A knowledge-based approach of seismic interpretation : horizon and dip-fault detection by means of cognitive vision.

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Summary

The present paper presents preliminary results obtained through a new seismic interpretation methodology based on cognitive vision. This methodology consists in associating to the geological objects to be detected, horizons or faults, visual characteristics that allow to easily identify and correlate them on seismic images. The results presented show that the method is performing well and is easy to be integrated in Shared Earth Modeling workflows.

Introduction

Seismic data being the only source of continuous 3D information on oil & gas prospects, their interpretation is a starting point of capital importance for the reservoir building process. The efforts currently made to improve seismic interpretation are mainly focused on defining and refining sophisticated seismic attributes, whose exploitation relies for a good part on the professional experience of interpreters. Thanks to refined software tools, skilled interpreters are thus able to ever more efficiently identify the more or less complicated geological assemblages that will be further processed in the reservoir modeling workflow.

However, for oil & gas exploration, the challenge is no longer to simply produce accurate interpretations but also to operate “Shared Earth Modeling”, i.e. to open the possibility for the various engineers and experts involved in reservoir modeling to fully interact together. This supposes that the operators share not only data and results but also the various interpretations that are considered throughout the modeling process (Rainaud, 2005). Moreover, as reservoir modeling basically relies on geological expertise, SEM should preferably be based on geological knowledge sharing (Mastella, 2007).

The software tools that are currently used for seismic interpretation seldom allow to memorize the link that interpreters more or less empirically establish between the seismic image characteristics and the geological properties of the objects to which they are related. For this reason, seismic interpretation often remains blind and hardly fits SEM requirements. The present paper intends to cope with this difficulty by presenting first interpretation results based on a new knowledge-based methodology. The proposed approach operates an explicit linkage between visual seismic image concepts and geological properties. It is based on an emerging artificial intelligence methodology: cognitive vision.

The Cognitive Vision Approach

Cognitive vision has recently appeared as a science combining computer-based vision and cognition. A cognitive vision system is endowed with cognitive capabilities which allow it achieving, in an intelligent way, generic computer functionalities like detection, localization, recognition and understanding (Vernon, 2005).

We propose to use the cognitive vision approach developed by the ORION INRIA team (Hudelot, 2003; Maillot 2004, 2008). It basically consists in using a visual concept ontology for linking visual data and high level interpretation. In the case of seismic interpretation, it consists in linking geological objects and visual seismic attributes thanks to a visual concept ontology. This has been realized by defining visual geologic attributes and by formalizing them thanks to a visual ontology (Borst, 1997, p. 12). This knowledge formalization has two advantages. It not only allows an automatic detection of geological objects but also the recording of the various criteria used for this detection. By using a Semantic Web technology (Mastella, 2008), it is then possible to keep the memory of the seismic interpretation at all stages of the modeling process and to consequently meet SEM requirements.

The architecture of our cognitive vision based platform for seismic interpretation is based on a knowledge representation (which includes visual concepts, geological objects and their relations) and seismic data analysis (which comprises data management, visual characterization and geological correlation).This architecture is represented on figure 1.

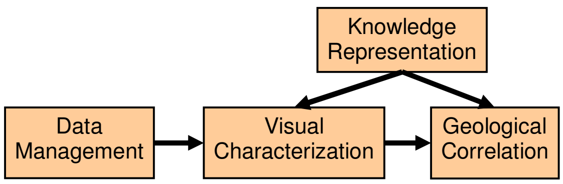

Figure 1 : Proposed cognitive vision workflow for seismic interpretation.

The results presented here concern horizon and fault detection. In each of these two cases, we first explicit the visual ontology that has been defined, then describe the identification workflow and finally present some significant results.

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Horizon Identification

Knowledge Representation

According to the Schlumberger Oilfield Glossary (1998), “horizon is an informal term used to denote a surface in or of rock, or a distinctive layer of rock that might be represented by a reflection in seismic data.

In seismic data, horizons are observed as sets of reflectors consisting in lateral successions of points having approximately the same amplitude. Reflectors corresponding to one horizon may appear disconnected as a consequence of noise or of the interference with another geological object. One can visually recognize that several disconnected reflectors are attached to the same horizon, by comparing their thickness, their orientations, their colors (amplitude value) and their time relationships with other reflectors. These various peculiarities can be formalized by means of the ontology represented on figure 2.

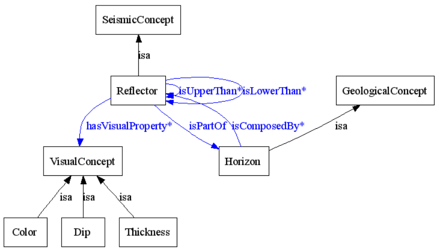

Figure 2 : The chosen conceptualization of a horizon for seismic interpretation

Workflow

Horizon identification is operated in 3 successive steps (Verney, 2008).

