

Artificial intelligence (AI) based geological feature mapping: A case study from KG Basin

Sumeet Mavani*, Sanjai Kumar Singh
mavani_summeet@ongc.co.in

Keywords

Mass Transport Complex, CNN, Deep Learning, U-Net, Supervised learning, geological feature, KG Basin

Abstract

Mass transport complexes (MTCs) have important implications for hydrocarbon exploration since they form a significant proportion of deep-water sediment fills, pose drilling risks, and can have both reservoir and seal potential.

Although the top and bottom of MTCs can be easily identified and mapped by a skilled interpreter, it is a time-intensive process. Auto-pickers that often accelerate the interpretation workflows, also perform poorly in mapping these reflectors due to lateral inconsistency of these reflectors.

Mapping these kinds of reflectors in a quick time requires an expert algorithm and hence, AI-based approaches are the need of the hour since they are data-driven, accurate, and fast. The present workflow utilizes the U-Net model architecture to identify MTC directly from seismic data. Supervised learning is used to train a U-Net model using images of a few seismic sections and associated interpretations of MTC. Once, the model is trained, it can be used to generate an MTC likelihood volume in 3D space. From this MTC likelihood volume, the top and bottom surfaces can be extracted which might have, otherwise, taken a considerable amount of human effort and time.

Introduction

Convolutional Neural Networks (CNN) for image classification have been around for more than two decades (LeCun et al., 1998). After a slumber of several years, there was a resurgence of these techniques after the breakthrough work of Krizhevsky et al. in 2012. Since then, the field has been expanding and has also found widespread applicability in seismic classification, fault mapping, geological body mapping, etc.

There are many published works on the mapping of geological bodies like MTC using machine learning

methods. The published literature can be divided into two methods. The first is based on unsupervised methods (Aqrabi et.al). The present work which falls under the supervised method uses the U-Net model (Ronneberger et.al, 2015) for the task of semantic segmentation.

Mass Transport Complex

Mass transport complex (MTC) is a general term used for an underwater landslide deposit that undergoes some combination of creeping, sliding, slumping, and/or plastic flow in a marine or freshwater lacustrine environment (Dott, 1963; Nardin et al., 1979; Moscardelli and Wood, 2008). Like most geological features, MTCs can be identified by their specific geometric patterns on seismic data.

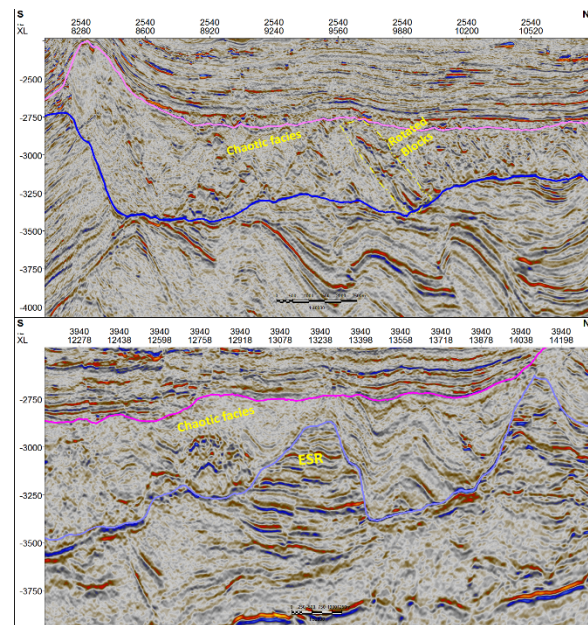


Figure 1. Internal Facies within Mass Transport Complex

Figure 1 demonstrates the internal features of MTCs that consist mostly of rotated and translated blocks,

Artificial intelligence (AI) based geological feature mapping: A case study from KG Basin

thrust blocks, and chaotic facies. Another interesting feature is the erosional shadow remnants (ESR) that are remnants of the erosion process.

Study Area

The study area falls in the Krishna Godavari (KG) basin on the eastern margin of India. Figure 2 shows the regional map of the Krishna Godavari basin with the study area highlighted in yellow. This highlighted area is characterized by extensive mass transfer deposits formed by the sliding and slumping of river sediments during the Mio-Pliocene epoch (Forsberg et al., 2007; Ramana et al., 2009; Shanmugam et al., 2009; Ramprasad et al., 2011).

