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HIGH RESOLUTION INTERVAL VELOCITIES

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The principal limit of the resolution of physical methods in the presence of random components (i.e. noise) is well known in statistical theory. However, there has been an increasing demand for a higher resolution of the physical parameters for exploration purposes. Therefore, an important research aim is to achieve a reasonable compromise between the two controversial requirements.

As demonstrated in this paper, the estimated interval velocities become very unrealiable and highly correlated if resolution is increased. To find a compromise, the reliability of interval velocity estimates must be increased to an acceptable level while ensuring that the estimates stay close to physical reality. This process should result, more or less, in smoothing the original rough estimates.

This paper consists of three parts. In the first part, the statistical description of interval velocity estimation errors is outlined. In the second part, the possibility of decreasing estimation errors is discussed by taking into consideration the highly correlated nature of interval velocity estimates via the computation of statistical residuals. In the third part a few synthetic examples of the application of the method is shown.

Keywords: interval velocity, Dix-formula, statistical estimation

1. Statistical behaviour of the interval velocity estimates

First let us look at the statistical description of the estimated interval velocity errors, the mean, the standard deviation, and covariance between various layers. Suppose that seismic measurements are made above a half space containing horizontal homogeneous layers. The spread parameters can be chosen arbitrarily. As a result of standard velocity analyses, we may have a great number of arrival time and stacking velocity pairs (t_0, v_s) corresponding to primary reflections spaced arbitrarily close to one another. All these hyperbolic parameters are supposed to contain statistical errors.The independence of the errors corresponding to each horizon is also assumed to be present. This is a realistic approach after a successful automated static correction.

The standard deviation and covariance of reflection hyperbola parameters, t_0 and v_s, can practically be deduced on the basis of the standard deviation, σ_t, of the random time shifts after the automatic static correction (see *APPENDIX A*). Thus, in the case of a known standard deviation, σ_t, the mean, standard deviation and covariance of hyperbola parameters, t_0 and v_s, can directly be estimated. These parameters can be regarded as secondary measurement data of known statistical behaviour.

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Now, the estimation of interval velocities by the well known Dix formula can be discussed. The formula is expressed by the error terms of each quantity:

$$(V_i + \Delta V_i) = \sqrt{\frac{(v_{s_i} + \Delta v_{s_i})^2 (t_{0_i} + \Delta t_{0_i}) - (v_{s_{i-1}} + \Delta v_{s_{i-1}})^2 (t_{0_{i-1}} + \Delta t_{0_{i-1}})}{(t_{0_i} + \Delta t_{0_i}) - (t_{0_{i-1}} + \Delta t_{0_{i-1}})}} \quad (1)$$

where: V_i is the interval velocity of the i-th layer
ΔV_i is the error term of V_i
v_{s_n} and t_{0_n} is the stacking velocity and the zero offset arrival time of the n-th reflection, respectively.

The mean, standard deviation and covariance of interval velocity error term, ΔV_i, can be expressed after expanding the expression into Taylor series, retaining the linear terms and computing the expected values (see *APPENDIX B*).

In essence, it may be said that the interval velocity estimates are unbiased but, may have very large standard deviations in the case of small layer thicknesses or high noise level. The considerably large negative correlation between interval velocity estimates of the adjacent layers is of further complication.

For example a stacking velocity error of a certain reflection affects two (the upper and lower) interval velocity estimates in the opposite sense.

For a quick impression, an example of the standardized form of covariance matrix **C** of ΔV_i is:

$$\begin{bmatrix} 1.00 & -0.47 & 0.00 & . & . & 0.00 \\ -0.47 & 1.00 & -0.61 & & & 0.00 \\ 0.00 & -0.61 & 1.00 & . & & 0.00 \\ . & . & . & . & . & \\ . & & & . & . & . \\ 0.00 & 0.00 & 0.00 & & . & 1.00 \end{bmatrix}$$

It shows that, the covariance can be characterized by a tridiagonal matrix. Because of the large negative correlation, the interval velocity estimates show non-minimum standard deviations. Evaluating these statistical parameters, the interval velocity estimates can also be regarded as secondary (or tertiary) measured data at a later stage.

