Using Statistical Techniques to Improve the QC Process of Swell Noise Filtering

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SUMMARY

The current approach for the quality control (QC) process of the swell noise filtering phase carries significant drawbacks. This abstract investigates the use of statistical techniques to improve the QC process. The main approach of this analysis is to combine attributes that capture properties of the filtering process and plot them against each other in order to identify "outliers". It is shown that cases which have been "badly" or not "properly" filtered will cluster away from the main group and may be detected using statistical methods such as clustering algorithms. Statistical techniques may potentially play an important role in the development of a data-driven automated QC platform.

Introduction

A common quality control (QC) tool for the swell noise filtering process is to visualise the root-mean-squares (RMS) maps of the data before and after the filtering in order to identify any anomalies. Anomalies are mainly “abnormal” high RMS values in the output map that are not consistent with their spatial neighbourhood, making them a discrepancy that is more likely to be attributable to bad filtering performance, rather than to a geological feature of the subsurface. Often after spotting these anomalies, the user visualises the corresponding seismic sections and performs further investigations.

Two main drawbacks characterise the above QC process:

1. The approach of identifying anomalies in colour-maps is sensitive to thresholds in the colour-code used to generate them. This introduces some user subjectivity; different users may end-up spotting different sets of anomalies.
2. The performance of the filtering is captured by only few attributes, e.g. two RMS values per shot (before/after the filtering), which constitutes a considerably coarse representation. The number of attributes is limited as a result of the human assimilation limitation to simultaneously inspect and inter-correlate a different set of maps at a time.

In order to improve the QC process, one needs to include more attributes that quantify the performance of the filtering and to adopt a data-driven method to detect anomalies. This can only be achieved if the process of attribute analysis that includes inter-attribute dependency extraction and anomaly identification is done by a computer program. Such an automated system would ease the QC process for the user and make it more streamlined.

This abstract investigates the use of statistical techniques to improve the QC step for swell noise filtering processes. The main idea is to combine two attributes: (1) amplitude reduction after the filtering and (2) statistical properties of the swell noise. The performance of the filtering process on the dataset (e.g. shots within a sailine) is visualised by plotting the two attributes in a scatter plot. A clustering algorithm (Fraley and Raftery, 2002) is used to identify the different clusters that exist in the scatter plot. Shots that have been “badly” or not “properly” filtered will cluster away from the main scatter of shots.

The prospective goal of this work is to lay the foundations for the development of an automated QC platform that can identify cases of undesirable filtering by taking advantage of machine learning and pattern recognition techniques. The above idea is expected to work better for a filtering process that targets high amplitude noise such as swell and seismic interference, as the properties of these types of noise are considerably different to the desired output of the filtering process; this allows more useful statistical inferences to take place.

Methods

Firstly, the input, output and difference RMS of seismic amplitudes per shot are combined into a single attribute, representing normalised energy reduction

$$ER_{shot} = \log\left(1 + \frac{RMS_{shot}(difference)}{RMS_{shot}(input)}\right).$$

This normalisation aims to eliminate variations related to the power of the seismic source. Secondly, statistical properties of the filtering can be obtained by computing for every trace within a shot the quantity

$$\lambda_{trace} = \log\left(\frac{RMS^2_{trace}(output) + RMS^2_{trace}(difference)}{RMS^2_{trace}(input)}\right),$$

and then by extracting some measures from the statistical distribution of λ_{trace} for each shot point. The motivation for considering this expression for λ_{trace} stems from the fact that the swell noise and the signal (geological events) are statistically independent. Hence for a case of good filtering, the difference (input – output) will be approximately equal to the noise. It then follows that

$$RMS^2_{trace}(output) + RMS^2_{trace}(difference) \approx RMS^2_{trace}(input),$$

therefore λ_{trace} should have a value close to zero for good filtering. This means that if the filtering is properly done for a given shot, we expect the distribution of λ_{trace} for that shot to have approximately zero mean. Any large deviation from the zero mean is therefore considered as an indication of undesirable filtering.

Moreover, swell noise, contrary to random noise, affects only a limited set of traces within a shot. This means that the variance of λ_{trace} for an ideal filtering is expected to be greater than the corresponding variance for a simple high-pass filtering which affects all traces within a shot. The reference to a high-pass filter is invoked here because it is considered a "bad" filtering method for swell noise. Therefore, the variance of λ_{trace} can potentially be an informative attribute that measures the performance of the swell noise filtering process.

The above three attributes (energy reduction, mean of λ_{trace}, variance of λ_{trace}) provide a per-shot quantification of filtering properties and can be plotted against each other in a scatter plot. Prior to this step, it is also possible to implement dimension reduction techniques such as principal component analysis (PCA) and independent component analysis (ICA) (Hyvärinen *et al.*, 2001) in order to obtain an optimally informative pair of attributes, which are easy to visualize in a scatter plot.

