Structural Similarity and Inverse Identification with constraints on the Eigenvalue in Travel Time method

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Abstract: A synthetic travel time dataset is provided without any information about the structures, we are going to apply delay-time and travel time tomography methods using the slope-curvature features to find out what the structures look like. Solve a first-arrival travel time tomography problem for layered earth model with sharp layer interfaces. The curvature-slope descriptors derived from the travel time curve will allow us to produce a clustering process using structural similarity. Each segment entry will time travel to reverse identification method with constraints on the eigenvalues with model regularization applied.

Introduction

In a series of paper [Berryman, 1989a: Berryman 1989b, Berryman 1990] the author has developed a stable iterative reconstruction methods for first arrival travel time inversion. The theory general behind this novel approach and its extension will be described in the present paper. The main idea behind the new approach may be summarized as follow: When an inverse problem can be for formulated so the data are minima of one of the variation problem of mathematical physics. Feasibility constrains of eigenvalue can be found for inversion linear problem. These constrains guarantee that that optimal solution of the inverse problem lie in a convex-concave feasible region of model space. Furthermore, point on the boundary of these convex –concave regions can be found in constructive fashion. For any convex –concave function over model space, a local minimum or maximum or inflection point of the function is also minimum or maximum global other case cross over point . in light of the structure similarity induced on the model space by the feasibility constrains , we can also obtain a series of results about the structure of the solution set presented for travel time inversion problem.

This paper presents an application from an analytic formula for the generalized inverse matrix associated with vertical seismic profile (VSP) and common-depth – point(CDP) travel time equations its functional form explicitly depends upon the source –receiver geometry and its validity is restricted to horizontally layered earth models where is negligible ray bending. The importance of the generalized inverse is that it can be used to derive closed-form expressions for the covariance matrix, condition number, resolution matrix, and average inverse eigenvalues for the travel time equations; these formulas are useful in designing source-receiver geometries which optimize velocity reconstruction by travel time inversion. These formulas also provide a fundamental understanding of some resolution limitations associated with earth tomography experiments.

A dynamic system, the pattern of behavioral of a model is characterized by slope change rate in the state variables. Using analysis of the eigenvalues, we conclude that the dynamic in each slope value in the trajectories is making up of a number determinate of behaviors; each associated with a set eigenvalue characteristic each system dynamic class. The relative significance of each mode the behavior is determinate by the state of model with respect the vector of slope values and the directions of eigenvalue right in consequent with the eigenvalues value.

For some problems, in addition to the measure of similarity based on the characteristics of the curvature and smoothness in the general behavior of the trajectories with to the oscillatory features, it can be important to consider the concrete parameters of wave simples that appear in the trajectories order to identify similar temporary patterns in the same ones.

A trajectory can be split in segment indicating the local Tendencies of such form that each segment is limited by means of a point of inflection or by a point of inflection end.

The bases conceptual for specific temporal parameters allow descriptions of the form of pattern of trajectories. Some examples are: The number and size of hills and duration, the slope and curvature, the moment of appearance and pattern duration, when its will change the factors of category. The change of status and move have an effect on the value of the parameters, the measurements similarity are avail for the recognition and comparison of specific pattern of trajectories.

Convexity properties of seismic inversion

Our principal example will be first arrival travel time inversion. The sentence of problem is this: Given the locations of sources and receivers of some type of exciting waves (seismic) and the first arrival travel time t_i

for waves propagated between the m pairs of sources and receivers(labeled by $i = 1,...,m$) deduce the eigenvalue by weighted square error in the travel time in the region probed by these waves.
Fermat's principle (Born and Wolf 1959) say that first arrival travel time for i-th ray path is given by

$$t_i = \min_{path} \int s dl_i^{path} = \int s dl_i^* [s] \qquad (1)$$

Where l_i^{path} is the arc length along any connected path between the source and receiver and where $l_i^*[s]$ is the arc length along a ray path that minimizes the integral of the travel time for i-th path wave slowness s.
Some easy but import facts follow from the variation definition (1) of the first arrival travel time
Lemma 1: (concavity and homogeneity). The travel time $t_i(s)$ is a concave and homogenous function of the model slowness s. Note that, for $s_1 \succ 0, s_2 \succ 0$, $0 \le \lambda \le 1$.

