Diffraction denoising using self-supervised learning

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Abstract
Diffraction wavefield contains valuable information on subsurface composition through velocity extraction and sometimes anisotropy estimation. It can also be used for the delineation of geological features, such as faults, fractures and mineral deposits. Diffraction recognition is, therefore, crucial for improved interpretation of seismic data. To date, many workflows for diffraction denoising, including deep-learning applications, have been provided, however, with a major focus on sedimentary settings or for ground-penetrating radar data. In this study, we have developed a workflow for a self-supervised learning technique, an autoencoder, for diffraction denoising on synthetic seismic, ground-penetrating radar and hardrock seismic datasets. The autoencoder provides promising results especially for the ground-penetrating radar data. Depending on the target of the studies, diffraction signals can be tackled using the autoencoder both as the signal and/or noise when, for example, a reflection is a target. The real hardrock seismic data required additional pre- and post-autoencoder image processing steps to improve automatic delineation of the diffraction. Here, we also coupled the autoencoder with Hough transform and pixel edge detection filters. Along inlines and crosslines, diffraction signals have sometimes a similar character as the reflection and may spatially be correlated making the denoising workflow unsuccessful. Coupled with additional image processing steps, we successfully isolated diffraction that is generated from a known volcanogenic massive sulphide deposit. These encouraging results suggest that the self-supervised learning techniques such as the autoencoder can be used also for seismic mineral exploration purposes and are worthy to be implemented as additional tools for data processing and target detections.

KEYWORDS
autoencoder, deep learning, diffraction, ground-penetrating radar, mineral exploration, self-supervised

INTRODUCTION
Deep-learning methods are quickly becoming a part of seismic and ground-penetrating radar (GPR) data processing and interpretation workflows. They are used, for example, for noise attenuation (e.g. Birnie et al., 2021; Liu et al., 2022; Ni et al., 2022; Saad & Chen, 2020, 2021; Song et al., 2020), wavefield decomposition (e.g. Bauer et al., 2021; Lowney et al., 2021; Ma et al., 2020) and pattern recognition, such as strata, first breaks and faults, which correspond to either geological features or small-scale objects (e.g. Dell et al., 2020; Dou et al., 2017; Markovic et al., 2022b; Puzyrev & Elders, 2022; Tschannen et al., 2020). With the fast development of deep-learning algorithms, the self-supervised learnings, such...
as the autoencoder, have become popular because of their ability to exclude manual labelling of features of interest in the training step. The autoencoder technology offers a fast way to denoise an image (e.g. seismic section), particularly when there is enough dataset for data training. The best performance of the autoencoder application is showcased when there is a good correlation between the features in a seismic section, such as reflection signals, found in sedimentary geological settings (e.g. Dell et al., 2020; Bauer et al., 2022; Puzyrev & Elders, 2022). However, in hardrock or crystalline-rock geological settings, reflectivity and diffractivity patterns are not correlated as those of in the sedimentary settings because of strong heterogeneity, short reflectivity and poor signal-to-noise ratio (e.g. Adam et al., 1997; Bellefleur et al., 2012; Khoshnavaz et al., 2016; Donoso et al., 2021; Malehmir et al., 2021; Malehmir & Bellefleur., 2009, Manzi et al., 2012; Markovic et al., 2020; Westgate et al., 2021). Therefore, it can be challenging to employ the autoencoder, for example, for the wavefield decomposition and noise separation.

In this study, we focus on employing the autoencoder algorithm and forming a workflow for diffraction signal denoising and detection for hardrock seismic and GPR datasets. As a proof of concept, we first showcase the workflow using synthetic seismic data in a high-velocity medium (5900 m/s; resembling a crystalline rock setting) contaminated with both random and coherent noises. With minor adaptations, we then employ the workflow to a real GPR and a 3D hardrock seismic dataset. The focus was on diffraction signals because they might be generated from metallic deposits and are sometimes a good target for mineral exploration. The GPR dataset showcases the possibility of using the autoencoder either to treat diffraction signal as signal or noise depending on the target of the investigation, for example, when reflection signals are aimed to be enhanced. The 3D hardrock seismic dataset used in this study contains several diffraction signals, and one is generated from a volcanogenic massive sulphide deposit.

