflection variance, horizon length, horizon curvature) are stored in the header of the list. Automatic horizon following has been extensively treated in the literature [8,11,13]. We have used a method which is similar to that described in [13]. Horizon following is considered to be peak reflection following for reflections which are stronger than a predetermined threshold. Seismic image prefiltering by nonlinear filters [13,18] which sharpen reflection peaks is highly desirable and it produces less "jaggy" horizons. Let us suppose that we follow a horizon and that we are at a horizon peak located at pixel (i,j). Let also I(i,j) be the image (reflection) intensity at that pixel. The first coordinate denotes trace number and the second one denotes two way travel time. Then the pixels I(i,j-1), I(i,j), I(i,j+1) are examined for possible expansion of the horizon. Only those pixels are kept that are greater than the selected threshold. If more than one candidate remains, we decide expansion to the pixel having the largest value. If there is an ambiguity (i.e more than one pixels having equal maximal intensity, successors) we decide expansion to the most aligned candidate pixel. The criterion of alignment is associated with the computation of the previous and all possible current expansion slopes and their absolute differences in a local and global sense. This procedure is repeated for subsequent horizon expansions. The horizon is followed until its intensity falls below the threshold. If the horizon is too short, it is rejected. If not rejected, the pixels participating in this horizon are marked and the procedure is repeated for a new horizon. After horizon picking, the local and global information about the horizon is calculated. Local information is stored at each horizon node, whereas global information is stored on the header of the horizon list. The computation of most horizon features (e.g. length, average reflection strength) is straightforward. Local horizon slope is calculated by finding the linear piecewise approximation of the horizon. The computation and the representation of the of the reflection signatures is somewhat more complicated. We have used the representation scheme proposed in [11] for signatures. This scheme represents a signature in terms of 14 parameters. They are computed and stored on each list node. An "average" signature is computed by averaging all signatures along the horizons and storing it at the list header.

If horizons have been picked and their features have been calculated, the construction of 1-d or m-d feature histograms is rather straightforward. If the decision thresholds and decision rules have been chosen either manually or by the help of a learning procedure [14], the horizon clustering is also easily performed. At this step only the horizons and their corresponding pixels have been clustered. The "propagation" of this clustering to the rest of the seismic image follows.

4. REGION GROWING

The obstacle in using classical region growing techniques [4,5] on seismic images lies in the fact that the features we have extracted refer only to pixels participating in horizons, whereas in classical image segmentation features characterize every pixel in the image to be segmented. Region growing depends on the the order we examine pixels for similarity and the "seeds" are used to grow regions. In our case the "seeds" are obviously the pixels on horizons. We have to infer what information to assign to other pixels that do not participate in horizons, assuming that pixels close to horizons will behave similarly. Thus we have to investigate for proximity rather than for similarity.

The simplest approach would be to propagate the label of a horizon pixel to all pixels that are close to it upwards or downwards on the same seismic trace. If this process is repeated for all horizons, finally each seismic image pixel will be clustered to the same cluster as its closest horizon in the vertical direction. This scheme is justified by the nature of seismic traces. However, it has been observed that such a region growing produces jagged regions. The "jagginess" of the resulted image can be reduced somehow by filtering it by either a median filter or a *mode* filter [15].

A second approach to region growing is based on a combination of Voronoi tesselation [16] and mathematical morphology [17]. The horizon pixels are used as "seeds" for the Voronoi tesselation of the seismic image. They grow in successive steps until they cover the entire image. At each step it is checked if regions stemming from horizons of the same cluster have common boundary. If this is the case, these regions are merged. The boundary (if any) between two different clusters is "frozen" at each step. The growing of the image regions is performed by *conditional dilation* [17]. Let X_k, $k=1,..,K$ be subsets of the image plane Z^2 representing the image pixels which correspond to each texture cluster. Let also $X_k(i)$, $k=1,..,K$ be the sets representing clusters k=1,..K at step (i) of the growing procedure. At step (0), $X_k(0)=X_k$, and it contains the horizon pixels corresponding to cluster k. Let also B be a set, called a *structuring element*, whose size is equal to the size of the region growing at one step. Its shape governs the geometry of cluster growing. If uniform growing along all dimensions is required, the structuring element B must be a disk. However, in the Euclidean grid Z^2 not exact representation of a disk can be found. Thus, the structuring element CIRCLE shown in Figure 1 has been used instead. This produces an acceptable relatively uniform growing along all dimensions. The region growing at step (i) is given by the following recursive procedure:

$$X_k(i)=[X_k(i-1)\ \oplus\ B]\ \cap\ [\bigcup_{\substack{l=1\\ l\neq k}}^{K} X_l(i-1)] \qquad (3)$$

where $\oplus$, $\cap$, $\cup$ denote set dilation, intersection and union [17]. (3) permits the growing of a cluster k in the image regions which have not already been covered by other clusters. The main disadvantage of this approach is that it enhances small patches corresponding to noise, which are found inside much larger regions. Therefore, a third growing scheme has been developed which is much more robust to noise.

