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Inpainting: a new way to restore geophysical data corrupted by culture noise and missing data gaps

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Summary

Geophysical data such as magnetic can become corrupted during acquisition by cultural noise, or they could have missing-data gaps due to acquisition obstacles which is a common problem among all geophysical data. In either cases, it is important to restore the affected areas of the geophysical data, especially magnetic, prior to any processing and interpretation works. Otherwise, they would degrade the quality of the data, and they could produce poor and inaccurate interpretation results. Airborne magnetic surveys are often flown at low altitudes over areas with wells, pipelines, railroads and power lines. These iron-rich infrastructures generate non-geological magnetic anomalies known as cultural noise. Cultural noise could pose a serious problem to geophysical data, particularly to high-resolution aeromagnetic data, because it interferes with local-scale genuine magnetic anomalies, such as those that are generated by relatively shallow geological sources whose spectra overlap with the cultural noise spectrum. For these reasons, there is an urgent need to restore geophysical images corrupted by cultural noise, or by missing-data gaps. Ideally, an image restoration of corrupted magnetic data by cultural noise can be achieved by removing the corrupted area from the magnetic data and filling-in the generated gap with new data that are closely matching the texture and the structure of nearby unaffected areas. Traditionally, there are two ways to restore magnetic images that have been corrupted by cultural noise. The first method is by applying a low-pass or any other noise suppressing filter to the data. However, this method is not a favourable one because it affects the whole image and reduces its overall spatial resolution. The second traditional method, which is more favourable than the first one, is to manually cut-out the affected area of the data and fill-in the generated gap with new data by using interpolation algorithms such as the minimum curvature or the B-spline polynomial. However, the manual approach is very tedious, time-consuming and produces poor results especially if the corrupted or the missing-data gap areas are relatively large. It is also difficult or impossible for the manual approach to fill-in the affected areas with new data that are consistent with the surrounding areas in term of texture and structure. In this study, we tested a novel approach called "inpainting" to restore geophysical images corrupted by cultural noise or by missing-data gaps. Inpainting is a digital imaging process of restoring corrupted areas or missing-data gaps in images by replacing the affected areas with new data that have similar characteristics to the one in the surrounding areas. Inpainting assumes that the data in the corrupted area and in the surrounding areas share the same properties and it aims at creating an image that has a close resemblance to the original image and preserve its overall continuity in term of texture and structure. In addition to restoring corrupted magnetic images, inpainting can be used to efficiently fill-in missing data gaps that occasionally seen in other geophysical data such as seismic. There are a number of image inpainting techniques described in the literature but among them, the diffusion-based and the exemplar-based, are the most popular ones. The diffusion-based, uses a modified version of the heat partial differential equation (PDF) to restore images and it treats the pixel's intensity

values of the image as temperature values. This technique work well with small or narrow elongated corrupted and missing-data gap areas but it is not suited for large areas. The exemplar-based inpainting technique, restores images by using a copy and paste approach. In this technique, the corrupted or missing-data gap areas are replaced by pasting patches that are copied from the nearby unaffected areas of the image. The pasted data should have the same statistical properties of the nearby areas so that the texture and the structure of the restored image are well preserved. In this study, we used the exemplar-based technique because it is more efficient in restoring images with large corrupted areas or large missing-data gaps and also because it produces good results. This study, therefore, shows the results of two examples in which exemplar-based inpainting was applied to geophysical images. In the first example, inpainting was applied to a magnetic image that is corrupted by several oil pipelines. In the second example, inpainting was applied to a seismic section with synthetic, or imitated, missing data gaps. Both examples demonstrate that inpainting was able to preserve the overall texture and structure of the affected areas and maintain a good coherence between the restored parts of the image and the surrounding areas.

