

Automatic compensation for seafloor slope and depth in post-processing recovery of seismic amplitudes

Diogo Caetano Garcia
Universidade de Brasília
Faculdade UnB Gama
diogogarcia@unb.br

Ricardo Lopes de Queiroz
Universidade de Brasília
Dep. de Ciência da Computação
queiroz@ieee.org

Marcelo Peres Rocha
Universidade de Brasília
Instituto de Geociências
marcelorocha@unb.br

Luciano Emídio da Fonseca
Universidade de Brasília
Faculdade UnB Gama
luciano.unb@gmail.com

Abstract—Acoustic remote sensing remains the main tool for seafloor exploration across large areas. Acoustic-reflection analysis and acoustic-backscatter analysis allow for the remote estimation of several seafloor and underground properties, which can be further verified by other data such as seafloor cores and samples. Acoustic waves, however, respond not to just geological factors, like bulk density and sediment grain size, but also to the acquisition geometry, including bathymetry. Bathymetry is usually measured by single-beam and multibeam echo sounders, while high-frequency seismic data is acquired with sub-bottom profilers, boomers etc. In order to estimate geological parameters from high-frequency seismic data, it is important to compensate the seismic amplitude for depth and seafloor slope. The seismic acquisition gain can be automatically compensated in real time during the survey, or during post-processing. The former is more adequately used as a first approximation, while the latter offers results that are more precise. An automatic post-processing algorithm is here presented, which detects the sea-bottom for each time series recorded for each seismic trace. Once the bottom is detected, the algorithm calculates the average energy around the detection point, and applies gain compensation to this signal based on bathymetric and seafloor slope information, both obtained from the multibeam sonar data. In order to calculate the amount of gain compensation, least-squares estimation is employed to the average energy of the signal as a function of two-way travel time and wave incidence angle. The algorithm is then tested on real data captured at the Almirantado Bay in King George Island, Antarctica, showing promising results.

Keywords—*Seismic signals, sonar, automatic signal compensation, seafloor slope, seafloor depth*

I. INTRODUCTION

Seafloor exploration is a fundamental tool in oceanography, with applications on sealife characterization, oil reservoir discovery and exploration, among others. In order to analyze large areas, acoustic remote sensing is the main tool used by researchers, since many seafloor characteristics can be inferred directly from the sea surface, without the need for direct contact with the seafloor [1],[2].

Analysis of acoustic reflection and backscatter allows for the remote estimation of several seafloor and underground properties, and these results can be confirmed by other data such as seafloor cores and samples [3],[4]. Data acquisition for acoustic waves, however, are affected by several factors, such as bulk density, sediment grain size, water depth and bathymetry. The latter is usually measured by single-beam and multibeam echo sounders, while high-frequency seismic data is acquired with sub-bottom profilers, boomers etc.

Compensation of the aforementioned effects over acquired acoustic waves allows for the remote estimation of these factors. More specifically, the acquisition geometry can be calculated with great precision by single-beam and multibeam echo sounders, making it easier to remove these effects from high-frequency seismic data, which reaches higher depths in geology and can be used for geological parameter estimation [5],[6].

The seismic amplitude can be automatically compensated for depth and seafloor slope, either during the survey or during post-processing. The former is more adequately used as a first approximation, while the latter offers more precise results.

In this paper, an automatic post-processing algorithm for seismic data is presented, which accounts for the effects of seafloor depth and slope based on bathymetry from multibeam sonar data. The algorithm is then tested on real data captured at the Almirantado Bay in King George Island, Antarctica, showing promising results.

II. PROPOSED ALGORITHM

The proposed algorithm is composed of the following main steps:

- 1) Bottom detection;
- 2) Mean signal energy calculation around the seafloor;
- 3) Seafloor inclination estimation;
- 4) Mean signal energy compensation.

The algorithm starts by robustly estimating the sea bottom for each time series recorded for each seismic trace. Next, it calculates the average energy around the detection point, which is a very representative value of the reflected acoustic wave. Based on multibeam sonar data, seafloor inclination is estimated, and the average energy previously calculated is compensated accordingly. In order to calculate the amount of gain compensation, least-squares estimation is employed to the average energy of the signal as a function of two-way travel time and wave incidence angle.