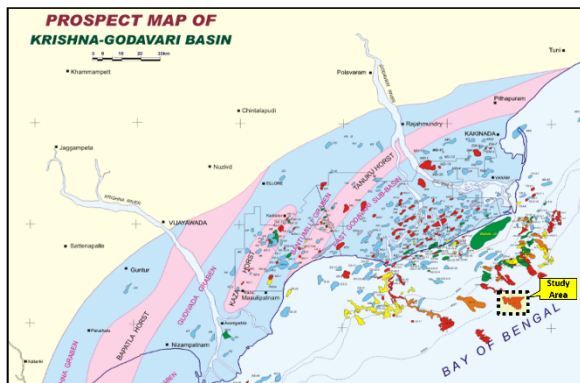


Figure 2. Basemap showing the study area in yellow

As already discussed, mapping MTCs is crucial for hydrocarbon exploration as they have both reservoir and seal potential (Alves et al., 2014; Cardona et al., 2016). They also represent a drilling hazard as they are often over-consolidated compared to unfailed sediments (Shipp et al., 2004). In the present study area, there is proven hydrocarbon in Mio-Pliocene but to explore deeper plays below MTC, mapping of MTC becomes important geo-technically.

Workflow

The proposed workflow for MTC mapping using an AI-based approach is demonstrated in Figure 3. There are seven key steps in the workflow out of which the first three cater to training data generation, the next two steps (4&5) correspond to model training and inference, and the last two steps correspond to the

post-processing of probability volume and subsequent extraction of top and bottom horizons of MTC.

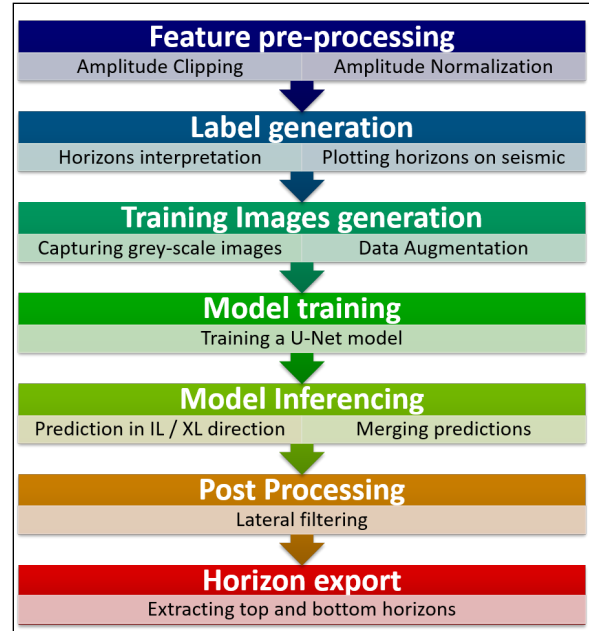


Figure 3. AI-based workflow to map geological bodies like MTC from seismic data

1. Feature preprocessing:

The first step in the workflow is feature preprocessing consisting of two steps viz., outlier removal to retain only 99% of amplitudes followed by normalization of the amplitudes to bring them between -1 and +1. This pre-processing step is to ensure the consistency of the training data seen by the U-Net model and its generalization.

2. Label generation:

Label generation is the most crucial part of this workflow that involves the manual interpretation of horizons corresponding to the top and bottom of MTC on a few inlines and crosslines. Once the horizons are interpreted, they need to be plotted on seismic sections and the samples between them need to be assigned the value of one (presence of MTC) and the rest of the samples are assigned the value of zero.

Artificial intelligence (AI) based geological feature mapping: A case study from KG Basin

3. Training Images generation:

Since the workflow uses supervised learning, the model needs to be trained using a pair of images corresponding to the feature and label. Figure 4 shows a seismic image (left) and its associated target label (right) that acts as a single training data point. The generation of the grey scale training images is done by a Python script to ensure the consistency of the image dimensions.

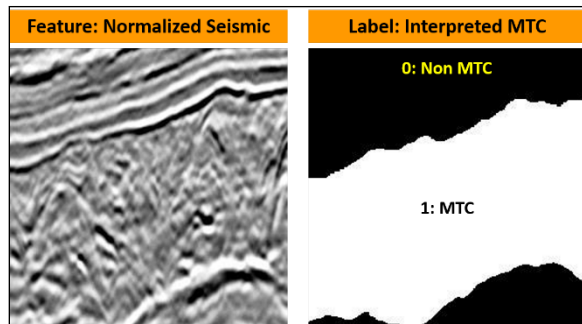


Figure 4. Example of training data: feature (left) and label (right)

To increase the number of training images, a mathematical transformation is also applied to the training data known as data augmentation (Figure 5). This process has led to the increased efficacy of the trained ML models. Some common data augmentation techniques include rotation, flipping, the addition of noise, random crop, etc. Currently, rotation operation has been applied on the dataset with five rotations viz. 11, 22, 45, 90, 135 degrees to generate 15360 training images from 2560 original training images.