Introduction

Occasionally, we notice that some parts of a geophysical data are corrupted by cultural noise or show missing data gaps due to acquisition obstacles. For example, magnetic data acquired by surveys flown over areas with oil wells, pipelines and power lines are often contaminated by non-geological, or artificial, anomalies known as cultural noise. The presence of areas corrupted by cultural noise in magnetic images could cause a serious problem, because they degrade the quality of the magnetic data and reduce their ability to produce an accurate and reliable interpretation results. Therefore, it is important to remove the corrupted portion of the magnetic image and fill-in the formed gaps with data that are matching the texture and structure of the surrounding areas. Traditionally, this is accomplished by manually removing the corrupted areas in magnetic images and fill-in the gaps with interpolated data using a generic interpolation algorithm such as the minimum curvature (Hassan *et al*., 1998; Hassan and Peirce, 2005). This approach, however, is very tedious, time-consuming and produces poor results, especially when the gap area is relatively large. For large gaps, traditional techniques lack the ability to infer data characteristics from the surrounding areas, thus the restored area often shows inconsistency and discontinuity in terms of texture and structure with the surrounding areas. In response to these challenges, we tested a novel approach based on 'inpainting' to restore images corrupted by cultural noise and images that contain missing-data gaps. Image inpainting is used in various field of interests and applications to restore images, and in most cases the results are intriguing and successful to a degree that it becomes difficult to tell the difference between the restored image and the original one. As a result of its successful and growing applications in many fields of disciplines, several inpainting techniques have been developed during the past decades. Most of the developed inpainting techniques, fall into two popular groups; diffusion-based and exemplar-based. The diffusion-based technique (Bertalmio *et al*., 2000) implements partial differential equation (PDE), a modified version of heat equation, to fill-in corrupted areas and missing data gaps by propagating the Laplacian functions along the image contour lines or structure directions. Heat equation (aka, diffusion equation) describes the diffusion of heat across an area and when it is used for image inpainting, it assumes that image pixel's intensity values represent the temperature values. The exemplar-based inpainting technique, on the other hand, fills-in gaps by using the copy and paste approach, in which data patches from unaffected nearby areas of the image are copied and pasted into the gap to ensure that image texture and structure are well preserved. In this study, we adopted an exemplar-based inpainting technique that was developed by Criminisi *et al.* (2004) to restore corrupted areas as well as missing-data gaps in magnetic and seismic images, respectively. We favoured the exemplar-based image inpainting technique over the diffusion-based technique because it is more efficient in restoring images with large corrupted or missing-data gap areas. The workflow of the exemplar technique used in this study is illustrated in Figure 1.

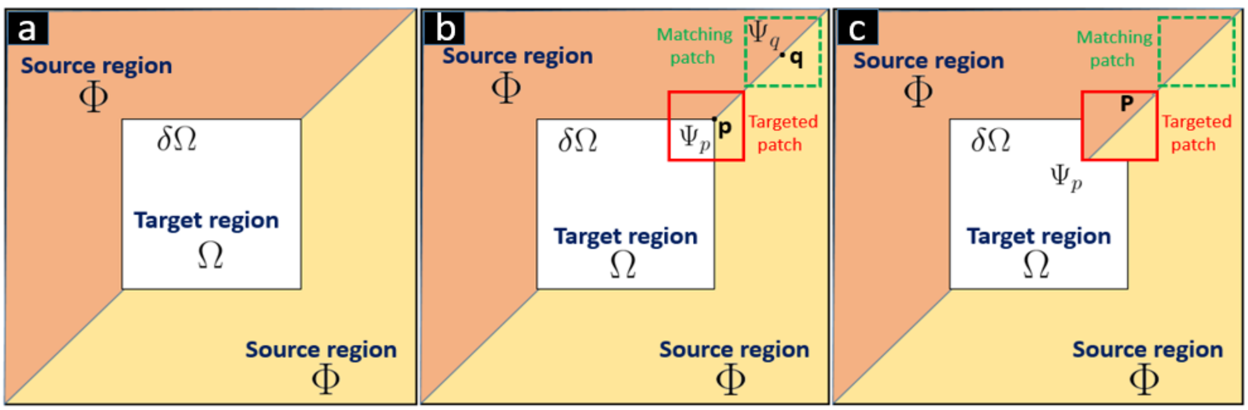

Figure 1. Workflow of exemplar-based image inpainting: (a) input image with target region Ω, its contour δΩ, and source region Φ; (b) target patch Ψ_p for filling-in by data from the matching patch in nearby source region Ψ_q; (c) best matching patch Ψ_q in source region was copied into Ψ_p to insure that texture and structure of surrounding areas propagate into target region.

Theory

In this study, we applied exemplar-based inpainting method (Criminisi *et al.*, 2004) as illustrated in Figure 1. Here, input image with the target region (i.e., corrupted area) is denoted by **Ω** and its boundary is denoted by **δΩ** (Fig. 1a). Then, we construct a square patch $\boldsymbol{\Psi_p}$ centered at point **p** and targeted for the fill-in by inpainting. Best matching patch $\boldsymbol{\Psi_q}$ is found in the source region **Φ** and it was propagated into the target region (Fig. 1b) to replace the corrupted portion of the targeted patch $\boldsymbol{\Psi_p}$ (Fig. 1c).

