Image Analysis for Core Geological Descriptions:
Strata and Granulometry Detection

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Abstract

Digital signal processing is commonly used in Geophysics. Methods combining core sample physical property measurements with image analysis are beginning to emerge. In this paper, we describe a digital processing method applied directly to core sample images. Our approach uses a number of time-frequency and scale-frequency transformations as well as morphological operators that reach a resolution equivalent to and even better than the geologist’s eye. The resources presented below are free from operator-related subjectivity and provide efficient, reliable and repeatable sequential descriptions of geological borehole samples that include both layer detection and grain analysis. Our process’s efficiency is demonstrated through analyses carried out on a number of core samples taken from Cretaceous to Upper Eocene volcano-sedimentary series on New Caledonia’s West Coast.

1. Introduction

As it is the case for deep drilling in the Ocean Drilling Program (ODP), when core drilling is undertaken and samples are collected, description of core sample logs is systematically carried out in advance. Recording logs by describing core samples is a long and painstaking process. Layer and fracture identification and particle analysis are performed by geologists (with the naked eye) at varying rates depending on their objectives, and using scales ranging from multiple-millimeter through centimeter graduations, for high resolutions, to meters for overall analyses.

Various methods for scanning and archiving the appearance of core samples are now available. Based on resulting images, initial efforts have been made for defining geological parameters and indices, depending on the needs of interested parties in the scientific and industrial communities. Carbonate facies identification based on a gray-level analysis method [10] and particle analysis on separate samples that identifies grain shapes and sizes using classification methods [9] are examples of such approaches.

In this paper, we present a new approach, developed in our laboratory, that uses digital images of core samples for combining in a single process particle analysis with sedimentary rhythm recognition. To achieve this goal, we have adapted and tested image-processing techniques on a specific set of indurated core samples. Our objective is to open up new prospects for interpreting sediment by providing a tool that can be adjusted to suit specific resolution needs by altering the interpretation’s chronological scale.

When attempting to understand deposit dynamics, Stratum recognition is an important step for detecting sedimentary rhythms, sequences and features. For example, identifying sedimentary features such as bioturbations and current casts and so on, helps to reconstitute paleoenvironments. And analyzing sedimentary rhythms contributes to cross-dating sedimentation and determining the surrounding water dynamics in sedimentation basins. Whenever the scale used for observing the phenomenon under investigation is changed, the description work has to start over again from scratching. We are suggesting that information should be gathered and stored in a one image acquisition procedure and then processed using an algorithm that recognizes stratification without any subjective influence.
Determining clast grain characteristics and morphometry is the standard approach used in sedimentation analysis. It is vital for studying paleoenvironments and, for instance, helps in assessing energy levels and forms of transport into sedimentary basins. Standard separated clast grain analysis methods vary according to particle size range. Scanning electronic microscopy (SEM) and laser counting (LPSA) are more efficient methods, but they require difficult preparatory phases for conglomerate clasts and it is rarely feasible to separate the grains [5].

In order to offer both an alternative solution to those various methods for determining clast grain characteristics and morphometry and an additional solution to stratum recognition, we propose a way for identifying all the shapes and providing a granulometry map for each stratum. The random distribution of grains on the processed core sample surface can be used to obtain a significant statistical representation of clast grain characteristics, as the drilling equipment provides a random cross-section of the investigated site.

In the following we first describe the equipment used for data acquisition and storage. Then we present image segmentation and analysis methods used for strata and fractures detection, and for grain recognition. Finally, we briefly present results obtained on a geological application and we conclude by giving some directions for future work.

2. Equipment used

For this initial work, we used a digital camera with a ¼-inch CCD sensor. We selected a wide field of vision for detecting strata by using a Global View protocol, and a high resolution for grain measurements by using a Zoom-In protocol. The selected resolution level provided images with 270 µm (Global View) and 47 µm (Zoom-In) resolution (Figure 1). By indexing the images by means of a procedure developed in the acquisition protocol, we were able to combine Global View with Zoom-in shots and archive them according to depth scale. The images obtained with this basic equipment were quite adequate for gray scale processing. And data was sufficient to extract useful information for geologists on both strata and particles.

