Playing with Fire: Noise Alignment in Trim and Residual Statics

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Summary

It is well known the cross-correlation procedure in trim statics can produce spurious reproduction of signal. This phenomenon is quantified and is shown, in the limits of large fold, small correlation window, and large maximum allowable shift, to behave as a simple function of these variables for physically reasonable wavelet lengths. These results allow one to predict what choices of cross-correlation parameters are likely to result in spurious alignment of noise. It is also shown that this function can help to indicate whether apparent signal is a result of the desired signal alignment, or simply constructed from random background noise. The effect of residual statics can also function as an indicator in this context.

Introduction

A well-known danger in trim statics is using too large of a maximum allowable shift. This can result in the apparent alignment of signal when in fact random noise is being aligned instead. This phenomenon of noise alignment is illustrated in Figure 1, in which a stack of band-limited random noise has been trimmed using a large maximum allowable shift, so that the stack closely mimics the displayed pilot trace used in estimating the trim statics. Unfortunately, there are sometimes cases when large maximum shifts may be desirable. In Middle Eastern data, for instance, where there can be large surface statics, and it may be unclear whether apparent structure is real, or simply the result of very large residual statics. How is one to proceed in this situation? Compounding this, Middle East data is often of high fold, which, as shown quantitatively below, compounds the peril of noise alignment.

Method

This study required the use of a number of random noise synthetic data traces. To generate a random noise data trace, every sample in a given trace is assigned a random number between –1 and 1. The trace is then cubed, and this result is convolved with an Ormsby wavelet of duration $\tau_v$ (denoted $\tau_v$ in the figures). A synthetic pilot trace would also be produced in this manner. To create a synthetic $n$-fold CMP stack of $M$ traces, a total of $nM$ data traces were also generated by the above procedure. When these traces are stacked, the result represents the NMO corrected CMP stack in a typical trim statics procedure. Since the emphasis here is on statics, this is referred to as the raw stack. Trim statics are then applied in a typical manner, calculating cross-correlation functions between individual data traces and the pilot trace. The individual traces are shifted by the time delay corresponding to maximum cross-correlation amplitude, and then restacked. This is referred to as the trim stack. The output of principal interest at this stage consists of the cross-correlation coefficient ($\text{ccc}$) between traces of the trim stack and the pilot trace. This quantity is averaged over the $M$ trim stack traces (which all use the same trim parameters) and is denoted $\langle\text{ccc}\rangle$. $\langle\text{ccc}\rangle = 0$ implies that no signal has been generated, while $\langle\text{ccc}\rangle = 1$ implies that the pilot trace has been perfectly reproduced. For Figure 1, $\langle\text{ccc}\rangle = 0.90$, congruent with the obvious visual similarity between the pilot trace and the trim stack.

The signal to noise ratio ($\text{SNR}$) of the trim stack may also be estimated as

$$\text{SNR} = \langle\text{ccc}\rangle / (1-\langle\text{ccc}\rangle).$$

(1)

The variables that can be adjusted for each calculation are the window size ($\tau_w$, in seconds, denoted $w$ in the figures), the maximum allowable shift ($\tau_{\text{max}}$, in seconds), the number of traces to be stacked ($n$), the wavelet duration ($\tau_v$, in seconds), the number of traces in the stack ($M$), and the wavelet parameters ($f_1 = 0.4/\tau_v$, $f_2 = 0.8/\tau_v$, $f_3 = 4.0/\tau_v$, $f_4 = 5.6/\tau_v$). Finally, a residual statics calculation can be carried out as well, if the calculation is designed in such a way that a unique source and receiver can be assigned to
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each trace. The result is referred to as the surface consistent stack.

Understanding noise alignment in trim statics

The first step is to understand how noise alignment occurs in trim statics. To do this, the parameters \( n, t_{\text{max}}, \tau_w, \) and \( \tau_v \) were independently varied, and their effect on \(<ccc>\) analyzed. The results are displayed below in Figures 2 through 5.

Figure 2. The variation with number of stacked traces (\( n \)) of the averaged cross-correlation coefficient (\(<ccc>\)) between a reference trace and stacked, correlated random noise. This is the same data as in Figure 2, but \( 1-<ccc> \) is plotted instead of \(<ccc>\), and \( 1/\sqrt{n} \) instead of \( n \). Furthermore, \( n \) is scaled by \( \tau_v/\tau_w \). Note the linear behavior for large \( n \), and that plots are grouped by their value of \( t \) (same as \( t_{\text{max}} \)).

Figure 3. The variation with correlation window (\( \tau_w \)) of the averaged cross-correlation coefficient (\(<ccc>\)) between a reference trace and stacked, correlated random noise. This is the same data as in Figure 3, but \( 1-<ccc> \) is plotted instead of \(<ccc>\), and \( \sqrt{\tau_w} \) instead of \( \tau_w \). Furthermore, \( \tau_w \) is scaled by \( 1/(n\tau_v) \). Note that lines are grouped by their value of \( t \) (same as \( t_{\text{max}} \)) in this Figure, and also that lines in Figure 4 with a given value of \( t \) are similar in the linear region to lines in this Figure with the same value of \( t \).