2. Correction of correlation terms

A tridiagonal matrix, whose off diagonals contain negative elements, describes an alternating, oscillatory stochastic process. It is also known that actual interval velocities vary systematically as sediment compaction varies therefore, interval velocities of different layers are not quite independent.

The residual computation method, well known from statistics, offers means to remove the correlation terms. The principle of the method is that terms predicted from all other estimation errors ΔV_k ($k \neq i$) are subtracted from each estimation error ΔV_i. The prediction can be carried out on the basis of a linear regression model, similar to the predictive deconvolution.

Let us introduce the variable ξ_i which is the difference of the interval velocity estimate, V_i, computed by Dix's formula, and an ideal estimate, v_i, to be determined later:

$$\xi_i = V_i - v_i \quad (= \Delta V_i). \tag{2}$$

(The statistical behaviour of ξ_i is the same as that of ΔV_i described in *APPENDIX B*.)

The residual η_i can be expressed by the inverse matrix **D** of the covariance matrix **C** (see *APPENDIX C*):

$$\eta_i = \frac{1}{D_{ii}} \sum_{k=1}^{M} \xi_k D_{ki} \tag{3}$$

where, D_{ki} and D_{ii} are elements of matrix **D** $(= \mathbf{C}^{-1})$ and M is the number of sedimentary layers. The values η_i are free from the correlation effect. The covariance of the residual has the following form (see *APPENDIX C*):

$$E\{\eta_i \eta_j\} = D_{ij} \cdot \det(\mathbf{D})/(D_{ii} D_{jj}) \tag{4}$$

This expression depends on the covariance matrix, **C** (and v_i) only. Equation (4) serves as the theoretical lower limit of the correlation between residuals, η_i and η_j. To achieve an estimate of minimum standard deviation, the sum square of the actual residuals $N = \sum_{i=1}^{M} \hat{\eta}_i$ must be minimized or decreased to the theoretical minimum formulated by eq. (4), where ˆ denotes the actual value during the iteration. Substituting ξ_i into the expression of η_i and norm N, a simple equation can be deduced, by equating the partial v_i derivates to zero:

$$\frac{\partial N}{\partial v_i} = \sum_j B_{ij} v_j - \sum_j B_{ij} V_j = 0$$

where,

$$B_{ij} = \sum_k D_{ki} D_{kj} / D_{kk}^2. \tag{5}$$

Trivial solution: $v_i = V_i$

Practical solution: $\sum_i^M (\hat{\eta}_i^2 / E\{\eta_i \eta_i\}) = M$

In spite of the meaningless trivial solution, the gradient vector can easily be used to decrease norm N step by step, starting from an arbitrary smooth velocity function $v_i^{(0)}$.

At the n-th step, N can be computed from $\hat{\xi}_k$ and **D**. The direction of the steepest descent of N can also be found varying the components $v_i^{(n)}$. Thus, $v_i^{(n+1)}$ $(i = 1, 2, \ldots, M)$ can simply be reached by a displacement of a certain length, within the direction mentioned above.

To start the iteration, a reasonable choice for a smooth velocity function is a simple stepwise function, which exactly obeys the local compaction trend and best fits to the interval velocities computed by the Dix formula.

To find a reasonable solution, a technique can be applied that is similar to the white noise addition method. All elements of covariance matrix **C** outside the main diagonal are multiplied by a constant α, with values between zero and one.

The case $\alpha = 0$ is equivalent to the application of the Dix formula without modification. If α is equal to 1, the result generally is a strongly smoothed stepwise function. An intermediate solution can be achieved by using α between 0 and 1.

3. Examples

A model example containing a velocity anomaly is shown in the next figures.*

Standard deviation, σ_t, of the random time shifts with which the original arrival time data were corrupted is 2 ms. (The source offset is 120 m, the geophone interval is 120 m and the coverage is 12 fold.) The solid line always shows the assumed noise-free model. The white lines (in the center of the grey zones) show the estimated velocities computed from noisy synthetic data. The grey areas show the standard deviations of the estimates. *Fig. 1* is the case of Dix's formula ($\alpha = 0$). The interpretation and decision on the existence of one (or more) low velocity anomaly are no easy tasks due to the large standard deviations.

