Automatic approaches for seismic to well tying

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Abstract

Tying the synthetic trace to the actual seismic trace at the well location is a labor-intensive task that relies on the interpreter’s experience and the similarity metric used. The traditional seismic to well tie suffers from subjectivity by visually matching major events and using global crosscorrelation to measure the quality of that tying. We compared two automatic techniques that will decrease the subjectivity in the entire process. First, we evaluated the dynamic time warping method, and then, we used the local similarity attribute based on regularized shaping filters. These two methods produced a guided stretching and squeezing process to find the best match between the two signals. We explored the proposed methods using real well log examples and compared to the manual method, showing promising results with both semiautomatic approaches.

Introduction

Reliable well-seismic tying is a crucial step in seismic interpretation to correlate subsurface geology to observed seismic data. Even though the method involves a well-known workflow (Hall, 2013), it turns out to be a hardly repeatable experiment. The ease and quality of the tying procedure depend on the availability of high-quality logs, the estimation of a suitable wavelet, and the interpreter’s experience. Excellent recipes by White and Simm (2003) and two short essays by Newrick (2012) describe good practices in the tying procedure. An initial statistical wavelet is estimated from the seismic data and convolved with the reflectivity calculated from the well logs (sonic log and bulk density log) to generate the first synthetic trace. Then, the interpreter finds the best match between the generated synthetic and the actual seismic trace. Following these steps does not guarantee the “correct” tie (Anderson and Newrick, 2008) because the entire process is prone to pitfalls due to subjectivities in interpretation and procedures.

The above-cited papers are good practices to follow to reach the best outcomes with the available tools. In this paper, we concern ourselves with the specific steps of optimal matching and quantifying the quality of that match. Hence, we assume that all the basic principles have been followed (White and Simm, 2003; Anderson and Newrick, 2008) and that we have a synthetic trace and a seismic trace to find the optimum match between both signals.

The first issue comes from the fact that the quality of the tie between the synthetic and the seismic trace is based on the correlation coefficient, which is limited to linear features. The time-variant nature of the seismic wavelet adds nonlinearities to the trace that cannot be easily followed by a linear metric, such as the correlation coefficient further represented in equation 1. We compare two nonlinear approaches to match these time series. Our procedures substitute the manual stretching and squeezing step by an optimization algorithm, which is still supervised by the interpreter. This improves the repeatability of the tying, while the critical and often abused stretch and squeeze (Newrick, 2012) is still under control. The first alternative to perform the automated tying is based on dynamic time warping (DTW) (Herrera and Van der Baan, 2012a, 2014), and the second approach faces the nonlinearity correction using the local similarity attribute (LSIM) (Fomel, 2007a). Both techniques share the quality-control step by monitoring the relative velocity change produced by the tying.

Nonlinear correlation of seismic time series has been previously explored in the context of well-to-well correlation (Lineman et al., 1987; Zoraster et al., 2004), in which well logs from different wells are correlated to infer common earth features. The crosscorrelation was unable to follow local distortions such as stretching or shrinking of stratigraphic intervals, typical of logs collected even from closely spaced wells. Essentially, these methods aim to correlate common features in various logs (Anderson and Gaby, 1983). An early approach to DTW is presented by Martinson et al. (1982) and Martinson and Hopper (1992). They develop a mapping function able to track stretching and squeezing in time series based on a correlation technique to
establish a point-for-point correlation between traces. Liner and Clapp (2004) propose a global optimization method to create pairwise alignments between seismic traces. More recently, Hale (2013) uses DTW in seismic image processing, which aligns seismic images with differences not limited to time shifts.

The first of our approaches follows the constrained optimization of Sakoe and Chiba (1978) with DTW, and it is not pairwise, but it allows for one-to-many connections in both directions between two traces (Herrera and Van der Baan, 2014). The second alternative, LSIM, considers as a local attribute controlled by the size of the neighborhood (Fomel, 2007a).

We start with a brief introduction to DTW and its implementation and follow with an introduction to the LSIM derived from global correlation. We then describe the quality-control tool based on relative velocity change. Finally, we illustrate the performance of both methods in a real well-seismic tie and compare the results with the manual method.

