Using a self-growing neural network approach to CCS monitoring

Camille Msika[1]* and Ross Findlay[1] show how a machine-learning workflow based on a Self-Growing Neural Network (SGNN) is an efficient and unbiased scanning tool for CCS monitoring, enabling faster identification of the confinement system.

Background

In carbon capture and storage (CCS) projects, monitoring of the storage site after CO_2 injection is crucial to understanding its evolution and verifying there is no major loss of containment from the intended storage reservoir. Time-lapse seismic data provides images of the storage area at different times, highlighting any spatial variations due to fluid migration. However, it can be difficult to know which attributes to apply, and it may be tedious to manipulate a large number of attributes for each time-lapse volume.

Using different seismic vintages from the Sleipner Field dataset (courtesy of Equinor), this article shows how a machine learning workflow based on a Self-Growing Neural Network (SGNN) is an efficient and unbiased scanning tool. When it comes to CCS monitoring, it enables the interpreter to quickly identify the evolution of the confinement system without the need for long quantitative workflows. Analysis of the confinement system includes CO_2 migration inside the storage formation as well as subtle variations in the seal which may be missed by traditional seismic attribute analysis.

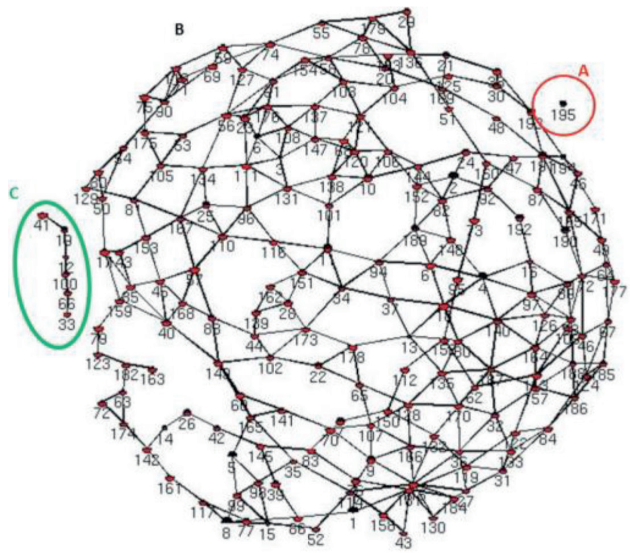

Figure 1 Projection of network topology on a disc during the learning process. (A) Neuron 195 will be eliminated from the network as it does not connect to other neurons. (B) The main network maintains edges between neurons. The edges evolve during the iterations. All the neurons do not have the same number of topological neighbours. (C) The network is already separated into two sub-networks: a massive network in the centre of the picture (B) and a linear satellite on the left.

Methodology

The AspenTech Attribute Clustering workflow utilises machine learning to create a facies volume and associated probability volumes. It uses a Self-Growing Neural Network (SGNN) – an unsupervised incremental machine learning algorithm. This is sometimes also known as Growing Neural Gas (Fritzke, 1995) because the model uses a vector-based network where the neurons behave like a gas during the training process.

The training dataset is composed of a number of seismic or attribute volumes. During the training process, the growing neural gas model is used to generate initial neuron sets which are representative of the training dataset. The process starts with two neurons connected by a vector in an n-dimensional crossplot, with each axis representing an attribute. The location in the cloud of these two neurons is then compared to a sample from the training dataset. The closest neuron may be moved, thus also modifying the location of the connected neuron, and a new neuron may be added as needed to best describe the data from the training dataset. The process continues with the neurons continually being modified as samples are selected from the training set and compared to the neuron set. Over time old edges connecting neurons may disappear if the connected neurons are no longer nearest neighbours. When a neuron becomes isolated it is deleted from the neuron set. The resulting neurons are then clustered using a hierarchical clustering method into neuron clusters known as classes, based on their data similarity.