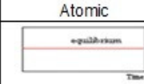
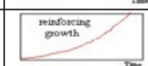
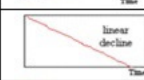
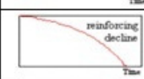
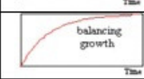
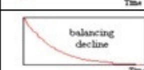
$$\lambda t_i(s_1) + (1-\lambda) t_i(s_2) \le t_i(\lambda s_1 + (1-\lambda) s_2) \qquad (2)$$

Lemma 2: (scale Invariance of ray path). A ray path with arc length $l_i^*[s]$ that minimize the travel time for s also minimizes the travel time for γs where γ is any positive scalar.
One method for solving the inverse problem is to guess a model s_g that might have giving rise to the measured data, compute the set travel time $t_i(s_g)$ for the trial model , and then use some method (often base on least-square fitting) to update the model and obtain a better fit to the data. However, such programing methods are generally limited by fact that it may be computationally difficult to find the exact $l_i^*[s_g]$ associated with the trial slowness.
Systematic inversion techniques have been applied to travel time data from marine refraction profiles in the Pacific Ocean and are compared with the conventional uniform layer solutions for the same profiles. Extremes bounds are obtained on the possible velocity-depth distributions which fit the travel time data. Also a linearized inversion is used to construct suitable velocity-depth profiles together with a measure of their resolution. The velocity structures obtained indicate that layer 2 is a region of strong velocity gradients while layer 3 is relatively homogeneous, although it does show an increase in velocity with depth. The inverse schemes offer a useful alternative to fitting models containing uniform layers to the travel times from a seismic refraction profile.
Shaping regularization is a general method for imposing constraints on the estimated model in the process of solving an inverse problem. In this paper, I extend the concept of shaping regularization to the case of nonlinear operators and show its connection to the nonlinear Landweber iteration and related iterative inversion methods. An example application is 1-D seismic inversion that extracts an interval velocity model from plane-wave (tau-p) move out analysis. I develop a nonlinear inversion scheme that utilizes local seismic event slopes and apply it to a synthetic data example to demonstrate an application of nonlinear shaping regularization. Different regularization strategies produce smooth or blocky (layered) models.

Structural similarity travel time curve.

The similarity structural refers to behavioral of patterns as "changes of shape in time" and considers our ability to recognize them as anything essential to understanding complex dynamic system. But, ¿ what are the essential shapes of dynamic behavior? We use seven unique behavior pattern based on the net rates of change of the variables of interest. (See Table I)[8].

Table 1 Even Rules and Atomic Behaviour

Slope Value	Curvature Value	Symbol Label	Alphabet Symbol	Pattern Atomic
S=0	C=0	(yellow)	y	
S>0	C=0	(black)	k	
S>0	C>0	(cyan)	c	
S<0	C=0	(magenta)	m	
S<0	C<0	(red)	r	
S>0	C<0	(blue)	b	
S<0	C>0	(green)	g	

The Trends in the absolute values of net rates changes can be used to uniquely identify seven atomic behavior patterns. The first pattern was called "growth reinforced" its behavior is concave upward, with a monotonic increase. The second pattern is well know how "linear growth" its behavior is linear increase. The third pattern is nominated how "growth balancing", behavior is concave, downward, with monotonic increase. Fourth pattern is denominate "decline reinforced" is concave downward, with a monotonic decrease; the fifth pattern is "linear decline" with linear decrease. the sixth pattern has a behavior concave downward with monotonic decrease, it's called "balancing decrease" and lastly the pattern (seventh) is a linear behavior and it introduce when there is "equilibrium"[3]

Method

The identification of parameters is characterized by a systematic process and complicated, possibly facilitated by an analysis of the structures of certain simple linear systems that can get to specify and implement computationally.

To identify the parameters from few training data sets, you have to make restrictions to estimate dynamic systems desirable. This restriction is based on dynamic stability, the key idea to estimate the dynamic stability is restricted to the eigenvalues.

The identification of the system without restriction is conditional if the time range [b, e] is represented by linear dynamical system D_i then we can estimate the transition matrix $\mathbf{F}^{(i)}$ and the bias vector g_i of the sequence of internal states $\left[x_b^{(i)},...,x_e^{(i)}\right]$, this to estimate the parameters problem becomes a problem with minimization the errors of predict[7].