Theory

DTW

The correlation coefficient is often used to measure the quality of the well-seismic tie (Hampson-Russell, 1999). Having two (time-dependent) sequences \( a_i \) and \( b_i \), both of length \( n \), the correlation coefficient is

\[
e(r) = \frac{\sum_{t=1}^{n} a_t b_{t-r}}{\sqrt{\sum_{t=1}^{n} a_t^2 \sum_{t=1}^{n} b_t^2}},
\]

where the denominator supplies the energy normalization term and the numerator is the dot product of two time series. The optimal time lag \( r \) is generally set at the maximum correlation coefficient. Values of \( c \) span from one for perfect correlation, zero for uncorrelated signals, and \(-1\) for perfect correlation of signals with reverse polarity (Fomel, 2007a).

This measure works well if a constant time shift \( r \) characterizes both signals. When this time alignment is constant, the problem is reduced to the correction of the time lag by crosscorrelation. But this measure fails to find the best matching in nonstationary cases (Herrera and Van der Baan, 2014).

Most geophysical applications have nonstationary time alignment problems (Anderson and Gaby, 1983). An alternative to crosscorrelation is to find the Euclidean distance (\( L_2 \)-norm) between the two time series (Keogh and Kasetty, 2003):

\[
D_{\text{euclid}}(a, b) = \sqrt{\sum_{t=1}^{n} (a_t - b_t)^2},
\]

where \( D_{\text{euclid}}(a, b) \) is the one-to-one distance between the synthetic trace \( a \) and the seismic trace \( b \). The index \( i \) is the discrete time representation, i.e., samples of each signal.

The Euclidean distance (\( L_2 \)-norm) in equation 2 is the most widely used distance measure. It is trivial to implement but also is very sensitive to small distortions in the time axis (Berndt and Clifford, 1994; Keogh and Kasetty, 2003). Taking the advantages of the Euclidean distance and adapting it for nonstationary matching, Berndt and Clifford (1994) propose DTW.

The DTW distance can accommodate stretching and squeezing in the time series by linear programming. It uses the Euclidean distance as the initial metric but allows for the one-to-many alignment. The warping distance is represented as the minimum path in a grid representation of both sequences; see Herrera and Van der Baan (2014) for a graphical representation of the warping matrix with an example.

In the warping matrix, the squared distance in the elements \((i,j)\) is calculated by

\[
\delta(a_i, b_j) = (a_i - b_j)^2.
\]

The optimal path that minimizes the total warping cost (Berndt and Clifford, 1994) is

\[
DTW(a,b) = \min_{W} \sum_{k=1}^{p} \delta(w_k),
\]

where each \( w_k \) corresponds to a point \((i,j)\), and each grid point \((i,j)\) corresponds to an alignment or connection between \( a_i \) and \( b_j \).

The dynamic programming approach uses the following recurrence to find the warping path (Berndt and Clifford, 1994):

\[
\gamma(i,j) = \delta(a_i, b_j) + \min\{\gamma(i-1,j), \gamma(i-1,j-1), \gamma(i,j-1)\}.
\]

where \( \delta(a_i, b_f) \) is the distance defined in equation 3 and the cumulative distance \( \gamma(i,j) \) is the sum of the distance between the current elements and the minimum cumulative distance of the three neighboring cells.

This mapping process produces stretched versions of the original signals with length \( k \). Only if the two signals are fully aligned from the start do we have \( i = j = k \).

For the final warping process, we compute a new argument \( \hat{i} \), by extracting the indices of the intersection of the two sets \( \{i_k\} \) and \( \{j_k\} \):

\[
\hat{i} = i_k(j_p) \leq \text{position of } \{j_k\} \text{ in } \{i_k\} \cap \{j_k\}.
\]

With the new argument \( \hat{i} \), we can now get the warped signal \( a_{\hat{i}} \) by selecting the \( \hat{t}_{\hat{i}} \) samples from \( a_t \). This signal is the best approximation of \( b \) following the optimum warping path \( (a_{\hat{i}} \approx b) \).