The third scheme is based on the following fictitious experiment: Let us suppose that a horizon pixel radiates according to the law 1/r. This means that the radiation received at a pixel (i,j) is inversely proportional to the distance of this pixel from the radiating horizon pixel. If all horizon pixels belonging to the same cluster are radiating at the same frequency, the energy received at a pixel (i,j) is the sum of the radiations of each horizon pixel of this cluster. The pixel (i,j) is assigned to the cluster sending the maximal radiation energy. By implementing this approach, we avoid having small noisy regions inside larger regions. The smaller regions radiate less and disappear. The radiation pattern can be described in terms of a function of the form:

$$h(i,j)=\frac{c}{r}=\frac{c}{\sqrt{(i/a)^2+(j/b)^2}} \qquad r<R \qquad (4)$$

Let $x_k(i,j)$ denote the position of the radiating pixels of the pixels belonging to the cluster k:

$$x_k(i,j)=\sum\delta(i_k-i,j_k-j)\ , \qquad (i_k,j_k)\in X_k \qquad (5)$$

$\delta(i,j)$ is the 2-d delta function. The radiation $y_k(i,j)$ received at each pixel (i,j) is given by:

$$y_k(i,j)=x_k(i,j)**h(i,j) \qquad (6)$$

where ** denotes 2-d convolution. The pixel (i,j) is attributed to the class l for which:

$$y_l(i,j)=\max_{1\le k\le K} y_k(i,j) \qquad (7)$$

The only disadvantage of this region growing model is its computational complexity, since it requires the computation of K 2-d convolutions. If uniform region growing is required at all dimensions, a circular radiation pattern is employed by choosing $a=b=1$. However, in seismic applications radiation patterns elongated at the horizontal direction are preferable. This conforms with the fact that most geologic structures are also elongated horizontally.

5. SIMULATION EXAMPLES

An example of the application of the above-mentioned method is shown in Figure 2. The original seismic image is shown in Figure 2a. The detected seismic horizons are shown in Figure 2b. The feature used for segmentation is the local orientation of the seismic horizons, i.e. we were interesting to find seismic image regions containing horizontal or tilted horizons. The thresholds used were -4, 4 degrees, i.e. all horizons having local slope in the range [-4,4] degrees were considered to be almost horizontal. The result of the region growing algorithm (7) is shown in Figure 2c. The white and dark regions in Figure 2c represent seismic image regions containing horizons having zero and negative slope respectively. The two regions still contain some small noisy patches corresponding to reverse local slope in the original image. These noisy patches can be further reduce by using mode filtering.

REFERENCES

[1] R.E.Sheriff and L.P.Geldart, *Exploration Seismology*, Vol. 2, Cambridge University Press, 1983.

[2] R.M.McQuillin, M.Bacon and W.Barclay, *An Introduction to Seismic Interpretation*, Graham & Trotman Ltd., 1979.

[3] H.R.Nelson Jr., *New Technologies in Exploration Geophysics*, Gulf Publishing Co., 1983.

[4] B.H.Ballard and C.M.Brown, *Computer Vision*, Prentice Hall, 1982.

[5] M.D.Levine, *Vision in Man and Machine*, McGraw-Hill, 1985.

[6] I.B.Hoyle, "Computer techniques for zoning and correlation of well logs", *Geophysical Prospecting*, 1986, Vol. 34, pp. 648- 664.

[7] M.M.Roksandic, "Seismic facies analysis concepts", *Geophysical Prospecting*, 1978, Vol. 26, pp. 383-398.

[8] N.Keskes and P.Mermey, "Seismic horizon extraction by heuristic methods",*Proc. of IEEE Int'l Conf. on ASSP*, 1984, pp. 95- 100.

[9] P.L.Love and M.Simaan "Seismic signal character recognition using texture analysis techniques", *Proc. of IEEE Int'l Conf. on ASSP*, 1982.

[10] R.Haralick, "Statistical and structural approaches to texture" *Proceedings of the IEEE*, Vol. 67, No.5, May 1979, pp. 786-804.

[11] P.Bois, "Some applications of pattern recognition to oil and gas exploration", *IEEE Transactions on Geoscience and Remote Sensing*, Vol. GE-21, No.4, October 1983, pp. 415-426.

[12] P.Bois, "Fuzzy seismic interpretation", *IEEE Transactions on Geoscience and Remote Sensing*, Vol. GE-22, No.6, November 1984, pp. 692-697.

[13] I. Pitas, A.N. Venetsanopoulos "Towards a knowledge based system for automated geophysical interpretation", *Signal Processing*, vol. 13, pp.229-253, 1987.

[14] I. Pitas, E.Milios, A.N. Venetsanopoulos "Minimum entropy rule learning in image interpretation", *IEEE Transactions on Systems, Man and Cybernetics*, under review.

[15] G.B. Coleman, H.C. Andrews "Image segmentation by clustering", *IEEE Proceedings*, vol. 67, No. 5, pp. 773-785, May 1979.

[16] F. Preparata, M.I. Shamos *Computational Geometry: an introduction*, Springer Verlag, 1985.

[17] J. Serra *Image analysis and mathematical morphology*, Academic Press, 1982.