Let us regard now the practical use of the resultant interval velocity estimate against the parameter α in the case of the given model *(Fig. 2)*. In the case of low noise level** the improvement is not significant, but in the case of high noise or small layer-thickness the improvement is considerably better expressed by the r.m.s. difference between the original noise-free interval velocities and estimates computed from synthetized noisy (t_0, v_s) pairs. The ideal solutions are represented by the absolute minima of the curves. The range of the curves (the relative improvement) is certainly greater in the latter case. In most cases, the value $\alpha = 0.9$ results in nearly optimum fit.

In the case of $\alpha = 1$ the result is always an extremely smooth (biased) stepwise velocity function. These solutions are very similar to one another, even when the noise levels are quite different. This is the reason why the curves converge in the case of $\alpha = 1$.

* The situation represented by this model is similar to that of the interval velocity problem of marine gas hydrates where the aim is to estimate the interval velocity of the free gas bearing layer under the gas hydrate layer.

** Decreasing the noise level ($\sigma_t = 0.5$ ms instead of $\sigma_t = 2$ ms) is equivalent to increasing the spread length or the coverage, according to *APPENDIX A*.

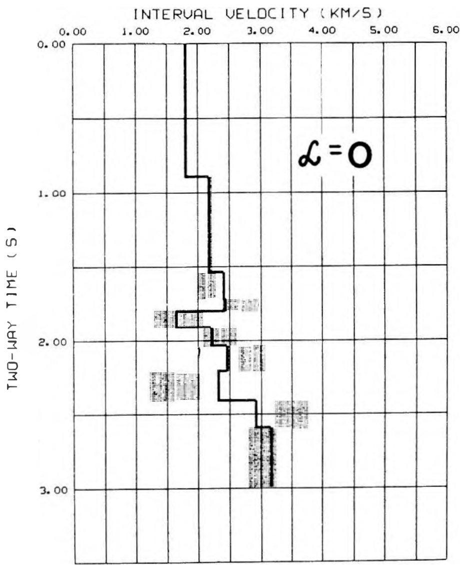

Fig. 1. Velocity function, computed by Dix's formula, for a model containing a velocity anomaly

1. ábra. Dix-formulával számított sebességeloszlás sebesség-anomáliát tartalmazó modellre

Рис. 1. Вычисленное по формуле Дикса распределение скоростей для модели, включающей в себя аномалию скорости

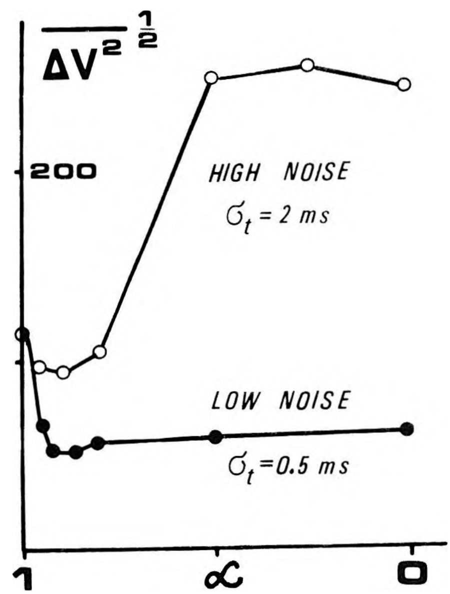

Fig. 2. Estimated interval velocity versus α

2. ábra. Becsült intervallumsebesség-értékek az α paraméter függvényében

Рис. 2. Оцениваемые значения интервальных скоростей в зависимости от параметра α

Figures 3. and *4.* show the results of the algorithm in the case of $\alpha = 0.9$ and $\alpha = 1.0$. The bulk of the large alternating errors was removed on the former and the anomaly is better recognizable. The latter result is rather smooth. The place of the anomaly is visible but its amplitude is rather small. Therefore, choosing $\alpha = 0.9$ is a compromise between an unbiased but inefficient estimate and an efficient but biased estimate. The estimate is biased because short interval velocity anomalies appear as gradual changes.

