SIGNAL PROCESSING V: Theories and Applications
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TEXTURE DESCRIPTION RULES FOR GEOPHYSICAL IMAGE SEGMENTATION

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ABSTRACT
The texture of a geophysical image is described in terms either of seismic horizon features (e.g length, mean reflection strength, geometrical appearance) or in terms of Hilbert transform features (magnitude, phase, instantaneous frequency) or in terms of features related to the generalized runs. Geophysical image segmentation rules are derived from examples by using minimum entropy rule learning techniques. A method based on Voronoi tessellation and mathematical morphology is presented for using geometric proximity to reference points in region growing.

1. INTRODUCTION

Reflection seismology [1] is a widely used method to construct an accurate profile of the subsurface geology. After processing seismic sections (images), the next step is to interpret them. One of the steps of the interpretation is seismic stratigraphy [1]. The aim of stratigraphic interpretation is to discriminate groups of reflections whose properties such as reflection pattern, amplitude, continuity, frequency differ from the properties of adjacent groups of reflections.

This paper discusses methods for the segmentation of geophysical images on the basis of stratigraphic information. Stratigraphic information is directly related to the texture information of the geophysical image. The texture of a geophysical image will be described in terms of features available in all pixels (reflection strength, Hilbert transform features) or in terms of features that can be evaluated on horizons (e.g horizon-length, mean reflection strength etc.) or in terms of features that can be calculated on runs (e.g run-length). Seismic image segmentation requires the use of a logical rule which is based on the feature vector and is applied to the entire image to be segmented. It is very desirable to construct a system that can infer the rule from examples given by the interpreter. Image regions which are representative of the different types of seismic textures are chosen by the interpreter. The appropriate seismic texture discrimination rule is created by using rule learning techniques based on the minimal entropy principle. If the features can be calculated on every image pixel, the derived rule can be used directly for the segmentation of the entire seismic image. However, if horizon/run features are used, only the image pixels corresponding to seismic horizons/runs can be segmented. All other pixels can be assigned to seismic image regions by using the geometric proximity to the already segmented seismic horizons or runs.

2.CALCULATION OF SEISMIC TEXTURE FEATURES

Hilbert transform analysis effects a natural separation of amplitude and phase information. It has already found several applications in seismic stratigraphy [2]. The Hilbert transform is the basis of the mathematical procedure that creates the complex trace from a real one. Hilbert transform relations are relationships between the real and imaginary parts of a complex sequence [3]. The complex trace s(n) is defined as

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$$s(n)=s_r(n) + j\, s_i(n) \qquad (1)$$

where $s_r(n)$ and $s_i(n)$ are real sequences. The real trace $s_r(n)$ is the already availabe seismic trace. The imaginary trace $s_i(n)$ is the Hilbert transform of the real seismic trace. Additional texture features can be evaluated (e.g instantaneous amplitude, phase, frequency) [3,8].

Automatic horizon following has been extensively treated in the literature [4,5]. A seismic horizon is described as a list [5]. Global information about a horizon (e.g average reflection, horizon length, global slope) is stored in the head of the list. Every pixel participating to a horizon is described as a node of the list. Information about local horizon features (e.g local reflection intensity, local orientation etc) are stored at each node of the horizon. The computation of most horizon features is straightforward. Local horizon slope is calculated by finding a linear piecewise approximation of the horizon.

A seismic image can easily binarized by using an intensity threshold. A binary run is a maximal collinear connected set of pixels having value 1 [6]. It is important to follow non-horizontal runs in seismic sections, because they have stratigraphic significance. A generalized run definition alleviates this difficulty [7]. An effective run following algorithm is presented in [8]. A run can be described as a list in a similar manner with the horizon description. Each run can be characterized by its length.

3. LEARNING TECHNIQUES IN THE DERIVATION OF TEXTURE DISCRIMINATION RULES. REGION GROWING.

Let us suppose that m features $x_1, x_2,..,x_m$ are used in the description of seismic texture and we want to discriminate K different texture classes, namely $C_1,...,C_K$. A pixel characterized by a feature vector x is assigned to class C_n, if a decision rule of the following form is satisfied:

$$\text{if } L_n(P_1,P_2,...,P_m) \text{ then } x\in C_n \qquad (2)$$

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

$$P_i:\ x_i \leqslant T_{i,opt} \qquad (3)$$

In (3) x_i, $T_{i,opt}$, i=1,...,m are the features and their corresponding optimal thresholds. The choice of optimal thresholds in (3) and the optimal rule in (2) can be done automatically by a similar learning procedure described in [9]. First of all the case of the discrimination of two different classes will be treated. A modification of this scheme capable of implementing multiclass rule learning will be described afterwards. Simultaneous optimization for the thresholds and the rule structure is very difficult. Therefore, the optimization is splitted in two suboptimal steps: (a) minimum entropy selection of thresholds $T_{i,opt}$ i=1,...,m (b) minimum entropy selection of rule L.