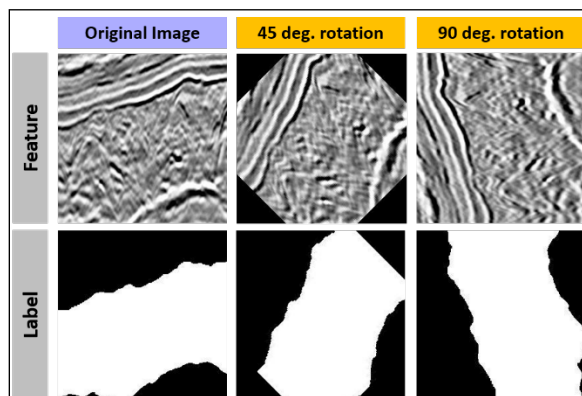


Figure 5. Example of data transformation: Rotation by 45 and 90°

4. Model Training:

Once the training images are ready, the next step in the workflow is to train a machine-learning model to be used for MTC prediction in 3D space. There are a lot of image segmentation architectures, but the one most commonly used in segmentation tasks is the U-Net (Figure 6) developed by Ronneberger et.al.

During the model training stage, it is important to fine-tune the hyper-parameters like the number of filters used, filter size, type of padding, stride, etc. Once all these hyper-parameters are optimized, the model is ready to be trained for MTC prediction using the training images and labels.

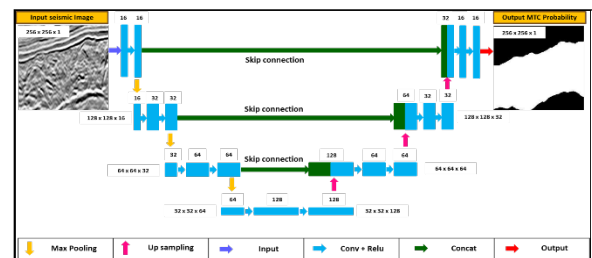


Figure 6. U-Net model to be used for MTC prediction in 3-D space

5. Model Inference:

In this step, a seismic volume is given as input to the U-Net model trained in the previous step to obtain a 3D MTC probability volume as shown in Figure 7.

The process of model inference or prediction is currently applied twice on a seismic volume viz., once in the inline direction and the other in the cross-line direction. The idea of scanning the seismic in multiple directions and combining the results stems from the fact that the lateral extension of a particular feature could be better illustrated in a particular direction. To get better results, it's always advisable to scan the object (MTC) from multiple orientations before concluding.

Artificial intelligence (AI) based geological feature mapping: A case study from KG Basin

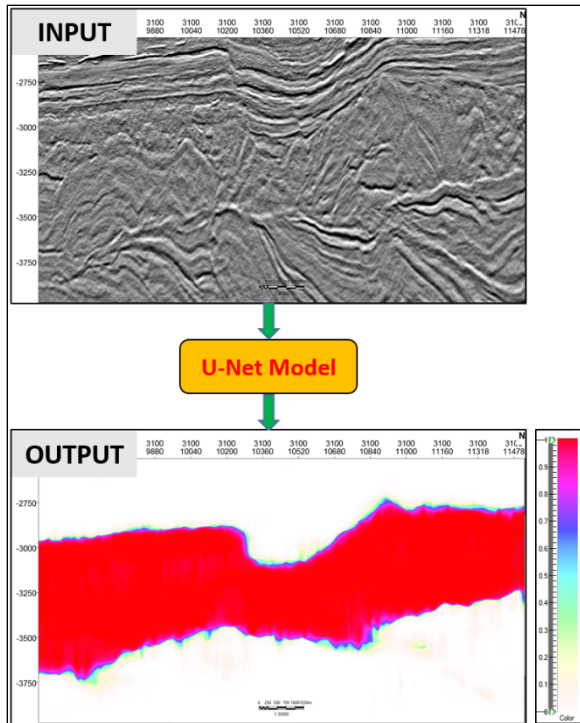


Figure 7. Prediction of MTC probability in 3D space: Input seismic after passing through the U-Net model

A geological body can also be extracted from the MTC probability volume which is demonstrated in Figure 8. It can be seen that a post-processing step needs to be incorporated into the workflow to improve the lateral continuity of geobody before extracting horizons from it.

