

Extraction and Visual Analysis of Seismic Horizon Ensembles

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Abstract

Seismic interpretation is an important step in building subsurface models, which are needed to efficiently exploit fossil fuel reservoirs. However, seismic features are seldom unambiguous, resulting in a high degree of uncertainty in the extracted model. In this paper we present a novel system for the extraction, analysis, and visualization of ensemble data of seismic horizons. By parameterizing the cost function of a global optimization technique for seismic horizon extraction, we can create ensembles of surfaces describing each horizon, instead of just a single surface. Our system also provides the tools for a complete statistical analysis of these data. Additionally, we allow an interactive exploration of the parameter space to help finding optimal parameter settings for a given dataset.

Categories and Subject Descriptors (according to ACM CCS): I.3.8 [Computer Graphics]: Applications—

1. Introduction

Fossil fuels are the most important energy sources for today’s societies. Using the full potential of existing reservoirs is increasingly necessary. For planning production wells to drill into oil and gas reservoirs, one needs an exact model of the subsurface, including the different subsurface layers and their boundaries—the so-called *seismic horizons*—, but also *faults*, and other structures. To create such a model, usually a *seismic survey* is acquired which contains seismic reflection data. These data need to be *interpreted*. The term interpretation most of all describes the extraction of geological structures from the seismic cube. These structures, however, are often ambiguous and not very well defined. This results in high uncertainty in the extracted features.

This work presents a novel framework for the quantification of uncertainty in extracted seismic horizons, by introducing ensemble computation and visual analysis to this process. We first automatically sample the parameter space of the cost function underlying a global optimization technique for horizon extraction [HBG*11, HFG*12]. This results in a family of surfaces, i.e., a *horizon ensemble*, for each horizon in the original data. Visualization then enables the user to perform interactive exploration and statistical analysis of the ensemble data. This process guides the user to regions of high uncertainty in the extracted horizons. In addition, by allowing the user to interactively constrain the parameter ranges in order to explore the parameter space, our system facilitates finding optimal parameter settings for a given dataset. The major contributions of this paper are:

- Ensemble computation for seismic horizon extraction based on sampling the parameter space of the cost function used for surface extraction.
- An interactive system that enables analysis and visualization of the extracted ensemble data and facilitates real time exploration of the parameter space of these data.

2. Related Work

Our framework is based on previous work for interactive seismic horizon extraction using a global optimization approach [HBG*11, HFG*12]. However, in this paper, instead of computing a single surface for each horizon, we compute *ensembles* of horizon surfaces, by sampling the entire parameter space of the cost function. The uncertainty represented by these ensemble data can then be analyzed interactively. A good overview of other techniques for horizon extraction is provided by Pepper and Bejarano [PB05]. Faraklitioti and Petrou [FP04] employ connected component analysis for fully automatic horizon extraction. Patel et al. [PBVG10] propose an interactive workflow for the manual combination of building blocks computed in a preprocessing step.

Frameworks for visualization of ensemble data computed for weather simulation include *Ensemble-Vis* by Potter et al. [PWB*09], and *Noodles* by Sanyal et al. [SZD*10]. A good introduction to uncertainty visualization is provided by Pang et al. [PWL97], who present a detailed classification of uncertainty, as well as numerous visualization techniques, including several concepts applicable to (iso-)surface data, like fat surfaces. Johnson and Sanderson [JS03] give a

good overview of uncertainty visualization techniques for 2D and 3D scientific visualization, including uncertainty in surfaces. For a definition of the basic concepts of uncertainty and another overview of visualization techniques for uncertain data, we refer to Griethe and Schumann [GS06]. Brown [Bro04] employs animation to visualize uncertainty in iso-surfaces. Pöthkow et al. [PH11, PWH11] and Pfaffelmoser et al. [PRW11] present techniques to extract and visualize uncertainty in probabilistic iso-surfaces. These approaches for visualizing uncertainty in iso-surfaces use a mean surface as the main representative surface and use uncertainty quantification provided by simulations.