A. Bottom detection

The proposed processing for seismic data $s[i][k]$, where i represents the time sample number and k represents the trace sample number, starts by detecting the start of the reflected acoustic wave at the ocean-seafloor interface. The first estimate $z_0[k]$ for each trace is taken to be the sample of biggest energy,

$z_0[k] = \alpha \arg \min_i (s[i][k]^2)$, considering that the trace value measurement unit is Volts. $\alpha = vT/2$ is a constant that relates the sample number i with the sample interval T and the sound speed underwater v . Division by 2 accounts for the two-way travel time of the acoustic wave.

This first estimate $z_0[k]$ for the start of the reflected wave can be very noisy, depending on how the traces were acquired. In order to measure this noise, the standard deviation $\sigma_{z_0}[k]$ for each estimate $z_0[k]$ is calculated, considering the two neighbouring estimates $z_0[k-1]$ and $z_0[k+1]$. The higher the value of $\sigma_{z_0}[k]$, the higher the noise in the first estimate $z_0[k]$.

Next, a better estimate $z[k]$ of the start of the reflected acoustic wave is calculated as $z[k] = \text{median}(z_0[k - \sigma_{z_0}[k]/4], \dots, z_0[k + \sigma_{z_0}[k]/4])$. The median is a very simple estimator, but also not very sensitive to noise, so that $z[k]$ presents much lower noise. By taking samples $z_0[k - \sigma_{z_0}[k]/4]$ to $z_0[k + \sigma_{z_0}[k]/4]$ into account, a better coherence among traces is obtained.

B. Mean signal energy calculation around the seafloor

Given the robust estimate $z[k]$, the algorithm calculates the mean energy of the signal $s[i][k]$ around the bottom of the ocean. Once again, noise plays a dominant role, so that its effects must be diminished, according to the following steps:

- 1) Migration: all traces were aligned based on the bottom estimation $z[k]$, and $2N + 1$ samples i around were separated, where N is the length in samples of the acoustic wave transmitted by the seismic-data acquisition equipment (sweep);
- 2) Stacking: a L -length moving-average filter was applied along the aligned traces, in order to reduce the noise;
- 3) Energy averaging: the average values $e[k] = \overline{s_{MS}^2}[k]$ of the square of the migrated and stacked samples was calculated for each trace k , in decibels.

C. Seafloor inclination estimation

In order to compensate the mean signal energy around the seafloor for the effect of the acquisition geometry, the latter must be known. The seismic data is acquired along the line of navigation, so that seafloor inclination parallel to the navigation line cannot be known *a priori*. Instead of estimating the inclination from seismic data, the algorithm employs bathymetry from multibeam sonar data in order to find the seafloor inclination.

Bathymetry data from multibeam sonar may be available in a regular XY grid. With knowledge of the XY positions of geo-referenced seismic traces, the corresponding seafloor inclination can be estimated as follows:

- 1) According to the estimated depth $z[k]$ and to the transmit and receive angles of the seismic data acquisition equipment, a region around the XY location is chosen. A deeper seafloor generates a larger imaged region, as shown in Fig. 1;
- 2) Based on the least-squares method, a plane is fitted to the region chosen;