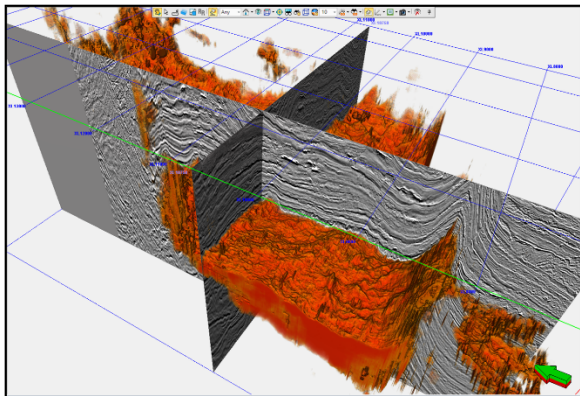


Figure 8. MTC extracted using an AI-based method in 3D space

6. Post Processing:

As already mentioned, two probability volumes are generated by performing model inference in two directions i.e., Inline and Cross line. For performing horizon extraction, a single probability volume would be required which has the information contained in both volumes. To get a single volume from the two directional volumes, two operations were tested:

- Sample-wise average
- Sample-wise maximum estimate

Sample-wise “Maximum” operation yielded better results than that of mean operation and hence the two directional volumes were merged using the sample-wise maximum operation.

A lateral filtering process is also required to smoothen the merged probability volume before going for horizon extraction. The laterally filtered volume can be used to extract the horizons corresponding to the top and bottom of MTC.

7. Horizon Export:

The horizons that were auto-extracted from the laterally filtered probability volumes had some spikes since the MTC probability volume generation step is completely seismic-driven. To remove these spikes, manual editing of the horizon is required. Refining the auto-extracted horizons doesn’t need much time and effort. Subsequently, time contour maps can be generated for the top and bottom of MTC as shown in Figures 9 & 10.

The basal surface of MTC deposits seen in Figure 9 has a stair step configuration towards the north of the study area which is a typical feature of the base of MTC. Overall, the reflector corresponding to the MTC bottom varies spatially from planar, to erosional, to stair step.

On the other hand, the top surface of MTC (Figure 10) is irregular and is eroded by overlying channels and related deposits.

Artificial intelligence (AI) based geological feature mapping: A case study from KG Basin