[18] I. Pitas, A.N. Venetsanopoulos "A general nonlinear filter structure for image processing", *Proc. IEEE Int. Symposium on Circuits and Systems*, pp. 949-952, Helsinki, Finland, 1988.

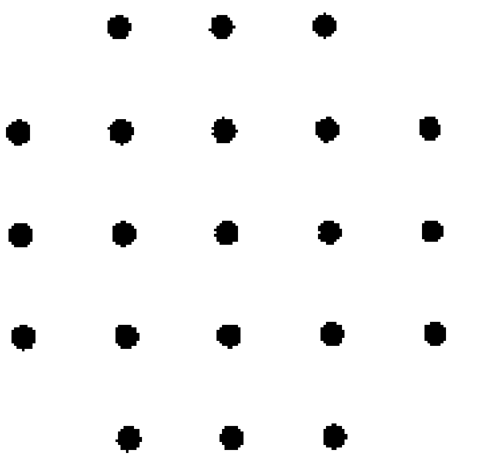
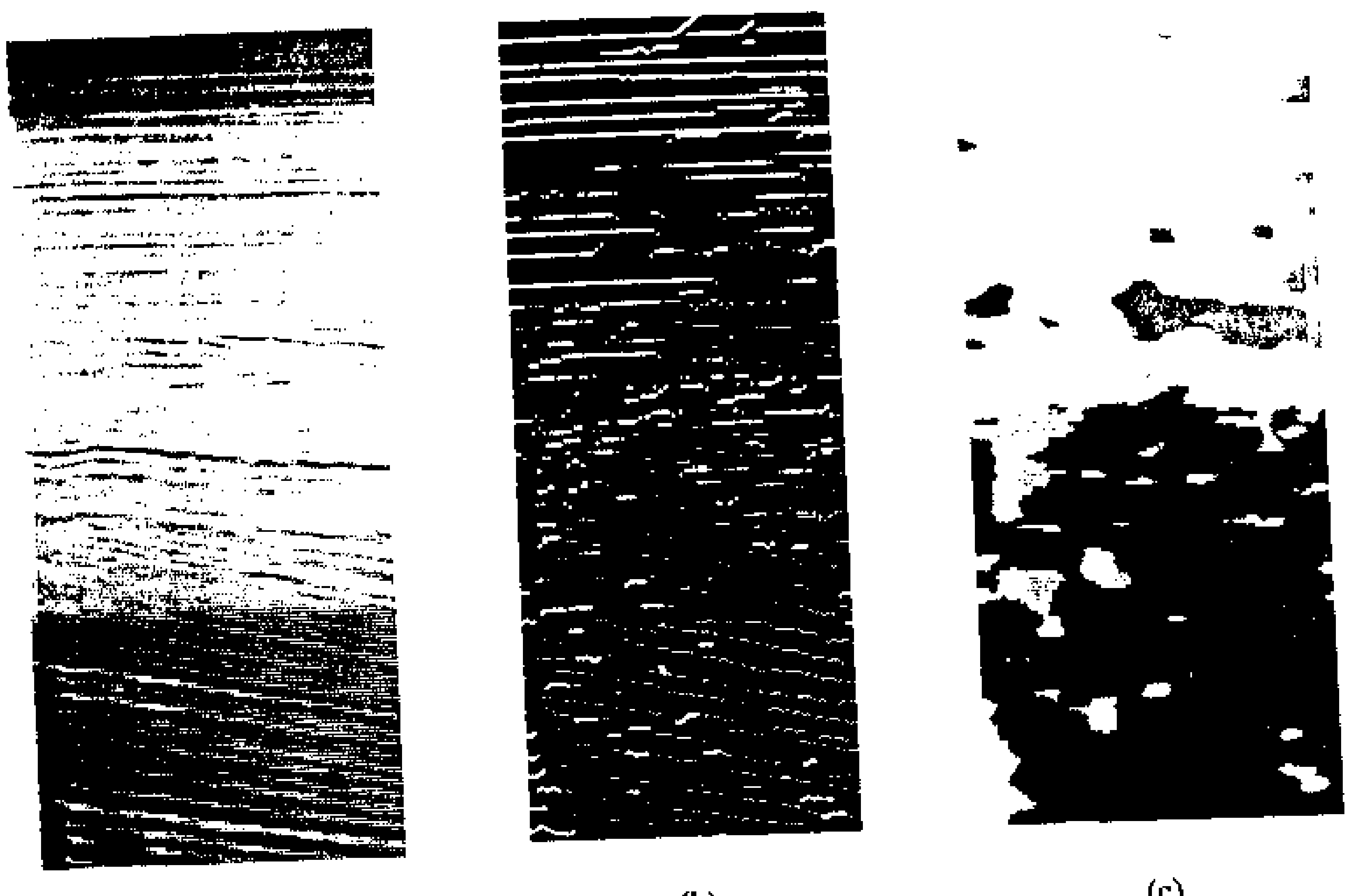


Figure 1: Structuring set CIRCLE



(a) (b) (c)

Figure 2: (a) Seismic image
(b) detected seismic horizons
(c) seismic image segmentation into regions containing horizontal horizons (bright regions) and horizons with negative slope (dark regions) respectively.