The methods we adapted and used to process and analyze the images are described below.

3. Methods

3.1. Strata detection

A stratum is defined as 'a sedimentary unit made up of two approximately parallel surfaces, i.e. breaks or sudden petrographic variations that clearly mark out the unit from the adjacent ground'. When starting the logs description, geologists first look for the strata joints that mark the sharpest contrasts in the considered series. If necessary, they will then refine their search by looking for other parameters, such as grain characteristics, current casts, fracturing, and so on. The boundary between two strata can be recognized as it fairly clearly separates two contrasting areas in terms of color, texture or structure, etc. Strata color values are secondary in terms of the objective, as only alternations are the matter in hand. A gray-level image is perfectly adequate for rhythm recognition, as shown by Figure 1a above, that displays a raw image of a core sample segment.

Image histograms generally point out unimodal distributions. In that case, the most appropriate segmentation methods would be frequency analysis ones, as small variations could thus be extracted. Two transformations can be used, Fourier and Wavelet transform.

In the Fourier series decomposition \( \frac{a_0}{2} + \sum_n (a_n \cos nx + b_n \sin nx) \), continuous term \( a_0 \) is not linked to a sinusoidal term. In practice, this term carries the information related to the signal average value. In order to restore as much detail as possible,
we therefore initially retained all the frequencies and
set the continuous term to zero.

The Wavelet transform decomposes the signal
into a sum of convolutions between an extended
wave, known as a wavelet, and a part of the signal [2]
and [6]. Wavelets provide all frequencies, but can
also be used to locate changes in them. In practice,
we used the discrete wavelet transform (DWT) which
is a multiresolution (or multiscale) representation. An
implementation of three-level forward DWT based
on two channel-recursive filterbank is shown in
Figure 2, where h_0(n) and h_1(n) are low-pass and
high-pass analysis filters respectively, and the block
\downarrow 2 represents the “downsampling by a factor 2”
operator. The original signal x(n) is recursively
decomposed into four subband signals: a coarse
signal, c_3, and three detail signals, d_1, d_2 and d_3,
corresponding to three different resolutions. The
indices stand for the scale level. The approximate
coefficient c_3 represents the average gray level, as
does the continuous term in the Fourier transform.
Wavelets can be considered as “mathematical
microscopes” that permit one to "zoom in" and
"zoom out" of images at multiple resolutions. The 2-
D DWT can be implemented by using the one-
dimensional DWT.

To detect the strata, we used all the details and
eliminated the approximate coefficient at one scale
level, as we did with the frequencies and constant
term in the Fourier transform.

Figure 3. Strata detection process

Figure 3 shows a core sample section in which
layers were difficult to distinguish.

As we can see above, the poorly contrasted strata
image (Figure 3a.) is better segmented by the
wavelet transform (Figure 3c.) than by the Fourier
transform (Figure 3b.). This can be explained by the
fact that the Fourier transform is a global
transformation. It effectively separates the strata, but
not in a very conclusive manner for very thin,
millimeter-scale strata with poor contrast. The
parameter scale in the wavelet analysis is similar to
the scale used in maps. As in the case of maps, high
scales correspond to a non-detailed global view (of
the signal), and low scales correspond to a detailed
view.

In the following paragraph, we will demonstrate that
the wavelet transform is actually more powerful than
Fourier transform for adjusting resolution as well as
to suit dimensions of strata to be extracted.
More precisely, we will demonstrate that strata can be
extracted selectively by choosing the best scale level
for Wavelet transform and stratification anomalies
can be detected by analyzing the gray level mean of
each strata localized in original image.
3.2. Fracture detection problem

Fractures are very often appeared during the drilling core. They are mainly due to drilling equipment decompression (mechanical fractures), but could also be caused by tectonic movements (geological fractures). The latter are most often related to recrystallization (see figure 4.). Our experiments on the stored core samples images have pointed out that fractures can only be identified as strata by Fourier transform, but that Wavelet transform can detect all fractures if the scale level is well fixed.