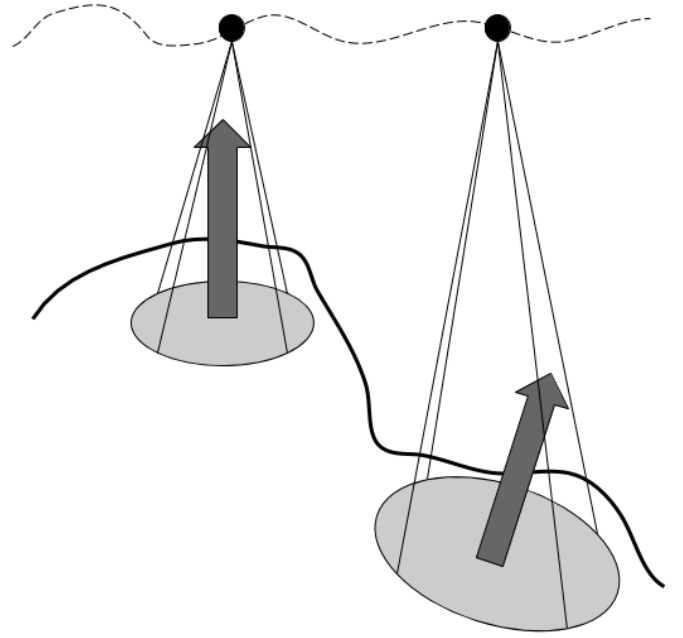


Fig. 1: Regions reached by the acoustic wave according to the transmit and receive angles of the seismic data acquisition equipment. A deeper seafloor accounts for a larger reached region. The arrows indicate the vector perpendicular to the reached region, which is used for its slope estimation.

- 3) Given the estimated plane, the normal vector to the plane can be found, as well as the normal vector's inclination $\theta[k]$, which is used as an estimate of the chosen seafloor region.

D. Mean signal energy compensation

The first three steps in the algorithm estimate the seafloor depth $z[k]$ and inclination $\theta[k]$ for each trace k , as well as the mean energy $e[k]$ of the signal reflected from the bottom of the ocean. In the last step, $e[k]$ is compensated by $z[k]$ and $\theta[k]$.

The effect of the seafloor depth $z[k]$ is compensated deterministically, as the acoustic wave decays proportionally to the square of the distance. Since $e[k]$ was calculated in decibels, the seafloor depth compensation was done by adding the factor $D_C = 10 \log_{10}(z[k]^2) = 20 \log_{10}(z[k])$ to $e[k]$.

The compensation of the effect of the seafloor inclination $\theta[k]$, on the other hand, requires more elaborate processing. As $\theta[k]$ increases, $e[k]$ decays according to the beam shape of the acoustic wave, which is not readily available. In this manner, it is necessary to estimate statistically how $\theta[k]$ affects $e[k]$, in the following manner:

- 1) A first correction $C_1(e[k])$ is applied as $C_1(e[k]) = e[k] + 20 \log_{10}(z[k])$, to account for the effects of the seafloor depth;
- 2) Instead of searching for the effects of $\theta[k]$ over $C_1(e[k])$, it is better to linearize the problem by expressing $C_1(e[k])$ as a function of $\theta_s[k] = \sin(\theta[k])$,

since the reflected acoustic wave is proportional to the sine of $\theta[k]$;

- 3) A small step δ is defined to be used as the bin size of the histogram $H(\theta_s[k])$ of $\theta_s[k]$;
- 4) Based on the values of $H(\theta_s[k])$, the histogram $H(C_1(e[k]))$ of $C_1(e[k])$ is calculated. In this way, the great variations in $C_1(e[k])$ are smoothed;
- 5) $H(C_1(e[k]))$ is approximated by a linear regression, $\hat{H}(C_1(e[k])) = \alpha H(\theta_s[k]) + \beta$, using the method of least squares.

III. EXPERIMENTAL RESULTS

Octave/MatLab® code was developed in order to read and process seismic data in the SEG-Y format [7], according to the steps presented in Section II. The proposed algorithm was validated using data collected by a SBP 300 sub-bottom profiler [8] at the Almirantado Bay in King George Island, Antarctica, in December 2013, with the following configuration:

- The sampling period of the traces lasted $48 \mu s$;
- The acoustic wave employed was a chirp whose frequency rose linearly from 2500 to 6500 Hz, in a 2 ms period;
- The traces were previously deconvolved with the input chirp signal by the seismic data acquisition equipment;
- Latitude and longitude information was given in degrees, minutes and seconds;
- Traces could begin with different delay recording times.

Prior to applying the proposed algorithm, the trace data had to be compensated by the delay recording times, or else the bottom detection method (Section II-A) would present incorrect values. Figure 2 presents the delay-recording-time compensation for a group of traces from the test data. Furthermore, the latitude and longitude values had to be converted to the UTM coordinate system, or else the plane fitting in the seafloor inclination estimation (Section II-C) would also be incorrect.