These classes are then used to classify all the samples in the dataset and propagated onto the seismic data to create a classification volume. With this methodology it is possible to focus the clustering on anomalies (Hami-Eddine, 2012).

Data

Carbon capture and storage has been performed at the Sleipner Field in the North Sea since its first injection in 1996 (Furre et al, 2017). Equinor has made a 4D dataset publicly available

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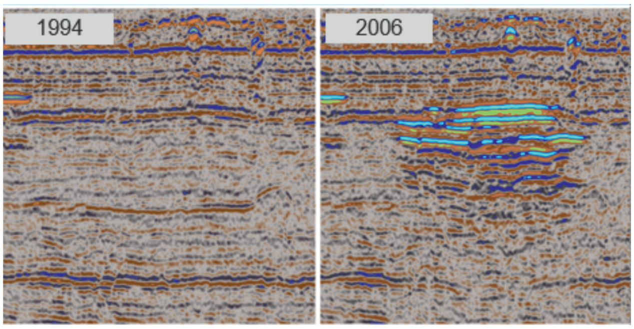

Figure 2 Comparison of seismic amplitude volumes before CO_2 injection in 1994 and after several years of injection in 2006.

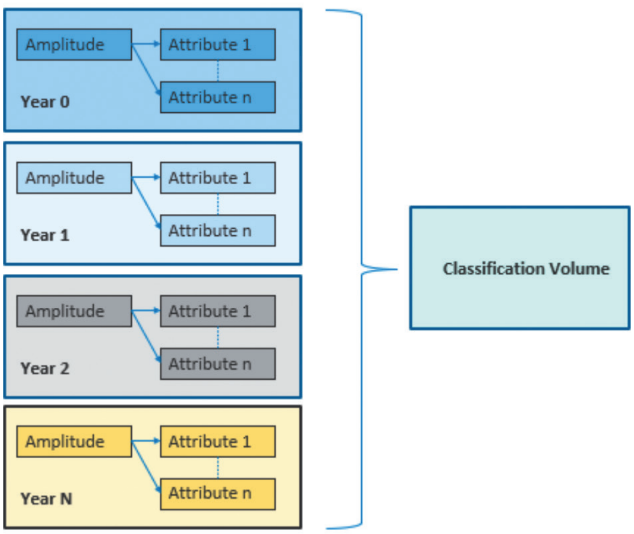

Figure 3 Volumes inputted into Self-Growing Neural Network (SGNN).

with a number of seismic volumes acquired between 1994 and 2010. This study uses seismic data from four vintages: 1994, 2001, 2004 and 2006. These were chosen because they were all reprocessed in 2007 and therefore the differences between the vintages related to processing should be minimised. Figure 2 shows two of these amplitude volumes – the 1994 baseline survey before injection and the 2006 survey after around ten years of injection of CO_2.

A combination of structural and stratigraphic seismic attributes was calculated for each of the four time lapse seismic volumes for input to the classification workflow.

Figure 3 shows how this classification workflow can be run using multiple vintages as input. In a carbon capture and storage scenario these anomalies can represent changes between the time-lapse seismic volumes related to injection. Alternatively, the SGNN classification can be run separately for each vintage, allowing comparison of anomalies over time. In this case study these techniques have been used to monitor the changes observed in two intervals – the reservoir and the caprock.

Reservoir monitoring

The analysis first focused on the reservoir interval, in which evident variations can be observed as shown in Figure 2, to generate one unique output aimed at highlighting the different variations over time due to injection.

RMS amplitude volumes were calculated from the 1994, 2001, 2004 and 2006 vintages and were found to give better results when inputted into the SGNN workflow rather than the original amplitude volumes. A time slice of the resulting classification volume is shown in Figure 4. This process highlights any anomalies, including those which are associated with injection. The number of output classes can be modified depending on the desired results. In this case, the use of seven classes was found to give the best result.