Considering the complexity of geology in hardrock environment, in our work, we additionally couple the Hough transform and pixel edge detection on top of the autoencoder to enhance the autoencoder-denoised solution for automatic picking of diffraction patterns. The Hough transform has been used for the detection of linear features in seismic data, and it is usually applied for seismic data interpretation, such as mapping faults or fractures (e.g. Chen et al., 2018; Wang & AlRegib, 2014; Jacquemin & Mallet., 2005; AlBinHassan & Marfurt., 2003) or detecting salt bodies (Orozco-del-Castillo et al., 2011). In our case, we use the Hough transform for circular pattern detection.

Our main objective, therefore, is to illustrate that the autoencoder has a good potential for diffraction enhancement; however, depending on cases, different strategies and adaptations are required. The paper comprises three pillars, starting with a short description of the autoencoder followed by its application to a synthetic seismic dataset, after which real GPR and seismic datasets are tested. Shortcoming and future possibilities are covered in the ‘Discussion’ section.

**CONVOLUTATIONAL AUTOENCODER ARCHITECTURE AND THE PROOF OF CONCEPT**

The self-supervised deep learning, in general, is based on the determination of a hidden pattern, or closeness, in the data. They help to avoid human involvement in the labelling of the data for training purposes. Autoencoders are among deep-learning solutions that benefit from this criterion (i.e. similarity pattern). For a successful implementation, it is crucial to have a clear and accurate representation of the features to be recognized during the training process, as well as an adequate amount of training images. The architecture of the autoencoder consists of an encoding part, which learns the best representation of the data using the convolutional neural networks and compresses the data through a latent space (Bank et al., 2020). The latent space is the reduced space that contains the most important feature of the data, which in our case is redundant features that is input into the autoencoder through the training step. The training session enables the network (model) to learn to differentiate which part belongs to signal and which part to noise. The encoder learns and maps the data in the latent space, which is a compressed representation of the signal. The decoder then projects the latent space into reconstructed signal, which contains the most useful information of the signal (Figure 1). Often an interpolation method is used for this reconstruction.

The above-mentioned autoencoder architecture can be described in a simplified mathematical representation (e.g. Azarang et al., 2019) using the following equations:

\[
\phi : \mathcal{X} \rightarrow \mathcal{F},
\]

\[
\psi : \mathcal{F} \rightarrow \mathcal{X},
\]

\[
\phi, \psi = \text{arg} \min_{\phi, \psi} \| \mathcal{X} - (\phi \circ \psi) \mathcal{X} \|^2,
\]

where Equation (1) represents the encoding function \( \phi \), and decoding function \( \psi \) is shown in Equation (2). The \( \mathcal{X} \) is the input data, and \( \mathcal{F} \) is the latent space. The output or autoencoder, in Equation (3), selects the encoder and decoder functions in such a way that requires the minimal information to encode the input image to be recreated in the output. Essentially, autoencoders are means to pass the most important information using their reduced sizes as initially developed for compressed data work applications.

There are several types of autoencoders, and for this study, we built the convolutional autoencoder with Keras using 2D...
The aforementioned autoencoder architecture was then applied as a proof of concept to a synthetic seismic dataset. For the synthetic dataset, we created over 150 zero-offset sections, which was sufficient to demonstrate the autoencoder workflow. The synthetic seismic sections were generated using a 50-Hz Ricker wavelet and 10 m trace spacing (Karimpouli et al., 2015). A 1D convolutional approach was used to reduce the computational time meaning that the amplitudes are not properly preserved nor represented here. A velocity of 5900 m/s, to represent some of our hardrock datasets (e.g. from Sweden and Canada), was used to calculate the diffraction travel times at different positions within the sections (Markovic et al., 2022a). In order to test the autoencoder denoising algorithm, the generated zero-offset seismic sections were contaminated with random noise (Gaussian-type distribution) such that