In time-domain signals, this monotonic transformation of the initial time interval into itself with different axis distribution is called curve registration (Ramsay et al., 2004).
The argument \( \hat{t} \) accelerates or decelerates the synthetic signal along the time axis to match the seismic trace, such that well tops can be matched to corresponding reflections.

To prevent the occurrence of nonphysical alignments between both signals, we use a global distance constraint \( r \) to limit the maximum allowed amount of stretching and squeezing (Sakoe and Chiba, 1978). Elements of the warping matrix are restricted by the warping window \( |i_k - j_k| < r \) where \( r \) is the window width. The constrained DTW prevents unrealistic velocity changes due to stretching and squeezing of the synthetic trace. Proper specification of the allowed warping window guarantees meaningful results in the tying process. A large value of \( r \) allows more stretching, which is sometimes undesirable, but also provides better matching. Its choice allows for a trade-off between algorithmic performance and physical meaning. This initial value of the window width should be based on experience and by monitoring the quality of the resultant tie.

**LSIM**

The LSIM starts with the observation that the squared correlation coefficient given in equation 1 can be split as the product of two factors \( c^2 = pq \) (Fomel and Jin, 2009), with the first factor:

\[
p = \frac{\sum a_i b_i}{\sum a_i^2}
\]

being the solution of a least-squares minimization problem \( \min_p \sum_i (a_i - pb_i)^2 \). The first factor \( p \) normalizes the dot product \( \langle a_i, b_i \rangle \) with the energy of the seismic trace \( b \). The second factor \( q \) does the same but normalizes with the energy of the synthetic trace \( a \):

\[
q = \frac{\sum a_i b_i}{\sum a_i^2},
\]

and the least-squares minimization problem is the solution that minimizes the difference \( \min_q \sum_i (b_i - qa_i)^2 \) between the seismic trace and the synthetic trace.

This is a two-way minimization problem, and we can provide \( p \) and \( q \) with local properties, such that \( p_i \) and \( q_i \) become the solution of a regularized least-squares problem (Fomel and Jin, 2009):

\[
\min_{p_i} \left( \sum_i (a_i - p_i b_i)^2 + R[p_i] \right),
\]

and

\[
\min_{q_i} \left( \sum_i (b_i - q_i a_i)^2 + R[q_i] \right),
\]

where \( R \) is a regularization operator designed to enforce a desired behavior such as smoothness, estimated from shaping regularization (Fomel, 2007b).

The application of local similarity to the well-seismic tying problem consists of squeezing and stretching the synthetic trace with respect to the seismic trace while computing the LSIM. By picking the strongest similarity trend from the attribute panel, we identify the corresponding shift to correct the synthetic trace (Fomel and Jin, 2009). These time shifts form a vector that is similar to the warping path used in DTW.

The procedure is then to create a warping function \( w(t) \) from the local similarity scan by means of a shortest-path ray tracer (Fomel, 2007a). At this point, the warping function is just a new time scale \( \hat{t} \), like the one estimated with DTW; i.e., \( w(t) = \hat{t} \approx t \).

**Quality control: The relative velocity change**

Both methods create a warping function \( w(t) \) that maps the synthetic trace onto the seismic traces by the following transformation: \( a(w(t)) \approx b(t) \).

The base two-way traveltime is

\[
t = 2 \int_0^{H_0} \frac{dz}{v_0(z)}.
\]

where \( v_0(z) \) is the base velocity as a function of depth \( z \) and \( H_0 \) is the base depth, where base stands for reference values. The warping path is related to the new velocity \( v_1(z) \) by (Fomel and Jin, 2009)

\[
w(t) = 2 \int_0^{H_1} \frac{dz}{v_1(z)} = \int_0^{t + \Delta t} \frac{\hat{b}_0(\tau)}{\hat{b}_1(\tau)} d\tau,
\]

where \( H_1 \) is the depth in the well logs, \( \hat{b}_0(\cdot) \), and \( \hat{b}_1(\cdot) \) are the old and updated sonic velocities as a function of time, and \( \Delta t \) is the time shift caused by the stretching or squeezing \( \Delta t = 2H_1 \frac{dz}{v_0(z)} \).