Thanks to the different classes represented by the associated colours, it is possible to see the extent of the CO_2 plume around the 15/9-A-16 injector well at the different times. In this case, it shows predominantly blues, purples and reds, representing Classes 2, 5, 6 and 7. Additional anomalies further away from the injection site can also be seen. These are predominantly shown in green representing Class 4.

A parallel plot is a useful tool for better understanding the meaning behind these classification results (Figure 5). This provides a quick way of visualising how the values of each facies class correspond to each input volume.

Each vertical line in the parallel plot represents a different input volume to the SGNN workflow. In this case each volume was acquired at a different time, earliest on the left and most recently on the right. The vertical axis shows the range of values. These have been equalised in order to aid interpretation of the plot.

Each line that goes from left to right and intersects the vertical axis represents a data point from the neuron set. These are colour-coded according to their class.

Figure 5 shows four of these classes representing three different categories:

The first category is a **background class** as represented by Class 1 in the brownish-red colour. This appears flat, with normalised values of around 0. This means that there is no specific seismic response or difference in values between input volumes; therefore, it can be said that this does not alter over time. This class is not significant for this evaluation but may be useful as a reference to compare to other classes.

The second category can be referred to as a **consistent anomaly**. In this case the values of the class are not zero, but they do not vary significantly between input volumes (representing different acquisition times). An example of this is Class 4 shown in green in Figures 4 and 5. In this case it can be interpreted that this is an anomaly which is present in the 1994

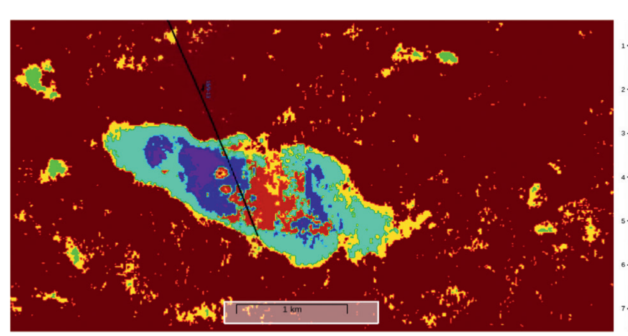

Figure 4 SGNN classification result over the reservoir calculated for the four vintages (94, 01, 04 and 06). The different seismic facies highlight anomalies, including the variations in vintages related to the CO_2 injection.

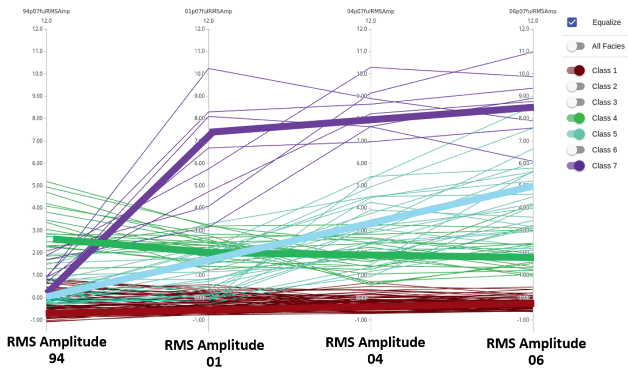

Figure 5 Parallel plot presenting amplitude variations through time; each facies class shows background (Class 1), consistent (Class 4) and evolving anomalies (Classes 5 and 7).

baseline survey and does not change substantially in subsequent volumes. Therefore, it can be interpreted as being unaffected by injection.

The third category can be referred to as **evolving anomalies.** In this case the attribute values vary between volumes and thus represent a change over time due to injection. Examples of this category are Class 5 in pale blue and Class 7 in purple in Figures 4 and 5.

We can therefore see that the classes associated with the main CO_2 plume (e.g. Classes 5 and 7) change over time as injection continues. However, the green anomalies away from the injection site (Class 4) do not vary on the parallel plot and therefore can be seen to have a consistent value over time. These are interpreted to be associated with small natural gas accumulations (Chadwick et al, 2014) which can be seen in the 94 volume and have not been introduced or affected by injection.