\[
data\ noise = true\ data + (rand \times true\ data\ size - 0.5) \times noise\ percentage,
\]

where the random noise is generated within the size of the true data, and its intensity is controlled by a fraction (noise percentage) of maximum amplitude amplitude of the true data. On top of the random noise, a randomly distributed coherent (von Karman-type distribution with a correlated scale length) noise was also added (Cheraghi et al., 2013).
FIGURE 2  Two common ways of representing denoised images using pixel (from zero to one) or waveform amplitudes. A tile example of (a) original input, (b) noise model and (c) autoencoder denoised (using pixel values) synthetic diffraction signals with mixed random (Gaussian model) and coherent (von Karman model with a prespecified scale length) noises. Yellow arrows in (c) point at the tails of one of the diffraction hyperbolas within a tile. The yellow-shaded area in (c) marks two diffraction tails crosscutting each other where the signal is still clear after the denoising. (d and e) Tiles of the original and predicted noise converted to waveforms, and (f) the difference between the two where the yellow-shaded area is more attenuated, however, using the waveform representation the overall diffraction signal quality appears much better.

The autoencoder-denoised tiles for some of the sections are shown in Figure 2. Most of the coherent noise was successfully predicted, and after the removal, diffraction signal was well preserved and better delineated even in the parts where coherent noise was completely masking the diffraction signal.

The signal output in this case (Figure 2c) is the absolute subtraction of the original input image (tile) and the predicted noise of the input image (tile). The absolute subtraction is performed to convert the pixels with negative values to positive values, whereas the regular subtraction would turn negative pixel values into zero value. The input tile and predicted noise were then converted from image to a waveform section (Figure 2d,e) and subtracted as if they were seismic sections. The results (Figure 2f) show that there are zero values in some of the regions, as the input and predicted data have similar amplitudes. Although the diffraction signal appears not continuous in the denoised section, the advantage of the image-to-waveform conversion is that it is possible to better visualize the results of the autoencoder.

REAL DATA EXAMPLES

To showcase and validate the convolutional autoencoder on real data, we employed the algorithm on 2D ground-penetrating radar (GPR) and 3D hardrock seismic datasets. All real case datasets were used to study the autoencoder performance both when the diffraction is evidently strong and when the diffraction has similar amplitude strength (pixel value) as the reflection. Signal output for the GPR datasets was calculated by subtracting the image-to-waveform converted input data from the predicted noise data. The hardrock seismic data signal output was obtained through the subtraction of the input image from the predicted noise, resulting also in negative pixel values, which were automatically assigned a zero-pixel value (i.e. black colour). The image domain was kept for this dataset as the additional image processing tools were used, including the Hough transform for circular pattern detection.

Ground-penetrating radar dataset

The first GPR section contains a pronounced diffraction signal. Before passing it through the autoencoder algorithm, we applied a static shift to the dataset to remove the strong clutter noise dominating the signal. This helped enhanced the diffraction and enabled the autoencoder to better find a spatial correlation and delineation of the diffraction. The input section (image) was broken into tiles of 256 × 256 pixels with an overlapping of 64 pixels. This was an optimal tile dimension to choose in order to capture the signal within the tile (Figure 3). We then converted the input image and the predicted noise to a waveform section. The predicted noise (Figure 3b) included parts of the signal especially around its
FIGURE 3 A simple and real ground-penetrating radar (GPR) autoencoder denoised image-to-waveform converted data where (a) and (d) represent the original input, (b) and (e) are the predicted noise and (c) and (f) are the autoencoder-denoised diffraction signal. Yellow arrows in (d) and (f) point at the tails of the diffraction hyperbolas, which are not contained in the noise model. The autoencoder performs well as enhances tails of other possible weaker diffraction signals.

apex where the signal has the strongest amplitude. Nonetheless, the denoised tile shows a well-delineated diffraction (Figure 3c). Interestingly, the predicted noise model does not contain any diffraction signal where the signal amplitude is weaker at, for example, the tails (Figure 3e), and the denoised tile clearly retains the diffraction tails (Figure 3d).