For example, if the noise level is high, the outstanding feature of short interval velocity anomalies may be completely smoothed out. This draws the attention of the interpreter, that the given quality of the available seismic data is not sufficient for certain conclusions.

It is worth noting that the whole process is in close analogy with the standard predictive deconvolution. In the predictive deconvolution process there is an oscillatory shotpoint wavelet to be removed from the trace. The autocorrelation function (acf) of the wavelet can be estimated from the trace itself. The inverse operator is computed from this acf.

In the interval velocity estimation, there is also an oscillatory term to be removed. The acf of this term and the prediction operator can be computed theoretically. The smooth function, v_i, to be determined should be that, from which the result of Dix's formula can be predicted with a given (minimum) variance.

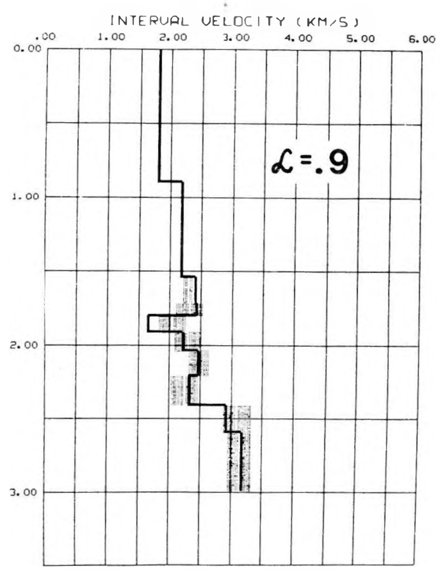

Fig. 3. Velocity function using the algorithm proposed ($\alpha = 0.9$)

3. ábra. Sebességeloszlás a javasolt algoritmus alkalmazásával, $\alpha = 0,9$ esetén

Рис. 3. Распределение скоростей при применении предлагаемого алгоритма, в случае $\alpha = 0,9$

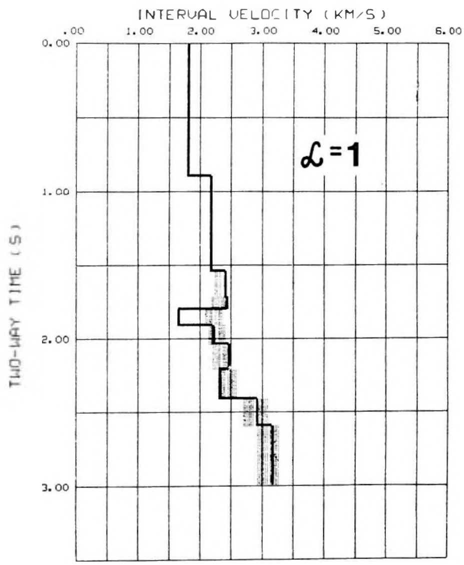

Fig. 4. Velocity function using the algorithm proposed ($\alpha = 1.0$)

4. ábra. Sebességeloszlás a javasolt algoritmus alkalmazásával, $\alpha = 1{,}0$ esetén

Рис. 4. Распределение скоростей при применении предлагаемого алгоритма, в случае $\alpha = 1{,}0$

4. Conclusions

— In the estimation of interval velocities no local maxima of the velocity spectrum have to be rejected in order to get small enough deviations. Such type of information loss can be avoided. Due to this feature, the method can comfortably be used for interpretation of automatically picked peaks on velocity spectra.

— The method retains the simple physical model during the interpretation. Some smoothing methods result in smooth curves or splines instead of such simple stepwise interval velocity functions.

— The method automatically assures that resolution increases, if the measured data are more reliable.

— The method is a useful tool to find efficient estimates in the case of highly correlated data.

— The display of standard deviations of the estimated physical parameters (interval velocities and depths) are especially useful for quick visual reckoning of the reliability of the interpretation.

APPENDIX A

Statistical description of the estimated reflection hyperbola parameters t_0 and v_s

A simple model of a reflection hyperbola located on a set of traces has the following form:

$$f_{ki}(A, v_s, t_0) = A\varphi\left(t_i - \sqrt{t_0^2 - \frac{x_k^2}{v_s^2}}\right) \tag{A.1}$$

where f_{ki} is a discrete element of a trace of a CMP (Common Mid Point) set, k is the "offset" index (k runs from 1 to the actual coverage number), i is the "time" index
A is the amplitude factor of the wavelet
$\varphi(\tau)$ is the known wave shape
t_i is the time variable
x_k is the offset variable
t_0 is the zero offset arrival time
v_s is the stacking velocity.