With this methodology, the interpreter can focus on interpreting the classes. The different classes are results of the algorithm, meaning there are no intermediate steps requiring manual input, which can be tedious and generate bias in the analysis (for example, defining polygons or relationships needed in other quantitative workflows). Thus, this approach streamlines and unbiases the monitoring workflow.

This analysis has shown how the SGNN classification workflow can be used for 4D monitoring, focusing on the reservoir interval where large variations are observed. The analysis can then be performed for the seal of the confinement system.

Seal monitoring

Seal integrity monitoring focuses on variations above the reservoir to verify there is no major loss of containment. In the case of CO_2 leakage into the caprock, two things would be expected – new vertical features (such as chimneys going from reservoir to caprock) or accumulations which would be represented by horizontal features consistent with the geology.

As with the reservoir interval, classification can be run for the overburden using multiple vintages as input. In this case, SGNN classification was first run for the overburden interval using RMS amplitude and a structural attribute for the four vintages. Various structural attributes were tested and the Fault Likelihood attribute (Hale, 2013) was found to be the most effective at capturing structural variations. Potential leakage pathways may be difficult to capture with conventional geometrical attributes, whereas this attribute allows the identification of subtle faults and fractures most likely to occur in caprock lithologies. The resulting volume is shown in Figure 6 for a horizon slice 50ms above the top reservoir.

The parallel plot analysis can again help to interpret the classification result (shown in Figure 7 for selected classes). On the lefthand side of the parallel plot are the RMS attributes for the various vintages, while the righthand side shows the fault likelihood attributes. In this case it can again be observed that the background class (Class 1 in brownish red) does not vary between volumes. The other classes have a plateau-like appearance with little variation between the different vintages for the different types of attributes – RMS amplitude and fault likelihood. These can be considered consistent anomalies within these groups of attributes.

This indicates that anomalies correspond to features present prior to the injection and show little variation over time. The Class 7 in this case can be seen to represent the natural gas accumulations outside the injection area, whereas the Class 4 do appear to be present above the injection site. We can, however, say that these features appear to be unaffected by injection. In this case, no evolving anomalies where values change over time can be identified.

As the methodology enables the integration of a large number of inputs, it was decided to investigate whether additional attributes could help to refine and increase confidence in the results.

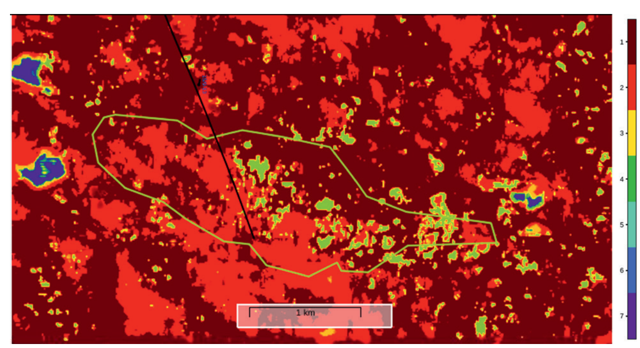

Figure 6 SGNN result for the four vintages on a horizon slice 50ms above the top reservoir. This highlights any anomalies, including the gas chimney features (shown in blue and yellow) which can be observed in the pre-injection 1994 vintage seismic. The extent of the injected CO_2 (from 06 volume) is shown by the green polygon.

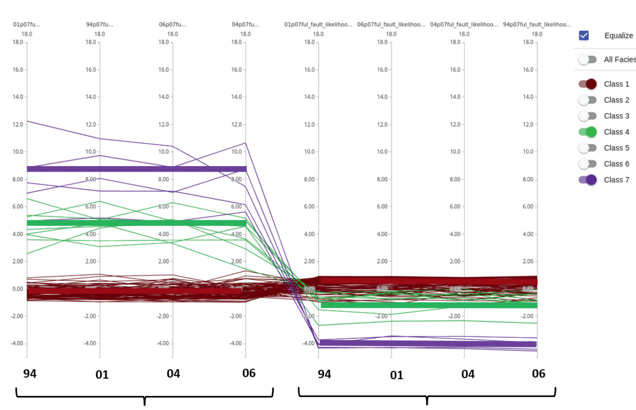

Figure 7 Parallel plot presenting no major variations through time for the background (1), or the anomalies (e.g. 4, 7).