The second GPR dataset used to test the autoencoder was collected along a concrete bridge deck for its stability assessment. In this case, we were interested in the autoencoder performance only for diffraction separation (denoising) rather than using it directly for the bridge evaluation proposes (e.g. Pashoutani et al., 2021). For the data training, we used both mixed low-noise level contaminated with the GPR sections and a few similar sections collected along the same bridge deck. The section was broken into tiles of 128 x 128 pixels due to the overall size of the section. The tiles were set to overlap at every 16 pixels, which significantly enlarged the number of training images (tiles). The tiles were assembled again into the section, and we were able to observe the autoencoder solution along the whole GPR section (Figure 4). Compared to the first GPR example, the predicted noise includes mainly reflection signals (Figure 4b), and the denoised section contains dominantly diffraction signals (Figure 4c). Here, it was also possible for the autoencoder to take the reflection signals as noise, which is interesting because if a reflection is of an interest, then the noise model can be chosen as signal output from the autoencoder workflow.

3D hardrock seismic data

To showcase a more complex application of the autoencoder denoising algorithm, we also applied it to a 3D hardrock seismic dataset acquired over a major volcanogenic massive sulphide (VMS)-bearing field in the Matagami mineral-endowed belt in Canada. The dataset contains several diffraction signals, and one of them was already validated as a response of a VMS deposit called Bell Allard (Adam et al., 1997). In the first step, we extracted several inlines from the unmigrated 3D volume that contained strong diffraction signals (Figure 5a). Before passing it through the autoencoder algorithm, it was necessary to process the seismic data to reduce several coherent and, to our judgement, spatially correlated reflection overlapping with the diffraction signals. An FK filter was first applied to attenuate some of the reflection signals showing less dip than the diffraction tails. This meant a careful filter design to contain the diffraction tails, followed by an FXY-deconvolution filter using (in the horizontal direction) a window size of 20 traces with an overlap of 10 traces, and (in the vertical direction) a window of 50 ms with an overlap 20 ms (along both inline and crossline directions) and a bandpass filter, of 5–15–60–80 Hz, to improve the continuity of the diffraction signals (Figure 5b). To make sure the signals were diffraction, we calculated possible diffraction traveltimes along the inlines. More than 50 noise-free synthetic sections with similar diffraction signatures were then
FIGURE 4 A more complex and real ground-penetrating radar (GPR) autoencoder-denoised section. (a) Original section, (b) predicted noise with all tiles merged and image-to-waveform converted (c) the autoencoder diffraction/denoised section. The autoencoder denoised section, although displaying tile footprint, shows enhanced diffraction signals.

FIGURE 5 An example (a) inline from the 3D hardrock seismic dataset (Matagami, Canada) and (b) processed further prior to the autoencoder denoising work using FK, FXY-deconvolution and bandpass filters. Yellow arrows point at several diffraction hyperbolas at different times, where D1 is judged to be from the known Bell Allard volcanogenic massive sulphide (VMS) deposit and is the target of the autoencoder denoising workflow.

generated in 2D mainly resembling the inline direction. We trained the model both with noise-free synthetic sections and the filtered real data along the inlines.

Despite these additional pre-autoencoder signal enhancement steps and tuning of the hyperparameters before the data training, the autoencoder failed to provide a suitable denoised diffraction image. This is because the autoencoder correlated the whole section and took everything as important information to be preserved. This warns on the use of the autoencoders where signals are correlated spatially and temporally and appear in all the training images. To be totally successful in denoising a diffraction signal using autoencoders, one requires a pair image in the training that has a noise-free representation of the diffraction signal. In our case, reflection signals were considered important information than the diffraction. Worth mentioning that although the dataset is 3D, the autoencoder used in this study is 2D; hence, we only used 2D images from the 3D dataset for the denoising purpose.
Taking the advantage of having the 3D dataset, this time we decided to employ the denoising algorithm on timeslices (still 2D) that have better circular patterns from the diffraction signals and would crosscut the reflection rather than overlap with them on their tails along inlines and crosslines. Several timeslices from the Bell Allard deposit show strong diffraction signature and are judged to be useful for a new round of autoencoder denoising work. A few additional timeslices were extracted above and below the pronounced diffraction circle of the Bell Allard to improve the training procedure. For the training, we used a mixture of original and filtered timeslices, broken into tiles of size $256 \times 256$ pixels, and for the testing and validation of the autoencoder, we used only the original images, that is, the timeslices (Figure 6a).