The relative velocity change can be estimated by simple differentiation of equation 12:

\[
\frac{dw}{dt} \approx \frac{\hat{b}_0(t)}{\hat{b}_1(t)}.
\]

The warping function produced by the local similarity method has been smoothed by the shaping filters (Fomel, 2007b). In DTW, an additional interpolation step is used to smooth out the discrete warping path before computing the derivative.

In a perfect correlation, the estimated velocity ratio should be close to one; i.e., the relative velocity changes due to the nonlinear transformation produce good correlation and no velocity variations. These variations are quantified by the relative stretch measure \( s(t) = w(t)/t \). Deviations of \( s(t) \) from one indicate possible misalignment and therefore velocity changes.

**Experiments**

We apply both approaches, DTW and LSIM, to obtain well-seismic ties between observed seismic data and synthetic traces created from well logs. The data set used in our experiment consists of a 3D poststack...
time-migrated seismic profile, with 13 wells and their corresponding logs. This data set is provided as benchmark seismic data within a commercial package (Hampson-Russell, 1999). Figure 1 shows a seismic section with one well at CDP 39. The well-seismic tie for this well is shown in the inset figure. We scanned the seismic section to find the best matching location, following White and Simm (2003), which is at CDP 41. The generated synthetic trace (red) and the corresponding seismic trace (blue) have been exported for postprocessing. The sampling rate is 500 Hz (2 ms), and both signals have the same length; i.e., the seismic trace has been shortened to the well log length. Also, both signals have been standardized in amplitude. The initial synthetic is created as the convolution of the computed reflectivity from well logs with a zero phase statistical wavelet. This zero phase wavelet is calculated from the seismic amplitude spectrum (Hampson-Russell, 1999).

Figure 2a shows how the synthetic (upper trace) and seismic traces (lower trace) match after constrained DTW with a warping window \( r = 10 \). The original (Figure 2a) and stretched versions (Figure 2b) are shown. The DTW technique allows for one-to-many sample connections in both directions. Note that the original signals have 423 samples and their stretched versions have 527 samples. This new length comes from mapping the initial time (length \( n \)) onto the warping path (length \( k \)). The gray lines connecting individual time samples are useful for quality control because they indicate time shifts between traces (forward or backward slanting lines) and changes in the relative velocity profiles (diverging or converging neighboring lines).

**Figure 1.** Seismic section with study well annotated at CDP 39. The inset shows the synthetic seismogram with the initial manual correlation of 0.77 in the time window 800–1144 ms.

**Figure 2.** Illustration of the warping process using DTW. In panel (a), the seismic trace (upper signal) is connected to the synthetic trace (bottom signal) through gray lines representing connected time samples. Note the one-to-many connections in both directions; that is, the connecting lines have either positive or negative slopes. The stretched versions of both signals shown in panel (b) are highly correlated, but the number of samples is increased compared to the original signals.
Visual inspection reveals that automatic matching leads to physically acceptable results for points 260–420 in the original series (Figure 2 top), but likely excessive stretching and squeezing have occurred in the first 200 points and around point 250.

To avoid unrealistic connections, the original observed data and the synthetic are subjected to the constrained DTW approach. We use a global constraint based on the Sakoe-Chiba band (Sakoe and Chiba, 1978), which constrains the alignment process to a limited window. This reduces the freedom of the warping path to align events within a limited distance. The estimated warping path is shown in Figure 3, where we used $r = 10$ samples to limit the maximum amount of permitted point-to-point shifting. With a sampling rate of 2 ms, two peaks can then still be aligned even if they are 20 ms apart. The relative velocity change is then estimated by computing the derivative of the smoothed warping path in Figure 3.