3. Ensemble Computation

We compute each individual surface in a horizon ensemble via a horizon extraction technique presented previously [HBG^{*}11, HFG^{*}12]. This technique employs a global optimization approach using a cost function, which comprises three components that are combined via two user-adjustable weights, and scaled by a third parameter. However, such a complex cost function can overburden the user. For this reason, we propose to sample the parameter space of the cost function automatically. For a detailed description of the cost function and the parameters, please refer to [HFG^{*}12]. However, the approach presented here is applicable to a variety of parameterized surface extraction techniques. We will therefore refer to the parameters generically as p_0 to p_n in the remainder of this paper.

To start the ensemble computation, only a single seed point is required. However, an arbitrary number of points can be defined as additional constraints to force the resulting surfaces through user-specified positions. The same seed point and set of constraints are used to compute all surfaces in the ensemble. Once the seed point and constraints are defined, the user can define a range and sampling rate for each parameter to compute the ensemble. For each parameter setting, the seed point and constraints, as well as the parameterized cost function, are given to the surface extraction algorithm. The result of each surface extraction step is a single horizon surface represented as a height field or function $f : \mathbb{N} \times \mathbb{N} \mapsto \mathbb{R}$, mapping each (x, y) -position on a regular grid to a single depth value. Even though we focus on height fields in this work, our approach would also be applicable to generic surfaces, as long as correspondences between the ensemble members can be established. For this paper, we assume that the (x, y) -position defines this correspondence. Moreover, as the surfaces for each parameter setting are computed independently from all others, the ensemble computation can easily be parallelized for faster computation of the ensemble data. This allows each node of a cluster and/or processor core to compute one surface at a time.

4. Statistical Analysis

To analyze the results of the ensemble computation, we compute a wide range of statistical properties. The basis

for these computations is provided by a 3D histogram, $h : \mathbb{N} \times \mathbb{N} \times \mathbb{N} \mapsto \mathbb{N}$, mapping each volume position (x, y, z) to the number of surfaces passing through that position. With the (x, y) -position as the correspondence between ensemble members, as described above, this 3D histogram resembles a set of 1D histograms mapping the depth value at any given (x, y) -position to the number of surfaces passing through that depth. As such, this histogram can also be interpreted as a probability distribution. Due to the fact that all surfaces in an ensemble share the same domain, we know that the sum of all surfaces passing through all depth values at any (x, y) -position equals the number of ensemble runs. We can therefore directly derive a probability for each voxel being part of a horizon surface, by dividing the number of surfaces passing through that voxel by the number of ensemble runs.

In addition, we compute the probability density distribution for each (x, y) -position. Based on this data, we compute a *maximum likelihood surface*. This surface is an actual surface from the ensemble, which is chosen according to an overall likelihood value assigned to each of the surfaces. This likelihood value is computed by taking the height- or function-value $f(x, y)$ at each (x, y) -position of the surface f , and summing over all the individual probabilities on the surface, which result from a look-up in the probability density function (pdf) at each position:

$$\text{likelihood}(f) = \sum_x \sum_y \text{pdf}(x, y, f(x, y)). \quad (1)$$

The ensemble member with the highest likelihood value is then defined as the maximum likelihood surface. This surface corresponds to a global measure, in contrast to a surface such as the mean surface, where each point is only locally the point of highest probability.

By interpreting the 3D histogram as a set of 1D histograms, we can also compute a complete set of statistical properties per (x, y) -position, such as mean, standard deviation, or kurtosis. Mean and median depth value, as well as the maximum mode of the pdf, can be used to synthesize additional surfaces. Other values can be used to get an idea of the distribution of the ensemble surfaces in the volume.