Finally, a clustering algorithm can be applied to detect groups of outliers in the scatter plot. This may be performed by machine learning techniques; either by an unsupervised learning algorithm (hierarchical, centroid, statistical clustering) or by a supervised learning algorithm. The latter case can be implemented to allow the user to preselect known cases of good filtering, thus defining a "rule" that can be used to infer the classification as "good" or "bad" for the remaining cases.

Examples

Figure 1 shows the result of applying two filtering methods to remove swell noise on a real seismic dataset and serves as an example that showcases divergent filtering performance. An optimised FX-de-spiking with prediction interpolation method (Schonewille *et al.*, 2008) achieves "good" filtering results, whereas a high-pass filter achieves "bad" results. Both filters are applied over the same frequency range of 0Hz-20Hz.

Figure 2 shows histograms of the statistical distribution for data belonging to a single test shot of λ_{trace} values for the high-pass filter (Figure 2-a) and the FX-prediction filter (Figure 2-b). Both distributions have a mean value close to zero. This was expected for the FX-prediction filter, but also for the high-pass filter because of the different frequency content of the difference and the output sections. This implies that if the taper range is large enough to encompass all swell noise frequencies, the difference and output datasets will be uncorrelated; if some swell noise is present in the output section, non-zero cross-correlation values are to be expected. This makes the mean uninformative, but the distinctly dissimilar shapes of these distributions can be easily captured by the second-order statistical moment of variance. It is obvious that the variance for the high-pass filter output is much smaller compared to the F-X prediction output; hence it is more informative as a measure of discrimination between these "good" and "bad" filtering outcomes.

The next objective is to validate whether the proposed attributes are informative with respect to filtering performance in a realistic situation. This can be attained by investigating whether they can provide a reliable detection of few cases of bad filtering in real data from a sailine, as this is usually the case in practice. To mimic this situation, some shots that have been filtered with the high-pass filter are mixed with shots filtered using the F-X prediction method. In Figure 3, the corresponding scatter plot of the variance of λ_{trace} versus per shot energy reduction is shown, displaying favourable results. The "bad filter" shots are only slightly distinguishable at the energy reduction (vertical) axis, but are clearly separated from the "good filter" shots at the λ_{trace}-variance (horizontal) axis. The combination of the two attributes conveniently creates two clear natural groupings of shots, the "good" group and the "bad" group. In this example, the classification is easily made by visual inspection, however for more realistic cases a clustering algorithm can be applied order to successfully reveal the desired groupings. It is also possible to modify the clustering algorithm to return a classification of more than two groups to allow for more complex data distributions.

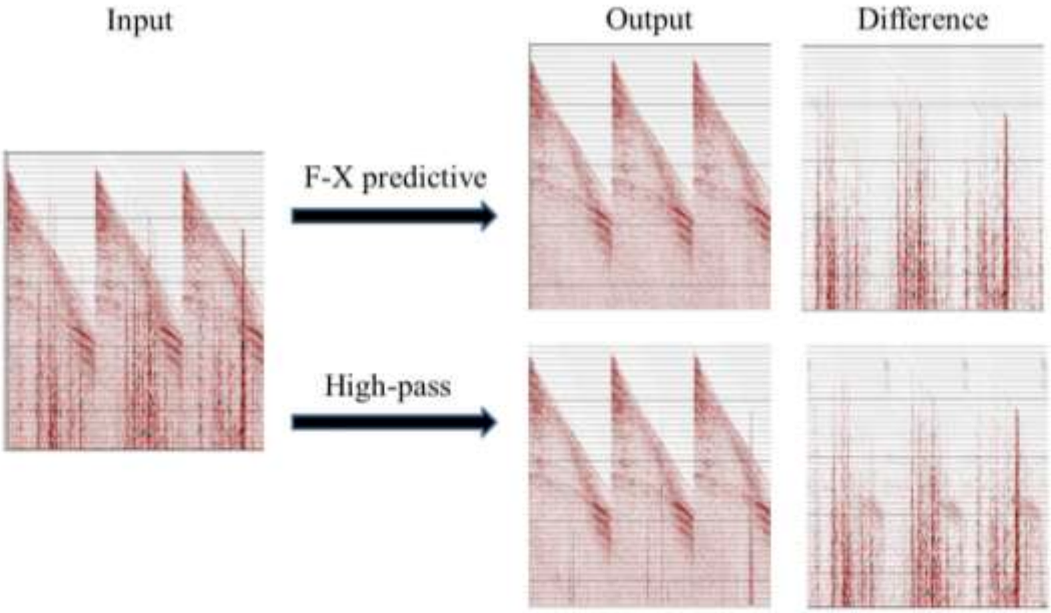

__Figure 1__ Comparison of the industry-standard FX-de-spiking with prediction interpolation and crude high-pass methods performance on the filtering of swell noise. The high-pass method clearly underperforms compared to the industry-standard, as it fails to remove large amounts of swell noise and also undesirably removes significant portions of primary signal as seen in the difference section.