In the case of a regular spread, x_k can be expressed in the following simple form:

$$x_k = \Phi + (k-1)G \tag{A.2}$$

where, Φ is the actual spread offset and G is the geophone spacing within the given type of CMP set. So, the statistical model of the correspondent traces y_{ki} can be written:

$$y_{ki} = f_{ki} + n_{ki} \tag{A.3}$$

where, n_{ki} is the correlated random noise component of zero mean and standard deviation, σ.

The statistical interpretation theory gives means to the optimal estimation of parameters, t_0 and v_s, in the presence of noise. As a by-product, the standard deviations and covariances also can be estimated [Holtzman 1971, Salát et al. 1982].

The effectiveness of the (pure quantitative) interpretation can be characterized by the information matrix **I**, which is the inverse of the covariance matrix of the estimated parameters in the above case.

The general element of the information matrix is:

$$I_{lm} = \sum_k \sum_i \sum_{i'} R_{ii'}^{-1} \frac{\partial f_{ki}(\bar{p})}{\partial p_l} \frac{\partial f_{ki'}(\bar{p})}{\partial p_m} \tag{A.4}$$

where, $R_{ii'}$ is the covariance matrix of the noise component, $\bar{p} = \{p_1, p_2, \ldots, p_n\}$ is the vector of unknown parameters.

Substituting (A.1) into (A.4), and applying indirect partial derivatives

$$\frac{\partial}{\partial v} = \frac{\partial}{\partial t_k}\frac{\partial t_k}{\partial v}, \quad \text{where} \quad t_k = \sqrt{t_0^2 + \frac{x_k^2}{v_s^2}} \tag{A.5}$$

and, using the spectral representation of quadratic forms, we get:

$$\begin{aligned} I_{vv} &= \frac{A^2}{\sigma^2} W \frac{1}{v_s^6} \sum_k \frac{x_k^4}{t_k^2} \\ I_{tt} &= \frac{A^2}{\sigma^2} W t_0^2 \sum_k \frac{1}{t_k^2} \\ I_{vt} &= -\frac{A^2}{\sigma^2} W \frac{t_0}{v_s^3} \sum_k \frac{x_k^2}{t_k^2} \end{aligned} \tag{A.6}$$

$$\text{where, } W = \frac{1}{2\pi} \int_{-\omega_0}^{\omega_0} \frac{\omega^2 |\Phi(\omega)|^2}{r(\omega)} d\omega \tag{A.7}$$

$\omega_0 = \pi/\Delta t$, Δt is the time spacing, $\Phi(\omega)$ and $r(\omega)$ are the Fourier transforms of the normalized autocorrelation functions of the wavelet φ, and the noise, respectively.

Inverting the 2×2 information matrix we obtain the covariance matrix of the estimated parameters:

$$\begin{aligned} D^2(v_s) &= \frac{\sigma^2}{A^2 W} v_s^6 \sum_k \frac{1}{t_k^2} / D \\ D^2(t_0) &= \frac{\sigma^2}{A^2 W} \sum_k \frac{x_k^4}{t_k^2} / (t_0^2 D) \\ E(v_s t_0) &= \frac{\sigma^2}{A^2 W} v_s^3 \sum_k \frac{x_k^2}{t_k^2} / (t_0 D) \end{aligned} \tag{A.8}$$

$$\text{where, } D = \sum_k \frac{x_k^4}{t_k^2} \cdot \sum_k \frac{1}{t_k^2} - \left(\sum_k \frac{x_k^2}{t_k^2} \right)^2$$

Fortunately, very similar expressions can be derived from the case when a hyperbola is fitted by the least squares method to the arrival times corrupted by random time shifts of standard deviation σ_t [Al-Chalabi 1974, Késmárky 1976, Marschall 1978].