5. Visualization

The surfaces resulting from the ensemble computation have significantly different properties than, for example, the probabilistic iso-surfaces presented in [PRW11] or [PH11]. Whereas the distribution of the probabilistic iso-surfaces can be modeled as a Gaussian distribution, each parameter setting in our approach can produce a completely different surface. In fact, typically there is very little variation as long as the surfaces tag the same horizon. In uncertain areas, however, it often happens that different parameter settings lead to surfaces tagging different horizons, which results in disconnected clusters of very similar surfaces in each cluster (compare Figure 1). Thus, the visualization techniques presented in [PRW11, PH11] are not applicable for our ensem-

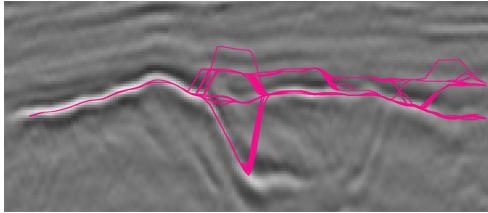


Figure 1: Accumulated rendering of 101 surfaces intersected with a planar slice. The clustering behavior is clearly visible.

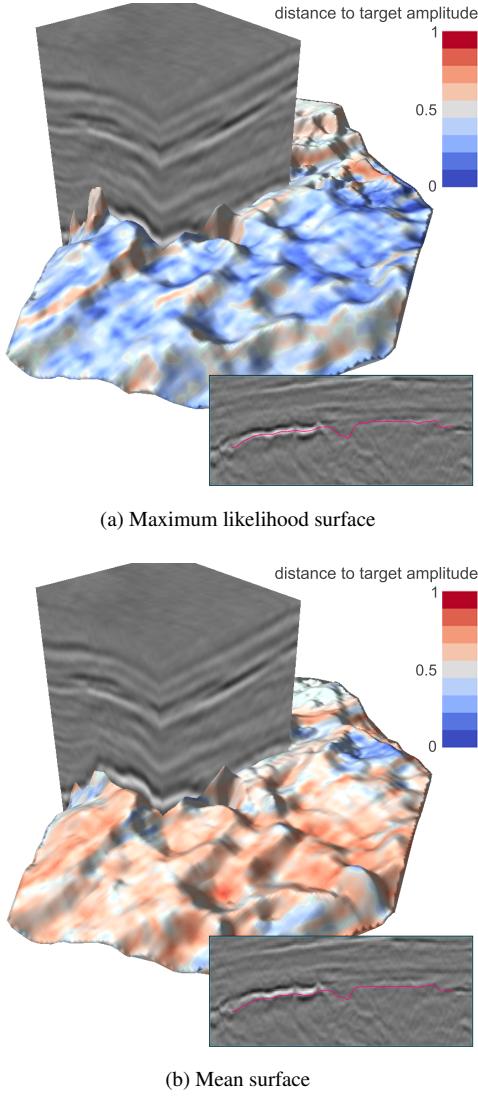


Figure 2: Comparison of the maximum likelihood surface (a) with the synthetic mean surface (b) extracted from a 101 surface ensemble, sampling parameter p_0 . The surface was seeded on the bright ridge line. The color coding indicates the difference between the amplitude at the volume position passed by the surface and the target amplitude. Blue means a small difference (better), red a bigger difference (worse).

bles. That is, the mean surface used in these approaches as a representative surface would not correspond to a horizon surface, since it would likely result in a surface in between two possible segmentations, but tag neither one correctly.

Instead of synthesizing a surface, we have decided to extract the maximum likelihood surface for use as the representative of the ensemble, as described in Section 4. An exemplary comparison of the maximum likelihood surface and a mean surface can be seen in Figure 2. Figure 2a shows an example of a maximum likelihood surface. Even though there is a somewhat large variance in the ensemble, the maximum likelihood surface fits the underlying data quite well. In contrast, the mean surface shown in Figure 2b is basically a mixture of two large clusters of surfaces and does not fit either one of the tagged horizons for large parts of the surface.

However, simply displaying the maximum likelihood surface itself without any additional information does not provide much information about the ensemble. Therefore, we also depict the results of the statistical analysis described in Section 4.