The following Subsections present the results of the algorithms described in Subsections II-A to II-D.

A. Results for the bottom detection algorithm

Figure 3 presents the detected bottom for a group of traces from the test data, where the blue lines and red dots represent $z_0[k]$ and $z[k]$, respectively. Clearly, the initial estimate $z_0[k]$ can be very noisy, specially for the first 500 traces. The proposed algorithm, however, presents a much smoother transition between traces, which better conforms geologically with the seafloor.

Figure 4 presents the standard deviation of the initial depth estimation $z_0[k]$ for the same group of traces from the test data. Direct comparison of Figs. 3 and 4 shows that high standard deviation values correspond very faithfully to noisy $z_0[k]$ samples, as expected. Note again the noisy results for the first 500 traces, which are smoothed in $z[k]$ (red dots in Fig. 3).

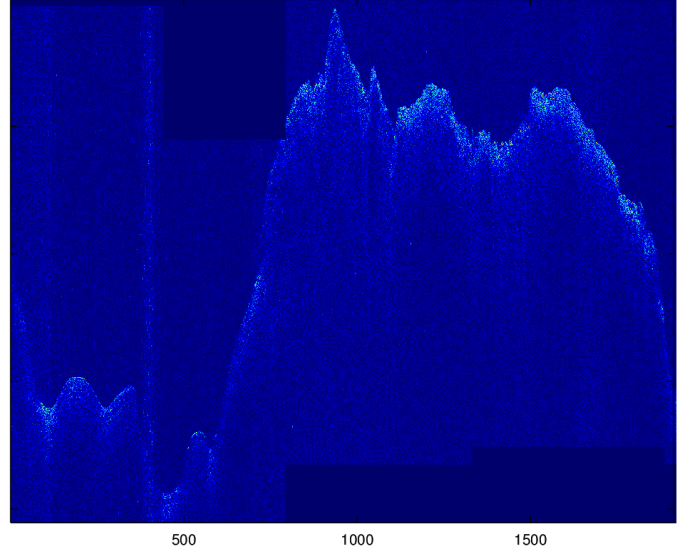


Fig. 2: Absolute values of the seismic data samples $s[i][k]$, after delay-recording-time compensation.

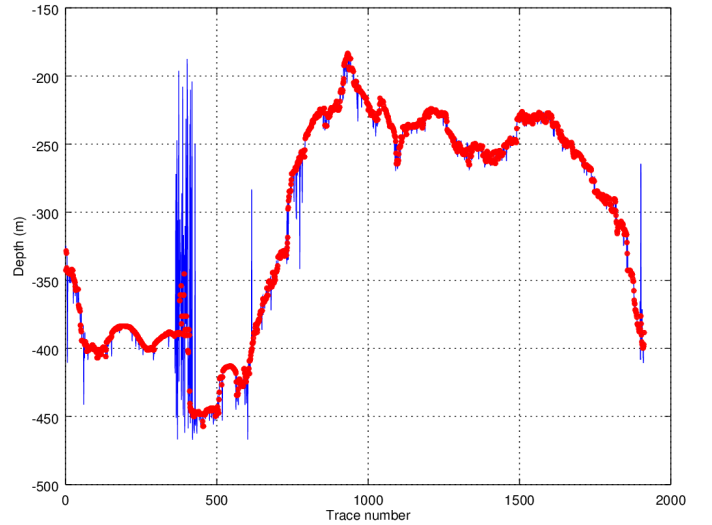


Fig. 3: Bottom detection for a group of traces from the test data (Subsection II-A). The blue lines represent the initial depth estimation $z_0[k]$, and the red dots represent the robust estimate $z[k]$.

B. Results for the mean signal energy calculation around the seafloor

Figure 5 presents the mean energy, in decibels, of the signal reflected by seafloor for the same group of traces from the test data. The blue and green curves represent the mean energy before and after the steps of migration and stacking are performed, respectively. The second curve is clearly less noisy than the first one, since stacking acts as a low-pass filter to the energy signal. Also, the overall energy is about 10 dB lower after migration and stacking, since the noise has been largely reduced.