The only difference is that the factors $\sigma^2/(A^2 W)$ and t_k in eqs. (A.8) are replaced by σ_t^2 and t_0, respectively. Thus

$$\frac{\sigma^2}{A^2 W} \approx \sigma_t^2. \tag{A.9}$$

σ_t can easily be estimated at the final step of the automated static correction. This latter approach is much more simple for practical use.

APPENDIX B

Statistical description of the estimated interval velocities, V_i

Expressing the error term, ΔV_i from eq. (1), expanding it into Taylor series according to Δv_{s_i}, $\Delta v_{s_{i-1}}$, Δt_{0_i} and $\Delta t_{0_{i-1}}$, neglecting higher than first-order terms, we obtain (omitting the subscripts s and 0):

$$\Delta V_i = \frac{1}{V_i(t_i - t_{i-1})}\left\{v_i t_i \Delta v_i - v_{i-1} t_{i-1} \Delta v_{i-1} + \frac{v_i^2 - v_{i-1}^2}{2t_i}[t_i \Delta t_{i-1} - t_{i-1}\Delta t_i]\right\}$$

The expected values of significance are as follows (assuming "non static type" random time shifts):

$$\begin{aligned}
E(\Delta V_i \Delta V_j) = \frac{1}{V_i V_j T_i T_j}\Bigg[& + v_i v_j t_i t_j E(\Delta v_i \Delta v_j) - v_i v_{j-1} t_i t_{j-1} E(\Delta v_i \Delta v_{j-1}) + \\
& + \frac{v_j^2 - v_{j-1}^2}{2T_j}[v_i t_i t_j E(\Delta v_i \Delta t_{j-1}) - v_i t_i t_{j-1} E(\Delta v_i \Delta t_j)] - \\
& - v_{i-1} v_j t_{i-1} t_j E(\Delta v_{i-1} \Delta v_j) + v_{i-1} v_{j-1} t_{i-1} t_{j-1} E(\Delta v_{i-1} \Delta v_{j-1}) - \\
& - \frac{v_j^2 - v_{j-1}^2}{2T_j}[v_{i-1} t_{i-1} t_j E(\Delta v_{i-1} \Delta t_{j-1}) - v_{i-1} t_{i-1} t_{j-1} E(\Delta v_{i-1} \Delta t_j)] + \\
& + \frac{v_i^2 - v_{i-1}^2}{2T_i}\Bigg\{v_j t_j t_i E(\Delta v_j \Delta t_{i-1}) - v_{j-1} t_{j-1} t_i E(\Delta v_{j-1} \Delta t_{i-1}) + \\
& + \frac{v_j^2 - v_{j-1}^2}{2T_j}[t_i t_j E(\Delta t_{i-1} \Delta t_{j-1}) - t_i t_{j-1} E(\Delta t_{i-1} \Delta t_j)]\Bigg\} - \\
& - \frac{v_i^2 - v_{i-1}^2}{2T_i}\Bigg\{[v_j t_j t_{i-1} E(\Delta v_j \Delta t_i) - v_{j-1} t_{j-1} t_{i-1} E(\Delta v_{j-1} \Delta t_i) + \\
& + \frac{v_j^2 - v_{j-1}^2}{2T_j}[t_{i-1} t_j E(\Delta t_i \Delta t_{j-1}) - t_{i-1} t_{j-1} E(\Delta t_i \Delta t_j)]\Bigg\}\Bigg]
\end{aligned}$$

where $T_i = t_i - t_{i-1}$

APPENDIX C

Linear prediction of correlated random variables

Let us determine the coefficients a_{1i} which satisfy the following condition [Vincze 1968]:

$$E\{(\xi_1 - a_{12}\xi_2 - \cdots - a_{1M}\xi_M)^2\} = \min. \tag{C.1}$$

Equating the partial a_{1i} derivates with zero, we get:

$$C_{i2}a_{12}+C_{i3}a_{13}+\cdots+C_{iM}a_{1M} = C_{i1}; \quad (i = 1, 2, \ldots, M) \tag{C.2}$$

where, $C_{ij} = E\{\xi_i\xi_j\}$.