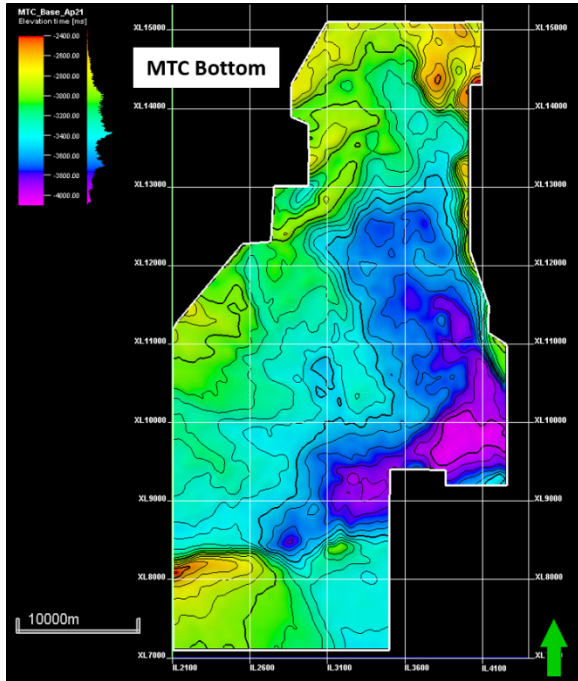


Figure 9. Time map (TWT) close to MTC Bottom

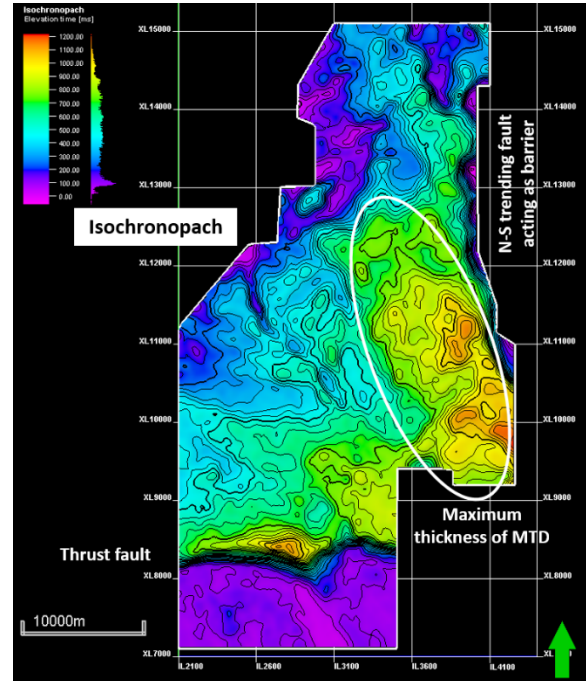


Figure 11. Isochronopach map depicting the thickness of MTC in the time domain

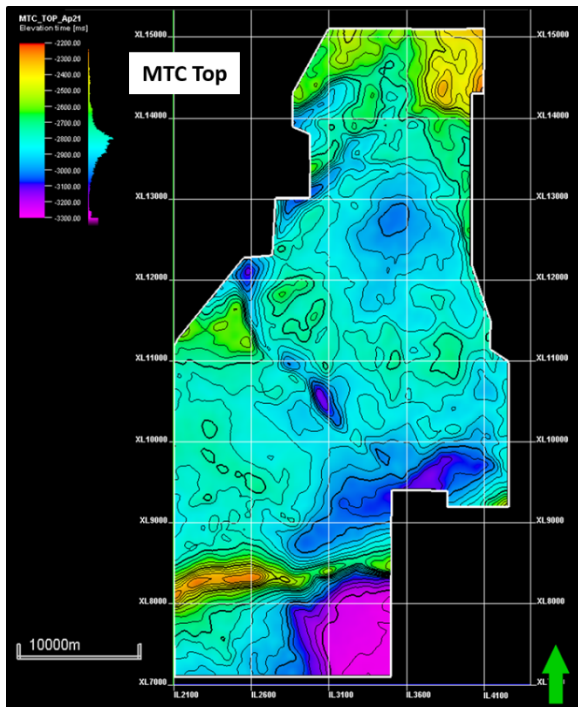


Figure 10 Time map (TWT) close to MTC top

Two major faults: the N-S trending eastern fault, and the East-West trending southern fault can be seen in the isochronopach map (Figure 11). Both these faults have a major control on the mass transport deposition since the thickness beyond these faults is quite negligible.

Comparison of AI-based results with that from earlier approaches

Figure 12 demonstrates the main benefit of utilizing the CNN-based (AI) approach. The surfaces in black have been generated after gridding the coarsely picked horizon (conventional approach). On the other hand, the surfaces in yellow are from the AI-based approach. It can be seen that the AI-based surfaces honor the seismic data much better than the gridded surfaces (black).

Mapping the top and bottom of geo-bodies like MTC has to be done in a very fine grid manually since auto-trackers fail to pick them. This is where the AI-based approach could come in handy eliminating the need to manually pick horizons in a very fine grid.

Artificial intelligence (AI) based geological feature mapping: A case study from KG Basin

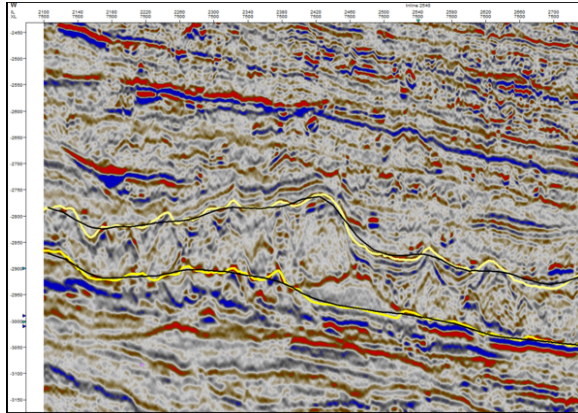


Figure 12 Comparison of MTC surface extracted through AI-based approach (yellow) with that from conventional approach (black)

Conclusion

A deep learning-based workflow has been developed to automate the task of mapping geological bodies, with a focus on mass transport complexes. This workflow can also be extended to map other geological features like gas chimneys, and salt domes just by retraining the base model using training data corresponding to the desired features, using transfer learning.

Key to our approach is the ease of training data generation which requires only the seismic data and the horizons interpreted on a few lines. The second advantage is the data-driven approach that provides a fairly accurate depiction of the lateral extent of the subsurface geo-bodies in a quick time. This process can be used as a starting point to extract surfaces corresponding to the top and bottom of the geological body which can be further refined by the user.

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Acknowledgments

The authors are thankful to the management of Oil & Natural Gas Corporation Limited (ONGC) especially GEOPIC for providing the opportunity and dataset to carry out this project. The authors would also express their gratitude to all the staff posted at GEOPIC for their support extended during the various stages of the project in the form of technical, software, hardware, and human resources.

The views expressed in this paper are solely those of the authors and need not necessarily be that of ONGC.