Let Ω_1, Ω_2 denote the sets of the examples and the counterexamples in a two-class discrimination problem. Both sets are consisted of training feature vectors of the form $(x_1,x_2,...x_m)$ Let us suppose that N_1, N_2 are the number of elements of Ω_1 and of Ω_2 respectively.Let us denote by $H_1(x_1,x_2,..,x_m)$ the histogram of examples and by $H_2(x_1,x_2,...,x_m)$ the histogram of counterexamples. We shall also denote by $P_{i,T}^k$ k=1,2 the probability of success of a predicate of the form (3) over the example and the counterexample sets respectively. These probabilities are given by

$$P_{i,T}^k = \text{Prob}[\, x_i \leqslant T_i \mid \Omega_k\,] = (1/N_k) \sum_{x_i \leqslant T_i} H_k^i(x_i) \quad i=1,...,m \quad k=1,2 \qquad (4)$$

where

$$H_k^i(x_i)=\sum_{\xi_j} \sum ... \sum H_k(\xi_1,...,x_i,...,\xi_m) \qquad (5)$$

In (5) the multiple summation is carried out over all m-tuples $(\xi_1, ...,x_i,...,\xi_m) \in \Omega_k$ and for the corresponding ξ_j j=1,...,m ,j≠i. $H_k^i(x_i)$ is the projection of $H_k(x_1,..,x_m)$ on the x_i axis. The probabilities of the complementary events are:

$$P_{i,F}^k = 1 - P_{i,T}^k \quad k=1,2 \qquad (6)$$

The polynomial counterpart of the entropy function to be minimized has the form [9]:

$$U(T_i) = -2\, (P_{i,T}^1 + P_{i,F}^2 -1)^2 \qquad (7)$$

We have m entropy functions (7), one for each threshold T_i, i=1,...,m. Therefore optimization can be done indepently for each threshold.

The optimal rule will have the following canonical form:

$$L= \bigvee_{I=0}^{2^m-1} a_I\ R_I^m \qquad (8)$$

where the Boolean constant a_I are either 0 or I depending upon whether the corresponding product term R_I^m is to be excluded from or to be included in the rule. The product terms R_I^m are defined as

$$R_I^m = P^{im}{}_m \cdots P^{i2}{}_2 \quad P^{i1}{}_1 \qquad (9)$$

where

$$P^{i_j}_j = \begin{cases} P_j & \text{if } i_j=1 \\ \text{not } P_j & \text{if } i_j=0 \end{cases} \quad (10)$$

m indicates the number of predicates, and $i_m i_{m-1} \ldots i_2\ i_1$ is the binary re- presentation of the decimal number I:

$$(I)_{10} = (i_m\ i_{m-1} \cdots i_2\ i_1)_2 \quad (11)$$

We shall drop the superscript m in the product terms for simplicity. The predicates in (10) are of the form (3). The probabilities of success of each product term R_I are defined as follows:

$$P_T^k(R_I) = \text{Prob[success of } R_I \text{ over } \Omega_k] \quad I=0,\ldots,2^m-1$$

where

$$P_T^k = (1/N_k) \sum_{P^{i_1}_1} \sum_{P^{i_2}_2} \cdots \sum_{P^{i_m}_m} H_k(x_1,\ldots,x_m)$$

and $k=1,2$ (12)

In (12) the multiple summation is carried out over $(x_1,\ldots,x_m) \in \Omega_k$ which belong to the solution of the set of predicates $P^{i_1}_1$, $P^{i_2}_2$, $P^{i_m}_m$. It can be proven that the optimal rule, in the minimum entropy sense, consists of the product terms that satisfy [9] :

$$\text{if } P_T^1(R_I) > P_T^2(R_I) \text{ then } a_I = 1 \quad (13)$$

This relation is interpreted as follows: the optimal rule consists of those product terms for which their success over examples is greater than their success over counterexamples.

The multiclass classification corresponds to a iterative procedure described by a binary decision tree. The rule which discriminates a class at a certain level is calculated as follows: For each unclassified example set we calculate the rule that discriminates this example set from the rest of the unclassified example sets. The rule that possesses the minimal probability of misclassification is chosen as the discrimination rule for this level. This procedure is repeated until a decision rule is obtained for each example set [8].

If the features can be calculated at each image pixel ,the learning procedure of this section infers the required rule which defines the segmentation for the entire image. If horizon features are used in the rule, the pixels belonging to horizons can be segmented initially. In this case region growing techniques must be applied, if segmentation of the entire image is required. A method for solving the problem under consideration has been proposed in [5,8]. This method is based on a modification of the Voronoi tessellation [10] which is implemented by using mathematical morphology techniques [11,12].