Figure 4. Mechanical and geological fracture example

As shown in figure 3c, the Wavelet transform at scale level 7 detects all strata and the geological fracture, but the mechanical fracture is merged in the sediment stratum. As mentioned in the previous paragraph, the low scales allow to distinguish the detailed information. Tests performed on many images with different strata and fractures have shown that the scale level 4 is suitable for mechanical fractures detection.

In figure 5a, we show the result of original image in figure 4 using the Wavelet transform at level 4. For each stratum detected in this new image, we compute the gray level mean from original image, we obtain the result in figure 5b. The distribution of gray level for this image result shows that there are tree classes of stratum. We performed the k-mean clustering method on this image (see figure5c). Each class of stratum have a new label which is the gray level mean. The minimum and maximum of this values (see figure 5d) correspond to fractures (mechanical and geological).

The Wavelet transform at scale level 4 allows as to localize the fractures. For the sediment stratum, we perform a new process on the original image using the wavelet transform with the another scale level value. This new value is fixed by each geologist depending on the resolution and details he needs and requires for his core analysis.

3.3. Grain Recognition

Mathematical morphology is one of the theories that are particularly suitable for granulometry analysis [7]. This theory allows constructing operators for image transformation. High and low intensity areas, or peaks and valleys in topographical terms, characterize different grain sizes. Some morphological operators can detect those areas, the most suitable being the regional maxima operator [8] (see Figure 6). A binary image is thus obtained on which connected components are then labeled.
For each labeled region (grain), the standard morphological properties used in particle analysis, such as the area, centroid, convex hull, and so on are measured. In the initial experiment presented in this paper, we decided to use grain size, calculated in terms of the ellipse minor axis length in pixels (Figure 7). The shape sphericity or elongation could therefore be estimated by calculating the major axis perpendicular to the previous one. Different shapes could be calculated separately.

Those quantitative results can be used as easily as data resulting from standard particle analysis methods, but an additional fact is that the particle distribution of light and dark clasts is obtained for each layer in a single process and without destroying the analyzed horizons. By using this information, access is gained to one of the keys for determining clast mineralogy, i.e. the distribution of leucocratic and melanocratic minerals that typify the various sedimentary provinces. The origin of the materials contributing to the investigated deposits can thereby be understood. As instance, Figure 8. shows the particle analysis results of the clear clasts from the clay/silt described in Figure 6a.

4. Geological application

Using our approach, we have been able to describe simultaneously the layers and their grain characteristics. The images taken in both Global View and Zoom-In mode were consistently indexed according to depth. It was then easy to restore each of them in the stratigraphic column. For the purpose of validation of our results, a joint analysis by a geologist and our algorithms is provided in Figure 9. The geologist identified a basic doublet formed by a dark layer made up of fine particles and a light layer made up of coarser particles. The combination is repeated throughout the examined sedimentary column. A standard description of the doublets provided by a logger’s visual observations would yield the following comments: typical elementary sequences from a turbiditic sedimentary series with alternating dark and light beds of irregular thickness ranging from a few millimeters to several centimeters. The darker layers are consistent with fine clay- or silt-size organogenic sediments. The lighter layers correspond to silico-clastic and silt-sand elements.

The layer boundaries detected by our algorithm and the light and dark level grain distribution perfectly match the description of the stratigraphic column. The geological conclusions drawn from our results would, therefore, be identical to those presented below.
5. Conclusion

Segmentation method using Wavelet transform and morphological operators have been used for many years in image analysis. The adaptation of scale-frequency transformation and morphological operators for the analysis of indurated core sample images proposed in this paper allows to simultaneously identify both sedimentary sequences and their granulometry. In addition, the depth-indexed database is built in a single acquisition pass. Analyses were conducted without destroying the sedimentary columns and with only a simple acquisition CCD Camera. Thus, this approach could be used in situ, which is not the case with other methods using heavy equipment's [1] and [4].

A few improvements could be introduced for a powerful, auto-adaptive analysis (layer detection and grain analysis). It would also be useful to link our image analyses with physical property measurements, such as resistivity, magnetic sensitivity, gamma-densitometry, etc [3]. The combination of all such properties added to geologists’ a priori knowledge could be useful for constructing a decision support system for sequence analysis on different scales.

6. References