The LSIM performs an automatic squeezing and stretching of the synthetic trace with respect to the seismic trace while computing the local correlation. This process leads to a local-similarity scan shown in Figure 4. The red color indicates high similarity, and from these pick values, we estimate the relative stretch measure $s(t)$, represented as a black curve in Figure 4. This curve is already the derivative of the warping path; thus, from equation 13 we can compute the velocity ratio.

Figure 5a shows the relative stretch $(d w_e / dt)$ for both methods. The LSIM method (in black bold) shows few variations, while the DTW result (dashed line) shows reliable stability in the bottom half of the display, i.e., little change between the synthetic and the seismic trace. These variations are reflected in the velocity changes shown Figure 5b. The original sonic log (thick gray) is almost overlapped by the LSIM result (black line), with little difference only at the initial samples. DTW (dashed line), as expected, produces more changes in the velocity curve in the areas where more stretching and squeezing was performed. It is known that DTW will find the best match between two events and improve the final correlation, but at the cost of more velocity variations (Herrera and Van der Baan, 2014). Careful control of the warping window should be taken to avoid unrealistic changes, such as the fluctuations in the shallower part, which could be amplified for wider warping windows.

In the final comparison, we perform a manual tie, following recommended practices in well-seismic tying (White and Simm, 2003; Anderson and Newrick, 2008). We first select a high-quality region of interest for the synthetic and seismic trace where the correlation window is placed. This region of interest comprises the main stratigraphic features and is situated where both signals are similar. In this case, the correlation window is between 800 and 1144 ms; only a constant time shift is needed in this region to reach the best match. Figure 6a shows that the correlation of the manual well-seismic tie is 0.77 inside this window. The shallower portion of the manual tie shows little similarity and would
require significant stretching and squeezing to obtain an acceptable fit; the global correlation including this area is 0.24. Because excessive stretching and squeezing are never recommended, we exclude this portion from the well tie, and we consider any automated matching in this portion as suspect for this reason as well.

DTW corrected the simple time shifts observed in the analysis window for the manual tie. It produces the best possible match in the shallower part with mostly reasonable velocity changes (less than 10%) except possibly between 550 and 850 m. Inspection of the relative stretch variations as well as the updated local velocities will reveal if and where the automated tying procedure has produced unrealistic stretching and squeezing. Such areas can then be discarded, or the warping window can be limited further. For the LSIM method, the local velocity variations are more stable. The correlation shows an actual improvement, considering that the correlation in the entire trace can improve from 0.24 to 0.68 with little velocity change.

Discussion

Well-seismic ties are challenging due to the high number of subjective decisions and pattern recognition tasks involved. Proper selection of the analysis window, identification of major corresponding reflections in synthetic and seismic traces and connecting them by the appropriate amount of stretching and squeezing, and accurate wavelet estimation are among these challenging tasks (Herrera and Van der Baan, 2014). We strongly advise interpreters always to verify their results using the quality-control measures described in this article. In particular, unrealistic local velocity changes or relative slowness perturbations are highly suspect, even if the final traces look perfectly matched.

In DTW, the warping window parameter should be carefully adjusted to satisfy the trade-off between good matching and reasonable alignment of events. This is similar to controlling the amount of stretching and squeezing in the manual method. This critical parameter keeps the velocity curve limited to realistic values, which is similar to controlling the amount of stretching and squeezing in the manual method. The controlling parameter in LSIM is the amount of regularization of the smoothing shaping filter along with the smoothing radius. In practice, start the method with strong smoothing and decrease it when the results stop changing and before they become unstable (Fomel and Jin, 2009).

The LSIM method produced a better correlation with few changes in the velocity pattern. The constrained DTW method performed in good agreement with the manual method inside the correlation window, which validates this approach. The matching outside this window represents the best possible tie, but it is the velocity variation that helps to identify when these changes are acceptable or not.