The autoencoder-denoised solution now displays a strongly noise-suppressed image, although the diffraction circle is not clear to a human’s eye (Figure 6c). We, therefore, decided to apply additional post-autoencoder image processing works to facilitate the workflow for their recognition.

First, the Canny edge detection filter was applied on the timeslices of the original, filtered and autoencoder-denoised images (Figure 7). The Canny edge filter was chosen as it is less sensitive to the noise and can detect weaker edges that belong to signal. Sensitivity thresholds varied for original, filtered and autoencoder-denoised images because they contained different ranges of pixel values. For example, for the autoencoder-denoised image, sensitivity threshold was set to 0.4, as most of the pixel values were towards zero (black colour). The original and filtered images apart from delineating the main diffraction circle also brings up reflection signals and smaller diffraction circles or bright spots (Figure 7a,b). The result of the application of the edge-detection method to the autoencoder-denoised timeslice shows no strong reflections but a discontinuous diffraction circle. It also contains a small portion of one of the smaller diffraction circles (Figure 7f). We, therefore, argue that the autoencoder performed satisfactorily, although it required further enhancement works.

At this stage, it was decided to employ a Hough transform for circle detection to study and compare automatic diffraction circle detection on the original, filtered and autoencoder-denoised pixel-edge enhanced timeslices (Figure 8). The Hough transform for the circle detection requires as the main input parameter the range of the circle radius, which is aimed to be delineated. When the curved or circular patterns are detected for each point along the edges (changes from zeros to one), a circle with a radius is drawn; the point where most of the circles intersect is the centre of a delineated circle or semicircle. A voting threshold is used to automatically extract the solution. Readers are referred to Cooper and Cowan (2004) for more information about the Hough transform applications in geoscience data. In our case, the autoencoder-denoised image narrowed down the candidates for the best fitting circle to only one circle because of the sharper delineation of the diffraction signal (Figure 8c) as compared to the other two images supporting that the autoencoder-denoised diffraction was better.

**DISCUSSION**

Diffraction denoising using the autoencoder methods can have a broad range of applications (e.g. Dell et al., 2020; Bestagini et al., 2021; Greiner et al., 2022; Ni et al., 2022; Temlioglu & Erer, 2022). In this study, we have shown examples using synthetic seismic data, two real ground-penetrating radars (GPRs) and one hardrock seismic dataset. Although the primary objective was to explore the possibilities of the autoencoder denoising for hardrock seismic datasets that usually contain a low signal-to-noise ratio, the autoencoder alone failed and required case-to-case parameter adjustments coupled with additional image enhancement works.

The synthetic seismic example demonstrated the ability of the autoencoder diffraction denoising when the section contained both random and strong randomly distributed coherent noises. Primary, the sections were generated to showcase the
complexity of the diffraction appearance and noise level in a crystalline setting medium. The predicted noise showed a potential to apply the autoencoder for the real complex cases because it removed most of the strong parts of the coherent noise and more encouragingly preserved the diffraction hyperbolas.

The first real GPR case was simple and contained only one diffraction with a strong amplitude. In this case, we could observe that the predicted noise retained weaker parts of the diffraction (tails), and the denoised tiles showed clear diffraction signatures. The simple GPR example demonstrated that the autoencoder workflow is suitable for diffraction denoising even though no real-noise free model was trained to mimic the noise in the training step. The diffraction signal was pronounced and coherent not only by amplitude but also by its shape (geometry) thus retained in the denoised image. The autoencoder denoising is, therefore, robust when similar shapes and geometries repeat themselves in the training dataset. The second GPR data example proved this concept as it contained multiple diffraction signals of the same shape and geometry. In that case, the reflection was predicted as noise but if needed it could be treated also as signal. The diffraction-denoised signals are so evident and isolated that they can now be used directly for migration and velocity estimations.