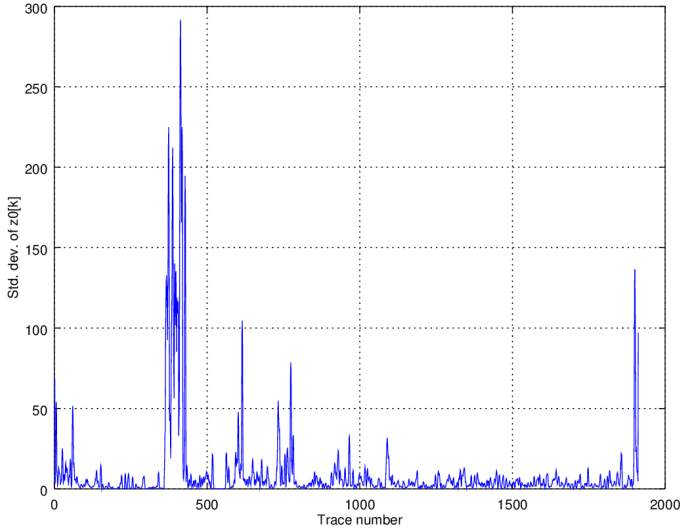


Fig. 4: Standard deviation of the initial depth estimation $z_0[k]$, as explained in Subsection II-A.

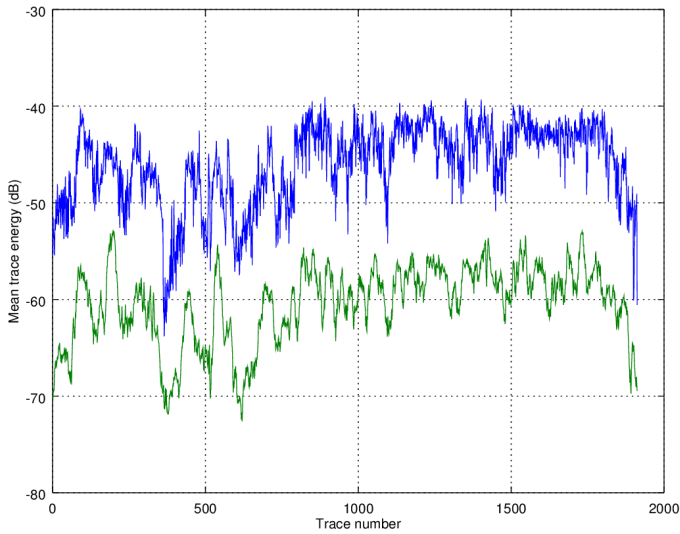


Fig. 5: Mean energy of the signal reflected by seafloor, in decibels. The blue curve represents the mean energy before the steps of migration and stacking are performed (Subsection II-B), and the green curve represents the mean energy after the same steps.

C. Results for the seafloor inclination estimation

Figure 6 presents the result for the seafloor inclination estimation for one of the traces from the test data. The red stars represent the depth values measured by the multibeam sonar data using the Geocoder software [9],[10], the red lines indicate the plane that contains these values, and the blue arrow is the vector normal to that plane. This is a typical result of the proposed algorithm, which offers a very clear estimate of the seafloor inclination.