We allow pseudo-coloring the surface with these results, using one of several pre-defined, or user-defined color maps. These properties immediately provide a good idea about how the surface extraction behaves in different areas, i.e. very stable areas are clearly visible throughout all properties, indicated by small values in range, standard deviation, variance, close to zero values in the skewness, or very large values in the kurtosis. In addition, it is possible to automatically animate all surfaces in a pre-defined range. Animating the ensemble gives a nice impression of the parameters that result in similar surfaces, as well as of which areas in the dataset react more or less to changes in the parametrization of the cost function. Similar surfaces or surface parts in the ensemble will result in little variation in the animation, whereas areas of large variance will show more movement and thus automatically draw the user's attention.

All the described techniques have in common that they can be used to visualize the complete ensemble or any user-defined subset. Using a slider, the user can define a subrange for each parameter and the statistical analysis is carried out on the fly for this range. This allows an interactive exploration of the parameter space, which is helpful to define interesting ranges for each parameter.

6. Results

We have computed several ensembles with different parameter samplings. Since we can give only a brief overview in this format, we present one ensemble, consisting of a total of 101 surfaces in this section. The ensemble was created by sampling the parameter p_0 in the range of [0..1] in steps of 0.01, while the other two parameters were fixed. Additional visualizations can be found at <http://www.thomashollt.com/eurographics13>.

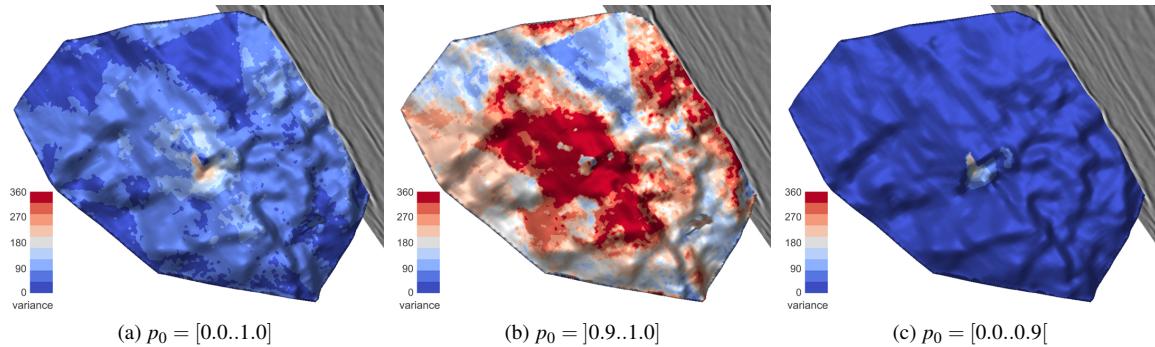


Figure 3: Exploration of a single parameter. The color coding represents the variance of the ensemble. Only looking at (a), it seems that there is a quite large variance over the entire surface. However, by looking at the two different parameter sub-ranges in (b) and (c), respectively, it becomes clear that nearly all of the variation is related to the parameter range from 0.9 to 1.0.

Figure 3 shows different visualizations of this horizon ensemble. The variance is depicted by color coding the maximum likelihood surfaces of the respective parts of the ensemble. Judging from Figure 3a, which resembles the complete ensemble, it seems that there is quite a bit of variance as there are very few dark blue areas. By splitting up the parameter range into two sub-ranges, one from 0.9 to 1.0 (shown in Figure 3b), and one from 0.0 to 0.9 (Figure 3c), it becomes clear that nearly all of the variation is in the upper ten percent of the parameter range.

Using this ensemble, for this specific dataset, we could quickly find out that the usable parameter range for p_0 is between 0.0 and 0.9, but also that a parameter in this range will have very little effect on the resulting surfaces, meaning that the user does not have to be very careful with this parameter, as long as it is between 0.0 and 0.9.

7. Conclusions

In this paper, we have presented a novel framework for the computation, analysis, and visualization of ensemble data consisting of extracted seismic horizon surfaces. These ensembles do not follow a Gaussian distribution. We have shown that our framework is helpful for identifying good parameter settings for the cost function, as well as for avoiding bad parameter settings. Our approach can also be used to find interesting features in the data, which might warrant closer manual interactive inspection.

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