4. EXPERIMENTAL RESULTS

In the following, the segmentation of the seismic image shown in Figure 1 will be described. The horizons, which have been followed by the technique mentioned in section 2 are shown in Figure 2. Four representative seismic image regions having different seismic texture are chosen by an interpreter and are shown as overlaid rectangles on the original seismic image of Figure 1. These image regions are denoted by R_1,R_2,R_3,R_4. The corresponding feature classes are denoted by C_k, $k=1,\ldots,4$. The following features have been used for texture description: mean reflection strength, horizon local slope and horizon length. Thus the feature vector x is described as a triplet (x_1,x_2,x_3), where x_1 denotes mean reflection strength, x_2 denotes partial slope and x_3 denotes horizon length. The seismic texture discrimination rule by using the minimum entropy rule learning technique described in section 3. is:

```
if (x1 ≤ 137) x ∈ C3;
else{
  if (x2 ≤ -12°) x ∈ C4;
  else{
     if ( x1 ≤ 142 or x3 ≤ 70) x ∈ C2;
     else x ∈ C1;
  }
}                                    (14)
```

where x_1 takes values in the interval [0,255], x_2 takes values in the interval [-90°,90°], x_3 takes values in the interval [0,255]. However only the image pixels corresponding to seismic horizons can be segmented into the four classes C_k, $k=1,\ldots,4$ by using (14). All other pixels can be assigned to seismic image regions by using the geometric proximity to the already segmented seismic horizon pixels. This can be performed by employing the Voronoi tessellation scheme mentioned in section 3. The image plane is segmented by using the SQUARE structuring element [12]. The segmented imageis shown in Figure 3. The segmented regions, which correspond to the classes C_k, $k=1,\ldots,4$ are shown by increasing brightness.

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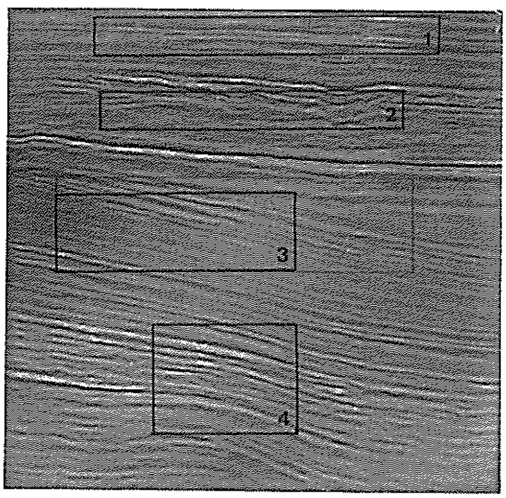

Figure 1: Original seismic image. The four regions different texture that are presented to the learning procedure are shown as over-laid rectangles

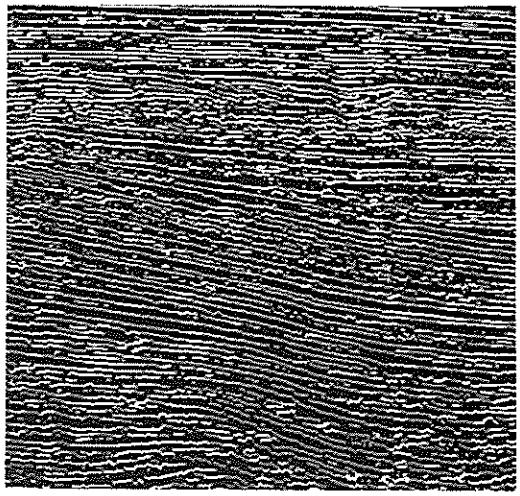

Figure 2: Detected horizons

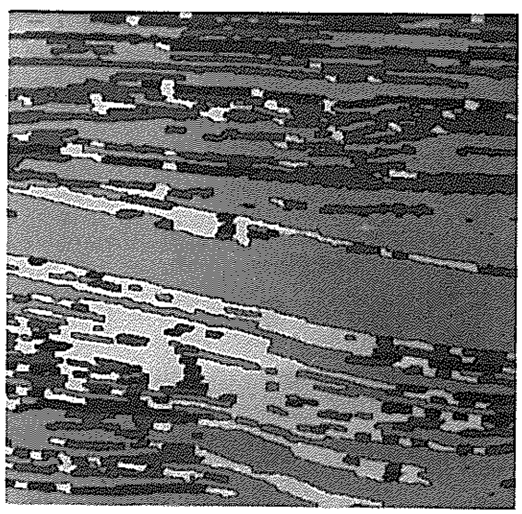

Figure 3: Segmentation of the original seismic image. Pixels that are assigned to class 1 are shown as black pixels. Those that are assigned to class 2 are shown as dark grey pixels. The ones that are assigned to class 3 are shown as light grey pixels. Finally the ones that are assigned to class 4 are shown as white pixels.