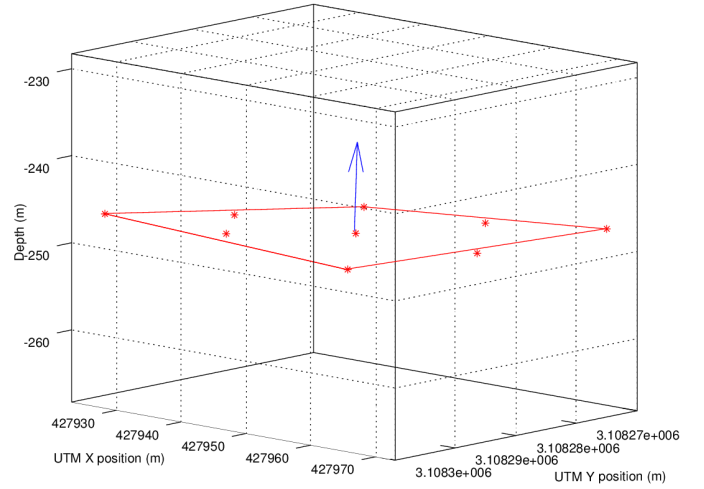


Fig. 6: Seafloor inclination estimation (Subsection II-C). The red stars represent the depth values measured by the multibeam sonar data, the red lines indicate the plane that contains these values, and the blue arrow is the vector normal to that plane.

D. Results for the mean signal energy compensation

Figure 7 presents the mean signal energy corrected by the depth estimate ($C_1(e[k])$) and the sine of the estimated seafloor inclinations ($\theta_s[k]$) for the whole test data. A large variation for $C_1(e[k])$ can be seen, which depends not only on $\theta_s[k]$ but also on geological factors, like bulk density and sediment grain size. This is the motivation for the calculation of the histograms $H(\theta_s[k])$ and $H(C_1(e[k]))$, to smooth out those variations.

Figure 8 presents the results for the mean signal energy compensation for the whole test data. The blue dots represent values of $H(\theta_s[k])$ and $H(C_1(e[k]))$, and the red line offers the least-squares estimate $\hat{H}(C_1(e[k])) = -19.7H(\theta_s[k]) + 61.8$, which has a correlation of 0.81 with $H(C_1(e[k]))$. It can be seen that the linear approximation is very faithful to the test data, specially in terms of the measured correlation factor. With the estimate $\hat{H}(C_1(e[k]))$, it is possible to remove the influence of $z[k]$ and $\theta[k]$ over $e[k]$, offering cleaner data for the seismic analysis of the geological factors of the seafloor.

IV. CONCLUSION

This paper presented an algorithm for the automatic compensation of seismic amplitudes for seafloor slope and depth. Given high-frequency seismic data and bathymetry information from multibeam sonar data, the algorithm performs bottom detection for the seismic data, calculates the mean signal energy reflected the seafloor, estimates the seafloor inclination from the bathymetry information and compensates the mean signal energy by the estimated values of depth and inclination. Experiments performed for real data captured at the Almirantado Bay in King George Island, Antarctica, showed promising results, with a correlation of 0.81 between the measured and the estimated mean signal energy.

The proposed algorithm allows for the post-processing of high-frequency seismic data, which is a powerful tool for acoustic remote sensing and seafloor exploration. By removing the effect of the seafloor's depth and inclination over the measured seismic data, other seafloor properties can be estimated, such as geological factors.

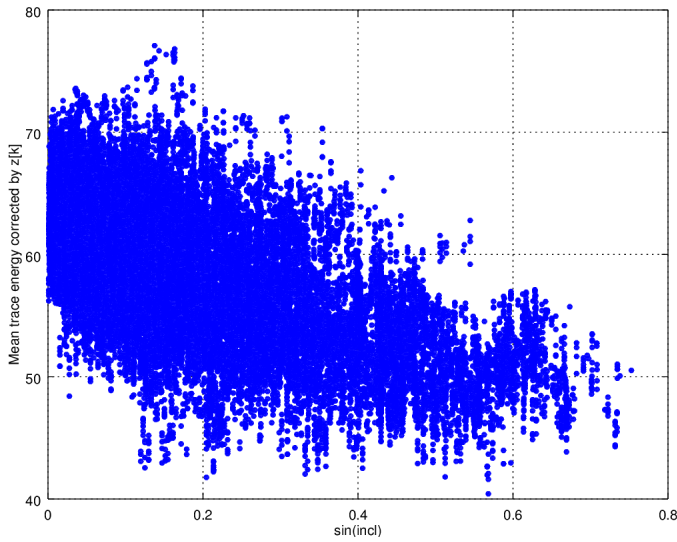


Fig. 7: Mean signal energy corrected by the depth estimate ($C1(e[k])$) and sine of estimated seafloor inclination ($\theta_s[k]$), as explained in Subsection II-D.