Step 1 consists in a pre-processing operated by means of a **data management module**. This enables detecting first order reflector continuity by using voxel connectivity within a definite amplitude range. These reflectors are parts of geological horizons detected by strong reflections. (Figure 3)

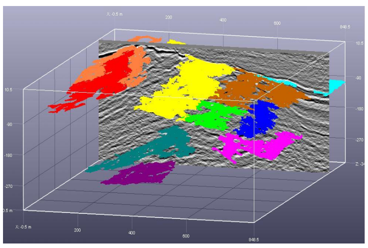

Figure 3: Main reflectors identified and associated graph

Step 2 is operated by a **visual characterisation module**, which affects to the detected reflectors the attributes and relationships defined in the visual ontology. At present, chronological relationships between reflectors are established considering that a reflector located upper in the image is a younger one. Upper/lower relationships are locally computed as shown on figure 4.

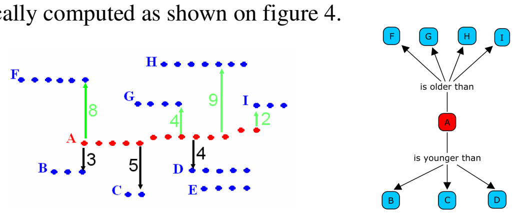

Figure 4 : Vertical distance computation and resulting graph

By merging the chronological relations related to the various reflectors, one obtains a global graph showing all vertical neighbor relationships.

Step 3 is a **geological correlation** step, which consists in identifying the geological horizons corresponding to the various detected reflectors.

In classical seismic interpretation procedures, this operation is not trivial and is frequently performed “by hand” by the interpreter. In our case, it is done by simplifying the global graph obtained at the end of the visual characterization step (Figure 5).

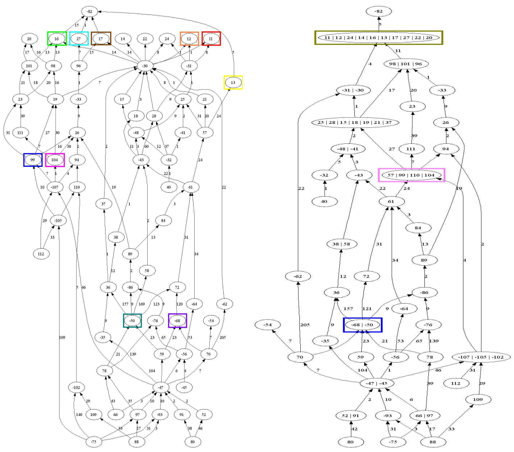

Figure 5**:** Graph before (left) and after (right) simplification.

For this, we fuse all the nodes which both:

- share similar visual attributes (amplitude, thickness, dip)
- are located at similar distances from at least one other reflector.

These two criteria are applied in accordance with tolerance rules defined by the user. An example of result corresponding to the fusion of the reflectors detected on figure 3 is presented on figure 6. About 25% of the reflectors were merged.

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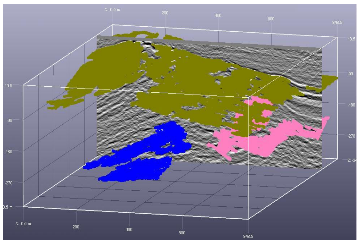

Figure 6: Main merged horizons

Fault Identification

Knowledge Representation

According to the Schlumberger Oilfield Glossary (1998), “a fault is a break or planar surface in brittle rock across which there is observable displacement. Depending on the relative direction of displacement between the rocks, or fault blocks, on either side of the fault, its movement is described as normal, reverse or strike-slip”. The only faults that are considered in the preliminary approach presented here are “dip-faults” (normal or reverse). A fault mirror is a small part of a fault surface that corresponds to the broken part of a given layer.

In seismic data, dip-fault mirrors are observed by a horizon vertical disconnection producing a "reflector gap" and/or by horizon interruptions (cf. Figure 7). Major faults can be detected by identifying successions of approximately co-planar fault mirrors. Faults also generally correspond to “noisy” zones.

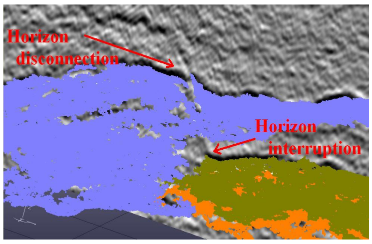

Figure 7: Dip fault mirrors

These peculiarities can be formalized as shown on figure 8

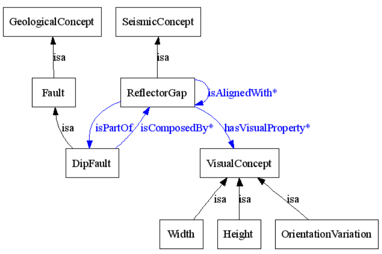

Figure 8: The chosen conceptualization of a dip fault for seismic interpretation

Workflow

It consists in 3 steps that are analogous to those defined for horizon identification.

Step 1 again consists in horizon identification operated by means of the **data management module**. It corresponds to the process that we just described above in this paper. The output of this module is a set of detected horizons computed from the seismic block.