Figure 4. The variation with maximum allowable shift (\( t_{\text{max}} \)) of the averaged cross-correlation coefficient (\(<ccc>\)) between a reference trace and stacked, correlated random noise. Note that the behavior is linear for large \( t_{\text{max}} \), but that the plots do not approach the origin.

Figure 5. The variation of \(<ccc>\) with the wavelet length, \( \tau_v \). Values derived from the cross-correlation procedure are given as points, while values from Eq.(2) below are given as corresponding solid lines. Note that \(<ccc>\) varies little with \( \tau_v \). Any increase is monotonic, in agreement with Eq.(2), and the two plots with the same value of \( \tau_w/n \) lie over top of each other, also consistent with Eq.(2).
By analyzing the above results and others, the following expression was empirically derived for $t_{\text{max}} > 0.06 \text{s}$, $\tau_w/n < 0.03 \text{s}$, and $0.02 \text{s} < \tau_v < 0.16 \text{s}$:

$$ccc \approx 1 - 0.18 \left[ 1 + 2 \sqrt{\frac{2(t_{\text{max}}/\tau_v) + 1}{(\tau_v/\tau_v)/n}} \right]$$  \hspace{1cm} (2)$$

The values of $t_{\text{max}}$ and $\tau_w$ are scaled by $\tau_v$, so that the result is dimensionless. Although Equation (2) is empirical, it is reasonable for $1 - ccc$ to depend on $1/n$, as a non-zero $t_{\text{max}}$ essentially imbues the trace with an effective signal, and this signal is enhanced as $\sqrt{n}$. However, if the correlation window size is doubled, there are twice as many points to align, and twice as many traces are required to produce the same result. This rationalizes the observed $\tau_v/n$ dependence. For a trace of random points, not convolved with a wavelet, shifting a trace with displacements of $\pm t_{\text{max}}$ relative to the pilot trace would be analogous to comparing the pilot trace to $2t_{\text{max}}/dt + 1$ different traces ($dt$ is the sample rate). Convoluting with a wavelet results in an auto-correlation length of $\sim \tau_v$, so that shifting the trace by $\pm t_{\text{max}}$ would be similar to comparing the pilot trace to $(2t_{\text{max}}/\tau_v) + 1$ different traces. Thus the observed $t_{\text{max}}$ dependence is rationalized by analogy to the dependence on $n$. Some of the numerical parameters, such as 0.18, might be replaced by functions of $\tau_v$, but the dependence appears to be weak, and Equation (2) was found to be reasonably accurate.

**Discerning Noise Alignment from Signal Alignment**

One immediate use of Equation (2) is to confirm that a chosen set of cross-correlation parameters will not result in significant noise alignment (i.e., if Equation (2) yields a value of, say, $ccc < 0.5$, or SNR < 1, then the chosen parameters are reasonable).

A second use, as will be shown next, is to discern after a cross-correlation procedure whether signal or noise has been preferentially aligned. This allows one to use parameters which predict $ccc > 0.5$, and to tell afterward whether the choice was justified.

To test the utility of these measures, synthetic data was created to model mixed signal and noise traces. A signal trace was created from random noise as before. The pilot trace and data traces for the stack were then created from a mixture of the signal trace and an independently generated noise trace. The data traces were then displaced by a static chosen from a Gaussian distribution. Because synthetic data was employed it was possible to generate a realignment measure, which was 0 for uncorrelated stacks, and varied from 1 to -1 for perfect signal alignment to 1 for pure noise alignment. It employed information obtained from creating the synthetic data and of course is not available with real data. It was used simply to test the validity of conclusions.

An example of the use Equation (2) in this fashion is shown below in Figure 6, where for two choices of parameters noise is aligned, and for two other choices signal is aligned (for sufficiently large $t_{\text{max}}$). Note that in all cases the predicted $<ccc>$ is larger than 0.5, so that random noise could potentially have been aligned, even when signal was aligned instead. This emphasizes the usefulness of this approach when one desires to use large maximum shifts.

![Figure 6](image)

**Effect of Surface Consistency**

Application of surface consistency tends to undo the alignment of noise, but is not able to align signal which has not already been aligned in a cross-correlation procedure. It can be demonstrated that this effect holds for this
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synthetic data, and provides an additional indicator to distinguish between signal and noise alignment. Figures 7 presents results from calculations with varying signal-to-noise ratio (snr) in the input data.

![Graph](image)

It is clear that for low snr the trim procedure can give a well-aligned appearance, which is then obliterated by the surface consistency calculation. There is an interesting dip in the trim <ccc> during the transition region. The difference between <ccc> before and after surface consistency, and also the average difference between the time shift before and after surface consistency both appear to be reliable indicators of whether signal is being aligned. This conclusion is obtained by comparison with the error estimation of the residual statics, which is available from information used in creating the synthetic data.

Analogous calculations were carried out using n = 101 as well, which give similar results to those in Figure 7. Thus these effects would be expected to appear in high fold data as well.

Conclusions

The noise alignment in trim statics has been quantitatively described in a functional format. This allows one to both avoid noise alignment in trim procedures, as well as to see after the fact whether alignment has occurred. This is especially useful in situations where large maximum allowable shifts are desired. The changes resulting from surface consistency are also useful indicators of signal vs. noise alignment.

References


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