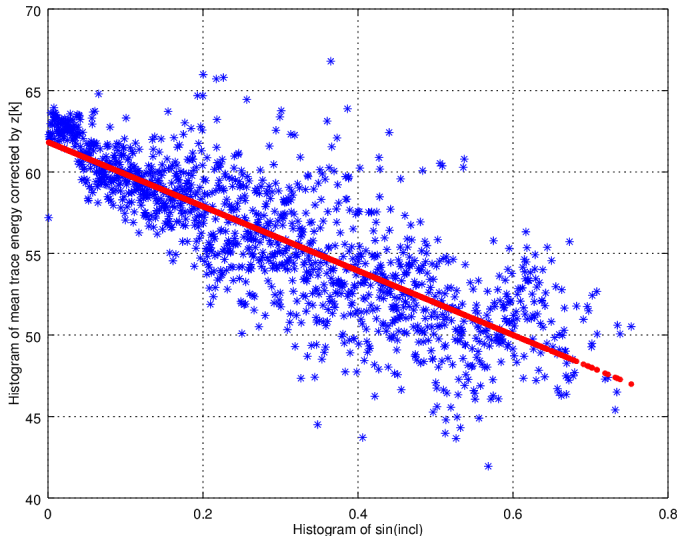


Fig. 8: Mean signal energy compensation (Subsection II-D). The blue dots represent values of $H(\theta_s[k])$ and $H(C1(e[k]))$ for all the test data, and the red line offers the least-squares estimate $\hat{H}(C1(e[k])) = -19.7H(\theta_s[k]) + 61.8$. A correlation of 0.81 was found between $H(C1(e[k]))$ and $\hat{H}(C1(e[k]))$.

REFERENCES

- [1] O. Yilmaz, "Seismic Data Analysis," *Society Of Exploration Geophysicists*, 2 ed., vol. 10. Tulsa, USA, 2001.
- [2] R. Sheriff, "Processing and interpretation of seismic reflection data: An historical précis," *The Leading Edge*, Society of Exploration Geophysicists, vol. 7, Jan. 1988.
- [3] F. Santana and A. Neto, "Use of seismic attributes for sediment classification," *IET Journal of Engineering*, Jan. 2015.
- [4] A. Neto, B. Mota, A. Belem, A. Albuquerque and R. Capilla, "Seismic peak amplitude as a predictor of TOC content in shallow marine sediments," *Geo-Marine Letters*, 36.5, 2016.
- [5] L. N. Fonseca, and L. Mayer, "Remote estimation of superficial seafloor properties through the application of angular range analysis to multi-beam sonar data," *Marine Geophysical Researches*, Vol 28, No. 2, pp. 119126, June 2007.
- [6] Y. Rzhano, L. Fonseca, L. Mayer, "Construction of seafloor thematic maps from multibeam acoustic backscatter angular response data," *Computers & Geosciences*, Elsevier, vol. 41, Apr. 2012.
- [7] SEG Technical Standards Committee, "SEG Y rev 1 Data Exchange format," *Society of Exploration Geophysicists*, release 1.0, May 2002.
- [8] Kongsberg Maritime AS, "SBP 300 Sub-Bottom Profiler," *Kongsberg Maritime AS*, Bremerhaven, Norway, 2009.
- [9] Kongsberg Maritime AS, "Kongsberg EM Series Multibeam echo sounder, EM datagram formats," *Kongsberg Maritime AS*, Bremerhaven, Norway, 2016.
- [10] L. Fonseca, and B. Calder, "Geocoder: an efficient backscatter map constructor," *Proc. of Hydrographic 2005*, Hydrographic Society of America, San Diego, CA, 2005.

ACKNOWLEDGMENT

This research was supported by Petrobras/Cenpes under the research project "Processamento de Sinais Sonográficos para a Identificação Direta de Hidrocarbonetos," SAP: 4600505474, 2014/00634-2. The work of R. de Queiroz was partially supported by Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq), Brazil, under grant 308150/2014-7.