This prediction error vector can be determined from equation (3) and have estimated the matrix $\mathbf{F}^{(i)}$ and the bias vector g_i and its formulation is:

$$\varepsilon_t = x_t - F^{(i)} x_{t-1} + g^{(i)} \qquad (3)$$

So the sum of the rules of the squares of all the errors vectors in the range [b, e] becomes [7]:

$$F^{(i)}, g^{(i)} = \arg\min\min \sum_{t=b+1}^{e} \left\| e_t \right\|^2 \qquad (4)$$

Finally we can estimate the optimal values of $\mathbf{F}^{(i)}$ and g_i by solving the following least squares problem.

Given a continuous state sequence mapped from the observation space, the parameters estimation of a transition matrix $\mathbf{F}^{(i)}$ from the sequence of continuous state vectors $\left[x_b^{(i)},...,x_e^{(i)}\right]$ becomes a minimization problem of prediction errors. Let us use the notations follow:

$$x_0^{(i)} = \left[x_b^{(i)},...,x_{e-1}^{(i)}\right] \qquad (5)$$

$$x_1^{(i)} = \left[x_{b+1}^{(i)},...,x_e^{(i)}\right] \qquad (6)$$

If temporal range [b, e] is represented a linear dynamic system. Then D_i, we can estimate a transition matrix $\mathbf{F}^{(i)}$ by the following equations:

$$F^{(i*)} = \arg(\min_{F^{(i)}} \left\| F^{(i)} x_0^{(i)} - x_1^{(i)} \right\|^2) \qquad (7)$$

By algebraic methods leads to:

$$F^{(i*)} = \min_{\delta^2} (\mathbf{x}_0^{(i)} \mathbf{x}_1^{(i)\mathbf{T}} \left(\mathbf{x}_0^{(i)} \mathbf{x}_0^{(i)\mathbf{T}} + \delta^2 \mathbf{I} \right)^{-1}) \qquad (8)$$

Where $\mathbf{I}$, is unitary matrix and δ^2 is positive real value (called regularization factor).

Gershgorin Circle Theorem to Estimate the Eigenvalues

For the constraints on the eigenvalues, the limit in the Equation (7) before $\mathbf{x}_0^{(i)} \mathbf{x}_1^{(i)\mathbf{T}} \left(\mathbf{x}_0^{(i)} \mathbf{x}_0^{(i)\mathbf{T}} + \delta^2 \mathbf{I} \right)^{-1}$ converges to a pseudo-inverse matrix $\mathbf{x}_0^{(i)}$ of Using Gershgorin's theorem of linear algebra; we can determine the upper bound of eigenvalue in the matrix from its elements. Supposition $f_{u,v}^{(i)}$ is an element in row $\mathbf{u}$ and column $\mathbf{v}$ of the matrix transition $\mathbf{F}^{(i)}$. Then, the upper bound of eigenvalues is determinate by $\mathbf{B} = \max_u \sum_{v=1}^{n} \left| f_{u,v}^{(i)} \right|$.

Therefore, we search a nonzero value δ^2, which controls the scale of element in the matrix, that satisfies the equation B=1 via an iterative numerical calculation [7].

Estimate Stable Dynamic

To identify the system parameters from only a small amount of training data of state variables of a dynamic system, we need constrains the eigenvalues of matrix transition for estimation of an appropriate dynamic. In this paper , we concentrate in extracting the behaviors of the segments of trajectories observed for example, the atomic behavior patterns linear , exponential and logarithmic; therefore , the restriction is based on stability of dynamic, that are suitable to find motion that converge to a certain state from an initial position. The key idea to estimate stable dynamic is the method that constrains eigenvalues. If all eigenvalues are lower than one, the dynamic system change state in a stable manner [7].