Certain features or fluids may be more apparent at particular frequencies. Consequently, spectral decomposition volumes may detect image anomalies which the other attributes may not. Therefore, five spectral decomposition volumes were generated for each vintage and incorporated in the SGNN classification alongside the RMS and fault likelihood volumes. The number of classes was raised from 7 to 15 to provide additional details. The refined classification results are shown in Figure 8.

In this new classification a similar pattern can be seen; however, as the anomalies are now represented by more classes, a more granular analysis is perceived. Additionally, the overall image is cleaner, with more distinction between the anomalies of interest and the background. For example, the Class 2 anomalies seen in Figure 6 are now largely incorporated into the background class.

Outside the lateral extension of the injected CO_2

In this new classification result the gas accumulation outside the injection area is represented by several classes – the most laterally extensive of which are Classes 15 and 12. The characteristics of these classes can be better understood by viewing them on a parallel plot.

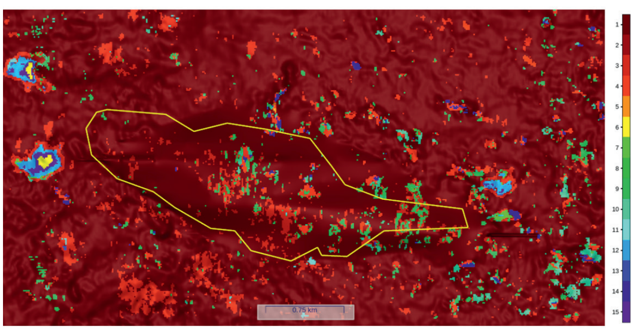

Figure 8 SGNN result including spectral decomposition on a horizon slice 50ms above the top reservoir. The extent of the injected CO_2 (from 06 volume) is shown by the green polygon.

The parallel plot in Figure 9 shows some of the classes associated with the previously identified natural gas accumulations. Due to the additional input volumes and classes, the parallel plot is now significantly larger; however, changes through time can still be evaluated by checking whether an attribute is background, evolving or consistent within the groups of attributes. The classes associated with the gas accumulations (Class 12 and Class 15) show increasing response associated with higher frequencies. When considering the variation of each attribute between the vintages, these again do not show much variation. They have a flat appearance; therefore these can be classed as consistent anomalies which have been unaffected by gas injection.

Inside the lateral extension of the injected CO_2

In Figure 8 some small anomalies can be detected above the area where injection has taken place. In this new classification, these anomalies are represented by different classes e.g. 3, 9, 10 and 14. Figure 10 shows the parallel plot comparing these classes with Class 15, which has been associated with the natural gas accumulations described in the previous analysis.

The first thing that can be noted is that these anomalies (Class 9 in green, Class 10 in blue, Class 3 in red) have a significantly different characteristic than the natural gas accumulations (Class 15 in purple). There is no notable variation between the different frequencies and RMS is low, whereas the gas accumulations show higher RMS amplitudes and variation between the low and high frequencies. Additionally, there is no significant variation for each attribute between vintages; therefore these classes can be regarded as consistent anomalies.