Rearranging of eq. (C.2) yields (completing the system (C.2) with its first row):

$$\boldsymbol{C}\begin{bmatrix} 1 \\ -a_{12} \\ -a_{13} \\ \vdots \\ -a_{1M} \end{bmatrix} = \begin{bmatrix} S \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \tag{C.3}$$

where S is a constant. Eq. (C.3) is the same as the system used at the design of prediction error (optimum spike deconvolution) operators, although, matrix **C** does not exhibit the so-called Toeplitz symmetry.

The solution can simply be written as:

$$a_{1j} = -\frac{D_{1j}}{D_{11}} \tag{C.4}$$

The general solution has the form:

$$a_{ij} = -\frac{D_{ij}}{D_{ii}} \tag{C.5}$$

where D_{ij} is the ij-th element of matrix $\mathbf{D}$ $(=\mathbf{C}^{-1})$.

Now, the residual η_i can simply be expressed:

$$\eta_i = \xi_i - \sum_{j\neq i}^{M} a_{ij}\xi_j = \sum_{j=1}^{M} \frac{D_{ij}}{D_{ii}}\xi_j \tag{C.6}$$

The covariance of η_i can be written in the same way:

$$\begin{aligned} E\{\eta_i\eta_j\} &= E\left(\frac{1}{D_{ii}}\sum_k D_{ik}\xi_k \cdot \frac{1}{D_{jj}}\sum_l D_{jl}\xi_l\right) = \\ &= \frac{1}{D_{ii}D_{jj}}\sum_k\sum_l D_{ik}D_{jl}C_{kl} = \\ &= \frac{1}{D_{ii}D_{jj}} D_{ij}\cdot \det(\boldsymbol{D}) \end{aligned} \tag{C.7}$$

because of $\sum_l D_{jl}C_{kl} = \delta_{jk}\det(\boldsymbol{D})$

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NAGYFELBONTÁSÚ SEBESSÉGFÜGGVÉNY-BECSLÉS

KÉSMÁRKY István

A szeizmikus sztratigráfiai kutatás fontos célja, hogy az intervallumsebességeket minél pontosabban, minél nagyobb felbontással lehessen becsülni. Az intervallumsebességeket a Dix-formulával becsüljük. A formula alkalmazásánál problémát okoz, hogy minél vékonyabbak a figyelembe vett rétegek, a becsült paraméterek szórása és korreláltsága annál nagyobb. Egy lehetséges megoldás, hogy csupán egy bizonyos korlátnál nagyobb rétegvastagságokat veszünk figyelembe.

A szomszédos rétegek becsült intervallumsebességei közti nagy negatív korreláció figyelembevételével az ilyen információveszteségeket csökkenteni lehet. Az eljárás kisebb szórású és kevésbé oszcilláló sebességfüggvény-becsléseket eredményez, egyezésben a megfigyelhető kompakciós trendekkel. A kapott függvények a paraméterek szórásaival együtt ábrázolhatók, tömör formában. Az eljárás jól szemlélteti az anomális sebességű vékony rétegek detektálásának elvi korlátait.

ОЦЕНКА УРАВНЕНИЯ СКОРОСТИ С ВЫСОКОЙ РАЗРЕШАЮЩЕЙ СПОСОБНОСТЬЮ

Иштван КЕШМАРКИ

Для сейсмических стратиграфических исследований очень важно как можно с большой точностью и с высокой разрешающей способностью оценить скорость исследуемого интервала. Интервальные скорости оцениваются с помощью формулы Дикса. При применении этой формулы, возникает проблема, суть которой заключается в том, что чем тоньше исследуемые слои, тем с меньшей точностью можно определить оцениваемые параметры, тем больше их корреляция. Для разрешения этой проблемы, можно выбирать для изучения такие слои, мощность которых больше некоторой предельной мощности.

Используя значительную отрицательную корреляцию оцениваемых интервальных скоростей соседних слоев, можно уменьшить такого рода потери информации. В результате, при использовании этого метода, получаем такие оценки уравнения скорости, которые имеют больший разброс и колебания, по отношению к наблюдаемым компакционным трендам. Получаемые уравнения вместе с разбросом параметров можно изобразить в компактной форме. При применении этого метода хорошо прослеживаются теоретические границы детектирования тонких слоёв с аномальной скоростью.