Examples

In the fig 1, it is illustrated the travel time one of the 11 geophone gathers. In this model, there are 600 shots evenly deployed on the surface, and 12 geophones evenly placed in the center well (offset 3000 m) at the depth range from 1900 m to 2120 m. From it we can see, migration of VSP multiples has a much larger imaging area than migration of VSP primaries

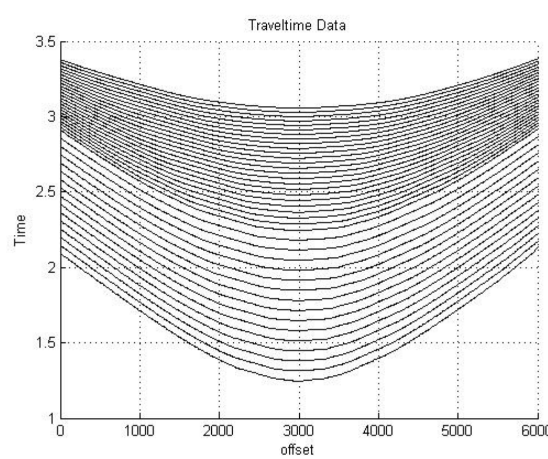


Fig 1. Travel time from gather

In the fig 2, it is illustrated the concept of structural similaridad, the curve trajectory of the travel time qualitative features variable labeled by different colors and the graphic of the inferior part corresponds to a behavior of a system in feature space. The pattern (blue, yellow, red, green, yellow and black) correspond a value of curvature and slope. They converge a zero.

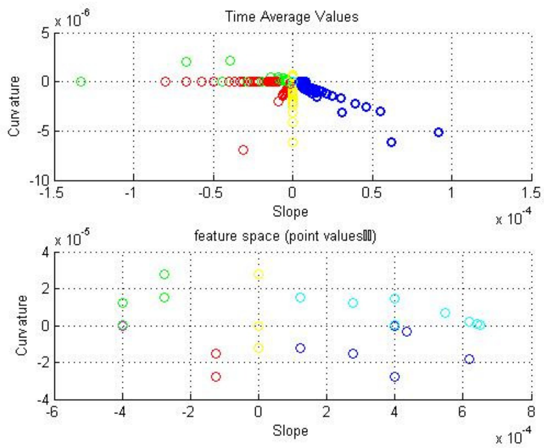


Fig 2 Pattern and Values of Features Space

A simple example of multiple solutions for a single, un-reversed travel time curve, obtained by identifying segments with refracting horizons in different ways, is illustrated by the curve of Figure 3a.

The Inflections corresponding to crossover points are nearly. Always it's manifested by a decrease in slope of the travel time curve (an increase in apparent velocity) with increased distance from the shot point as illustrated in the reversed travel time curves of bottom in the figure 3b. If changes in dip or velocity of overlying layers are involved, the crossover point may actually be marked by an increase in slope (a decrease in apparent velocity) with increased distance from the shot point, or by no inflection at all.

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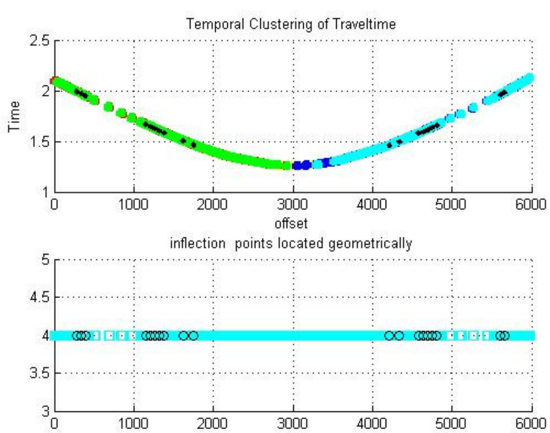