At step 2, the seismic cube is systematically explored by means of successive inlines (x direction) and crosslines (y direction) using the **visual characterization module**. On each slice, three conditions must be simultaneously satisfied for identifying a fault mirror (see Figure 9). They respectively concern:

1- <u>Local 2D orientation variations</u>:

On each slice, z corresponding as usual to the vertical direction, the orientation of a given reflector is locally expressed by a vector [Δx, Δz] or [Δy, Δz]. An average orientation is defined over a 10 pixel mobile window. The presence of a dip-fault mirror is likely to be signalled by a significant difference between the local and average orientations.

2- <u>The width of the horizontal fault gap</u>:

Since actual faults have very small widths, the detected Δx or Δy values must remain inferior to a definite threshold value.

3- <u>The height of the vertical fault gap</u>:

Detected Δz must be superior to a given threshold, very small Δz being likely to be irrelevant, since they generally correspond to mere noise. We recommend that the chosen threshold be equal to the half of the average thickness of the reflector from which the horizon has been extracted

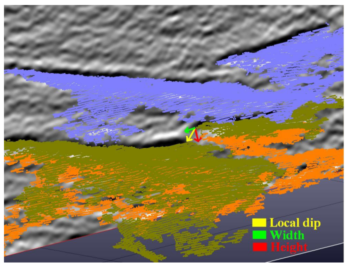

Figure 9: Dip fault visual criteria

At step 3, thanks to the **geological correlations module,** by applying the three above criteria, it is possible to identify couples of points respectively belonging to “ridge” and “ravine” lines (step 3-1). See Figure 10 for an example. We then try to reconstruct from these local data more or less continuous “ridge” and “ravine” lines corresponding to the intersection lines between the two parts of a horizon disconnected by a given fault (step 3-2). For this, we assume that couples of points belong to the same fault mirror, if both the ridge and ravine points of each couple are close to one another and if the vectors which respectively associate the ridge and ravine points of each couple have similar directions.

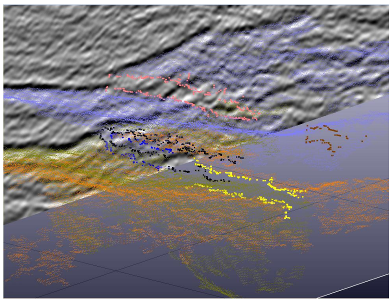

Figure 10: Ridge and ravine points detection.

The last step for fault identification (3-3) consists in associating fault mirrors related to various horizons and belonging to one fault. For this, we compare, on each seismic slice, the orientation of each couple of ridge/ravine points associated to a given horizon to the ridge/ravine couples associated to all the other horizons. An example can be seen on figure 11.

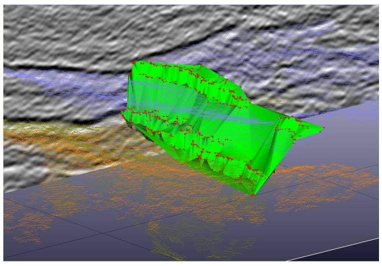

Figure 11 : Merged and triangulated dip fault mirrors.

Perspective

In the above exposed approach, we have always considered that a fault locally disconnects one or several horizons. This means that any considered horizon has been identified on the both sides of the fault. However, in some case the two parts of an interrupted horizon are likely to be interpreted as two different horizons. We should thus consider that a fault surface can sometimes be detected by considering horizon interruptions.

We intend to take into account horizon interruption by detecting at step 3-3 which interruptions happen to be coplanar with fault mirrors belonging to one same fault

Model Building

Generally, surfaces identified by the above methodologies cannot be directly introduced into a 3D earth model. The major reasons for this are the following:

- all surfaces are defined not as meshed surfaces but as clouds of points,
- the detected horizons correspond to a huge amount of data (up to millions of points),
- all surfaces (horizons or faults) are likely to contain “holes” corresponding to sections where little or no information is available. (noisy areas).
- a delicate fitting on well markers location is necessary

For these reasons, a surface reconstruction procedure must be put into place after horizon and fault identification. In connection with the present work, new developments concerning this issue have notably been proposed recently by Tran (2008). The results are regular well-shaped surfaces. These surfaces result from a complicated series of elementary operations. One must thus check that they still fit with the data resulting from the raw interpretation, i.e. with the sets of points corresponding to the various surfaces extracted by the methodology described in the present paper. Future work will accordingly be dedicated to coupling performing surface reconstruction procedures with cognitive vision based identification methods.

Conclusion

The methodology presented here has a double interest. The preliminary results presented above and others obtained on another seismic block first prove that the methodology is performing well. Moreover, it has the advantage of directly referring to the visual characteristics of the geological objects to be detected. These characteristics are specified by means of parameters that can be tuned by the user for optimal performance.

Thanks to the visual knowledge ontology that has been built, it will also be easy to get these parameters recorded by the system. Keeping the memory of the conditions in which seismic interpretation has been performed opens the possibility of re-operating this interpretation possibly with different parameters at any stage of the modeling process in the course of “Shared Earth Modeling” workflows.

Acknowledgements

We thank the Total company for having allowed us using and showing the seismic blocks, which illustrate the present paper.

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