**FIGURE 7** The timeslice example of (a) original, (b) filtered and (c) autoencoder-denoised diffraction. (d–f) Corresponding images after an edge detection filter. The edge detection of the autoencoder-denoised image (f) shows only the diffraction of the Bell Allard volcanogenic massive sulphide (VMS) deposit and contains no reflection as compared with the original and filtered timeslices. This implies that the autoencoder performed satisfactorily.

**FIGURE 8** Circular Hough transform detection (red circles) on (a) original, (b) filtered and (c) autoencoder-denoised timeslice. The autoencoder-denoised timeslice requires only one solution (one red circle). This means that the autoencoder performed relatively reasonable to contain the diffraction of the Bell Allard deposit compared to only an edge detection filter.
The most complex and challenging application of the autoencoder was on the hardrock seismic dataset given that both reflection and diffraction signals showed similar geometry and amplitudes. The autoencoder, when used along inlines and crosslines, failed in this case to even contain the diffraction signals in the noise model. The autoencoder workflow requires numerous noise-free (e.g. from reflection) training dataset that closely mimics the real data, which is not easily feasible given the complexity of the geology and reflectivity and diffraactivity pattern in hardrock settings. We, however, not only tried and generated additional synthetic sections resembling the real data but also cleaned up the inline sections as much as possible from reflection signals. Nonetheless, the autoencoder could not recognize the important part of the image, which is in our case the diffraction signal from the Bell Allard volcanogenic massive sulphide (VMS) deposit. Tackling the diffraction in the timeslices was the only way we could partly denoise the diffraction using the autoencoder solution. While partly successful, much of the diffraction signal went also into the noise model making its recognition with a human’s eye difficult.

In the hardrock seismic datasets, the autoencoder-denoised images required sharper representations; coupling the solutions with circular Hough transform was ideal. The circular Hough transform helped to justify the performance of the autoencoder by better delineating the diffraction response of the Bell Allard deposit on timeslices. Coupling the Hough transform with the autoencoder showed a great potential of the automatic detection of the diffraction circles.

Exemplified using the Bell Allard deposit, autoencoders along with other image enhancement methods can be used in mineral exploration seismics. Diffraction signals are sometimes related to isolated VMS bodies; hence, their delineation is of great interest for improved targeting and geological structure understanding.

CONCLUSIONS

We have presented the application of the autoencoder technology for diffraction signal denoising on the synthetic seismic, two real ground-penetrating radars (GPRs) and one real hardrock seismic dataset. The synthetic seismic data were used as the proof of the concept, and it was generated to resemble diffraction appearance in hardrock geological settings with a high-velocity medium generating steep diffraction tails. The autoencoder denoising workflow enabled the attenuation of most of the strong coherent noise and enhanced the diffraction signals. As diffraction signals are often seen in GPR data, we implemented the workflow on two cases, a simpler and a more complex one. The first one, a simpler, showcased the ability of the autoencoder to successfully distinguish not only the main diffraction but also its tails. The second GPR example, a more complex case, showed the reflection signals in the noise model. This implies a careful inspection of the autoencoder noise model might be useful, for example, if reflection signal is the target to be retained. We finally applied the autoencoder denoising algorithm on a hardrock seismic dataset. The combination of the autoencoder and the Hough transform resulted in promising outcomes and can be used for mineral exploration and deep-seated deposit targeting as a new toolbox. The Bell Allard volcanogenic massive sulphide deposit generated a clear diffraction, and this was reasonably well separated in the autoencoder-denoised image.

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DATA AVAILABILITY STATEMENT

Data associated with this article are available upon request to the corresponding author and will become available in https://snd.gu.se/en.

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