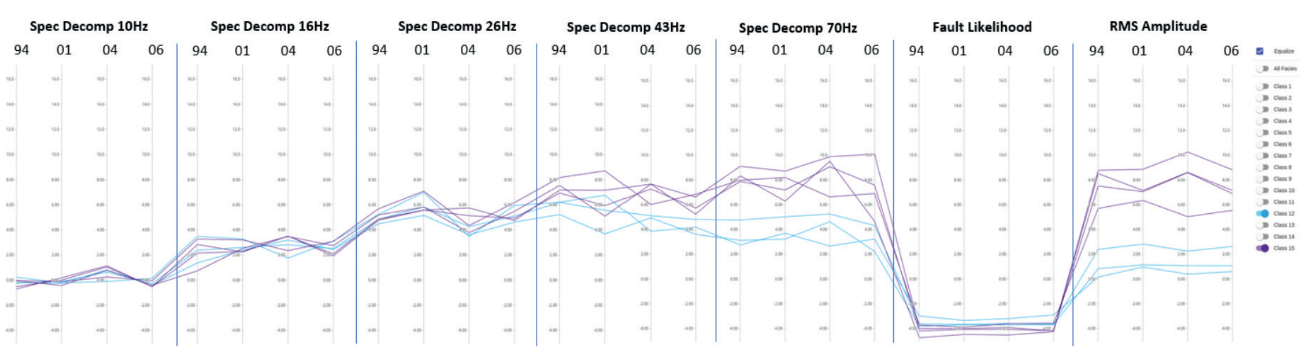

Figure 9 Parallel plot showing classes associated with natural gas accumulations.

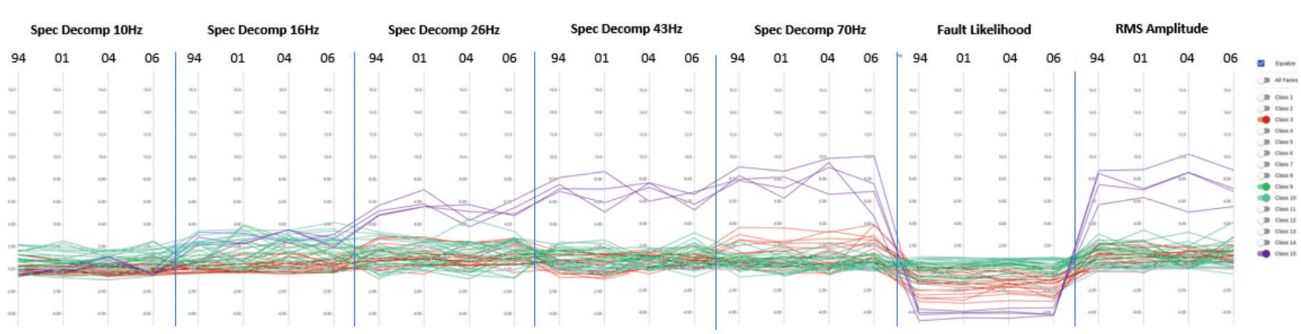

Figure 10 Parallel plot showing comparison of class 15 associated with natural gas accumulations and other anomalies.

In summary, the classification interpretation over the seal interval shows the following characteristics:

- Any anomalies appear to be present in the pre-injection base survey.
- No evolving anomalies, which would be characterized by variations for a given attribute over time such as those identified in the reservoir interval, were identified.
- Classification volume visualisation and analysis do not reveal any proof of significant new vertical features, lateral extension indicative of leakage or a fracture network.

This increases confidence that there has been no leakage from the reservoir.

Conclusion

This article describes how the AspenTech unsupervised SGNN classification can be used in a CCS case for two objectives: monitoring the evolution of the CO_2 migration inside the storage formation, and seal integrity.

Running classification on the reservoir interval clearly shows the extent of injected CO_2 and how this varies with time. The parallel plot is shown to be an important tool where different types of anomaly can be identified – e.g. consistent or evolving.

When the same process is applied to the caprock interval, anomalies can be identified. Analysis of the parallel plot shows that different anomalies have different characteristics; however, all identified anomalies in this case are present in the original 1994 baseline volume and therefore do not appear to be due to injection.

This methodology is an efficient scanning tool for CCS monitoring, providing a simple way of combining multiple vintages and attribute volumes, and outputting a single classification volume for a streamlined interpretation. The result is free from interpreter bias and can allow the identification of even subtle features which may have been missed by conventional 4D analysis.

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