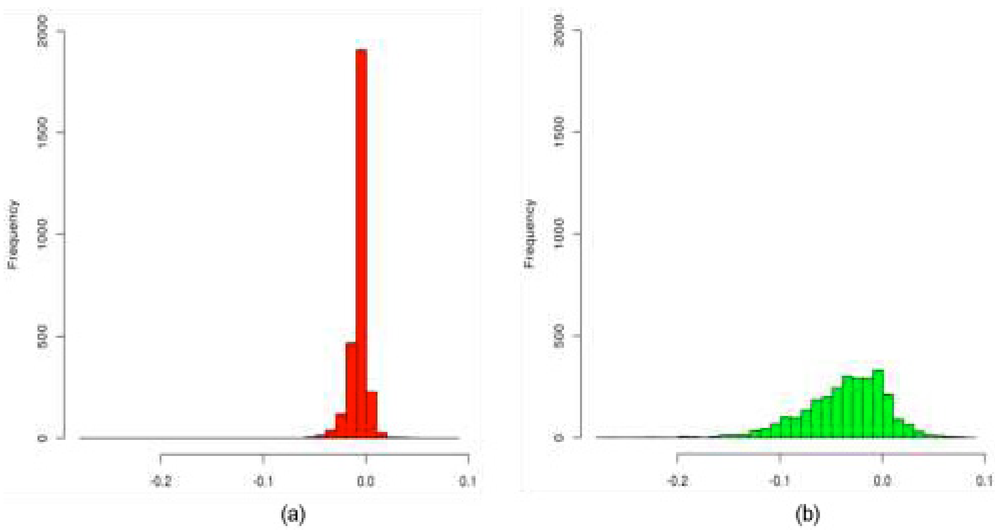

__Figure 2__ Histograms that show the distribution of λ_{trace} for data belonging to a single test shot filtered for swell noise with (a) the crude high-pass method and (b) the industry-standard FX-de-spiking with prediction interpolation method.

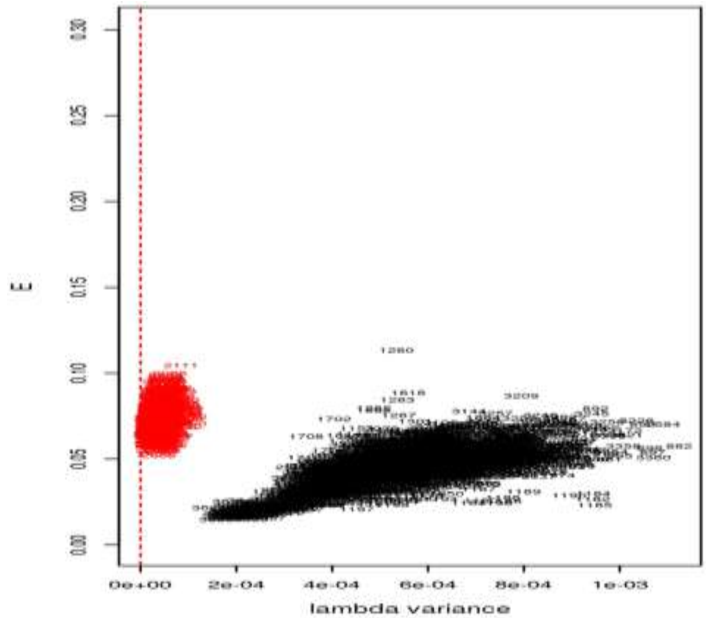

Figure 3 *Scatter plot of the per shot variance of* λ_{trace} *versus energy reduction for sailine data from a mixed dataset of "good filter" shots (black) and "bad filter" shots (red).*

Conclusions

Incorporating statistics-based information about the swell noise filtering process can help enhance the accuracy of the QC step in terms of its capacity to highlight locations where the filtering was not performed "well" enough. The visualisation of the attributes in a scatter plot rather than maps, accompanied with a visualisation of the corresponding seismic sections can be used to further explore potential relationships between observed attribute values and isolated anomalies.

Clustering techniques may also be implemented in order to automatically detect anomalies that are not clearly distinguishable by an initial visual examination. In addition to the above, the visualisation of, for example, a $\boldsymbol{\lambda_{trace}}$-variance map in addition to RMS maps of input and output could also provide more information about the performance of the filtering process.

The above methodology is an exploratory step towards the development of a data-driven automated QC platform that takes into account techniques from the fields of statistics and machine learning.

Acknowledgements

We would like to thank Prof Charles Taylor (School of Mathematics, University of Leeds) for his helpful input during the analysis stage and Paul LeCocq for his advices.

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