![Figure 5. Quality control. Relative stretch curves for LSIM (bold line) and DTW with r = 10 (dashed line) are shown in (a). The local velocity change for LSIM (black line) and DTW (dashed line) together with the original sonic log (light gray) are shown in (b). The LSIM velocity shows few variations, whereas the DTW velocity has local variations due to the warping process.](image1)

![Figure 6. Comparison of the automated approaches and manual well-seismic ties. The manual tie with correlation of 0.77 in the window 800–1144 ms is shown in (a), where the bold vertical lines indicate the correlation window. The DTW output with a warping window r = 10 is shown in (b); with this approach and using the full trace length, the correlation is 0.85. The LSIM output using the entire trace length as shown in (c) achieves a correlation of 0.68. In all displays, the upper signal is the seismic trace, the bottom signal is the synthetic trace, and black arrows indicate correlative reflections.](image2)
The methods vary in the matching criteria and extraction of the warping paths. DTW has one-to-many (point by point) sample matching, which causes issues. DTW finds the locally optimal path from point to point, but the LSIM method is allowed to jump across sequences (it is locally nonoptimal). This causes more local stretching/squeezing in DTW.

Our general recommendations extend previous works to the automatic approach (White and Simm, 2003; Anderson and Newrick, 2008):

1) First, an appropriate wavelet is to be estimated.
2) Then, choose the correct wavelet polarity.
3) Next, apply a global bulk shift, for instance, via a simple correlation; this precludes having large warping windows in DTW and produces faster convergence in LSIM.
4) For DTW, slowly increase the length of the warping window until the quality-control procedure indicates unrealistic stretching and squeezing results.
5) In LSIM, adjust the regularization parameter to generate a smooth relative stretch curve controlling the deviation from unity.

Wavelet estimation is a crucial step because it can greatly affect the ease and quality of manual and semi-automated well tying. The wavelet power spectrum is generally best estimated using spectral averaging (Herrera and Van der Baan, 2012b); however, this leads to a zero-phase wavelet, which is likely nonoptimal. For the appropriate wavelet phase, we recommend the use of kurtosis-based methods for constant-phase wavelets (Van der Baan, 2008) or short-time homomorphic wavelet estimation (Herrera and Van der Baan, 2012b) for frequency-dependent wavelet phases. These methods use statistical means to obtain the wavelet estimates directly from the data and have been shown to be reliable even for relatively low signal-to-noise ratios (Edgar and Van der Baan, 2011; Herrera and Van der Baan, 2012b).

Regarding the selection of wavelet polarity, our recommendation is to compute a crosscorrelation between the synthetic and observed trace first to check if there is a significant difference in the absolute value between the most positive and most negative correlation coefficients. If not, we suggest running the algorithm with the normal and reverse polarity and compare both outputs taking into account the effects on the velocity changes. The best tie connects reflectors with the same polarity and produces meaningful velocity changes (Herrera and Van der Baan, 2014).

Both automatic approaches compared here for well-seismic tying are good candidates for other applications in seismic data. These include log-to-log correlations and alignment of baseline and monitor surveys in 4D seismic data (Fomel and Jin, 2009; Hale, 2013). PP- and PS-wavefield registration for 3C data (Gaiser, 1996) is another field to explore with DTW because LSIM has already shown good results (Fomel, 2007a).

Conclusions

The two methods compared in the paper aim to guide the interpreter by supporting standard methodologies of well-seismic tying, but we strongly advocate interpreters to be wary of fully automated and unsupervised applications of these methods. Velocity changes and visual quality control of the end result remain highly advisable. Although fitting all the reflections is a mathematical goal because real seismic and well information can contain spurious data, it is still left to the interpreter’s judgment as to which reflections can be reliably correlated to well data. For example, low-amplitude, discontinuous reflections on the seismic may contain significant noise that masks weak events, and consequently whether these reflections have a good or poor well tie is moot. Similarly, logging tools may make erroneous measurements; consequently, a calculated synthetic reflection may have no counterpart in the real seismic section.

The main advantage of using automatic approaches is their objective repeatability and reproducibility of the tying process. Both automated methods create superior matches over the manual method and with just a few tuning parameters. The integration of the automatic well-seismic tie with the traditional method reduces interpreter bias and other subjective factors. The robustness of the tying process is improved in this guided framework. The interpreter should expect to see these automatic approaches integrated into the processing software in the near future.

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References


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