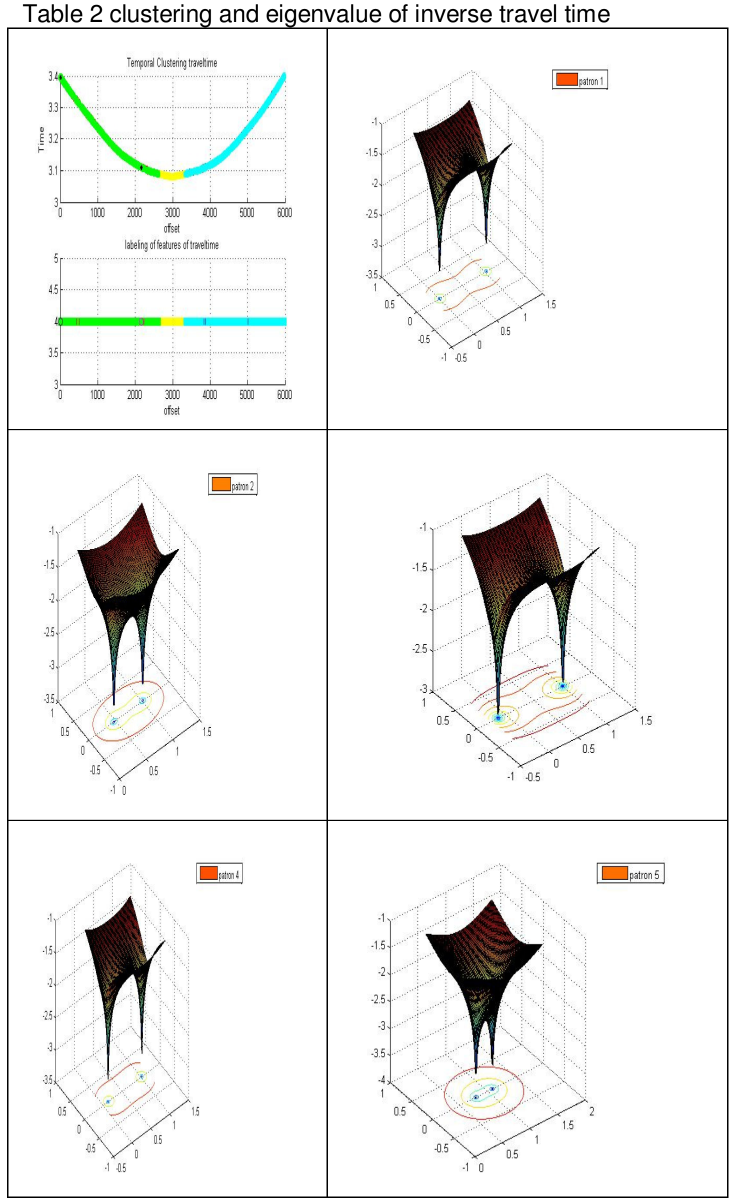
Fig 3 Temporal Clustering and Inflection Point

These examples illustrate the diversity of shapes of travel time curves that can result from relatively simple subsurface changes. As geology becomes complex, the resulting complexities increase to the point where simple identification of cause and effect is impossible. Figure 3, for example, illustrates a travel time curve with a marked inflection in one direction but none in the reverse direction. The computed model is the trough-like feature of laterally varying velocity shown as the basal layer in top of the figure (3).

Result experimental.

In table 2 we shows the clustering of travel time and eigenvalue from the application of circles de Gershgorin for matrixes estimated in inverse travel time methods.

Table 2 clustering and eigenvalue of inverse travel time



Conclusions

Multiple solutions may be obtained from singly reversed Profiles, it is shown in Figure 3a. One possible solution (Figure 3b) is based on the assumption that each line segment of the travel time curve corresponds to a different layer. An equally valid two-layer solution that might be obtained from shooting across an alluvial valley . Additional data are required to resolve the ambiguity.
Figure 3b shows the effect of a change in velocity of horizon with no change in dip. We note approximately equal intercept times for both shot points because depth is constant, and a higher apparent velocity of the travel time curves over the part of layer four with the higher velocity. For the case of a gradual change in dip or curved horizon with constant velocity (Figure 3b yellow colors), the intercept times at opposite shot points are significantly different and the apparent velocity of the reversed curves increases in opposite directions, similar to the effect an increase in velocity with depth.
These examples show that the interpreter must distinguish breaks in slope of travel time curves due to crossovers from those due to lateral geologic changes. This must be done before applying algorithms to calculate the lateral changes in velocity and depth of the individual horizons which satisfy the perturbations of travel time curves Lateral effects problem deals with the effect of the lateral changes along the upper refracting interfaces on the lower refractors. The recorded travel time curve from the lower refractors usually has pseudo number of inflection points and travel time elements. An increase or decrease in the number of the travel time elements along the travel time curve is a result of these lateral variations. Linear travel time elements are defined as linear segments with the same slope and consequently the same apparent velocity. Such travel time curves cannot be explained directly by most of shallow refraction seismic interpretation methods. To identify this problem two travel time parameters are used. These are layer reciprocal time and the apparent refractor velocity. Reversed profiling technique is essential. The ray tracing technique is used in this study to compute the synthetic travel time curves of first arrivals. Surprisingly, this problem is rarely discussed in literature, and if ever, it is often without suggestions for interpretation, so the name lateral effects is used to define it.

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