The exemplar-based inpainting algorithm implements a priority function *f*(p) to select which patch from the target region should be filled-in first. Patch with the highest priority is filled-in by the best matching patch found in the nearest source region area. After filling-in one patch, the corresponding priority of patches is updated promptly the process is repeated until the target region is filled-in completely. Priority function *f*(p) is defined by the confidence term C(p) and the data term D(p) as:

$$f(p) = C(p)D(p) \qquad (1)$$

$$C(p) = \frac{\sum q \in \Psi_p \cap (I - \Omega) C(q)}{|\Psi_p|} \qquad (2)$$

$$D(p) = \frac{|\nabla I_p^{\perp} . n_p|}{\alpha} \qquad (3)$$

Here, **α** is a normalization factor equal to 255 for greyscale images, $\mathbf{n_p}$ is the unit vector orthogonal to **δΩ** at point **p** and its value, or magnitude, is found by computing the gradient of source region at this point. $\nabla \mathbf{I_P}$ is the intensity and the direction of a linear structure, or isophote line, at point **p**. The data term *D(p)* propagates the geometry of the isophote line into the target region, while the confidence term *C(p)* describes the relationship between the patch $\boldsymbol{\Psi_p}$ and the surrounding pixels in the source region. Equation 4 is used to measure the degree of similarity between two patches:

$$\Psi_q = arg \min_{\Psi \in \Phi} d_{SSD}(\Psi_p, \Psi_q) \qquad (4)$$

Here, $d_{SSD}(\boldsymbol{\Psi_p}, \boldsymbol{\Psi_q})$ is the sum of the squared differences (SSD) of the filled-in pixels between two patches.

Results

Figures 2 and 3, show the results of applying the exemplar-based inpainting to two kinds of geophysical data; magnetic image and seismic section, respectively. The magnetic image is corrupted by cultural noise due to oil pipelines (Fig. 2a). The seismic section (Fig. 3a) is corrupted by several imitated, or synthetic, missing-data gaps (Figure 3a). Prior to applying image inpainting to the data, the magnetic and the seismic images were convolved with two masked images showing the locations of the affected areas of the two images. Masked image is a binary image of the same size as the input image, where the area we intend to remove or fill-in is assigned with zero values and remaining image area has values of one. Figures 2b and 3b show the results of applying the masked images to the magnetic and the seismic images, respectively. Final results of inpainting are shown on Figures 2c and 3c. These results demonstrate that inpainting was able to restore the magnetic and seismic images without compromising the overall resolution as well as texture and internal structural coherence of the original images.

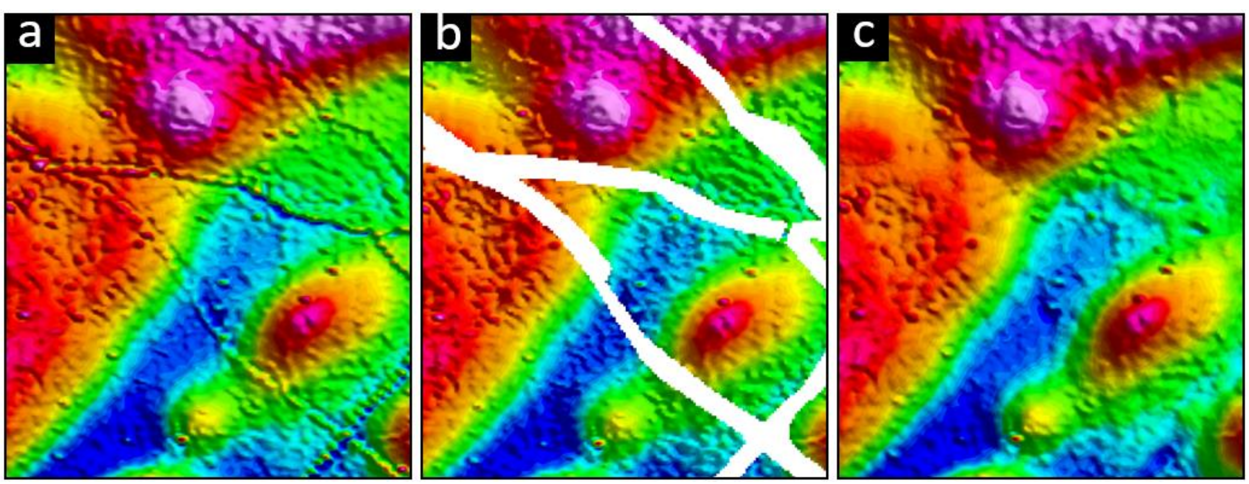

Figure 2. Results of applying exemplar-based inpainting to the reduced to the pole magnetic image: (a) image corrupted by cultural noise; (b) corrupted area removed from image; (c) magnetic image restored by inpainting.

Conclusions

In this study, we applied a novel technique called "inpainting" to restore a magnetic image corrupted by cultural noise and a seismic section with several missing-data gaps. Among several known inpainting techniques, we selected the exemplar-based one, because it is better suited for restoring images with large corrupted areas or with large missing-data gaps. The obtained results demonstrate the high effectiveness of inpainting in restoring corrupted images and images with missing-data gaps. The technique was also able to maintain the overall texture and structural continuity between the restored area and the surrounding areas of the inpainted image. This technique could be used to restore all kinds of other geophysical images including gravity and electromagnetic.

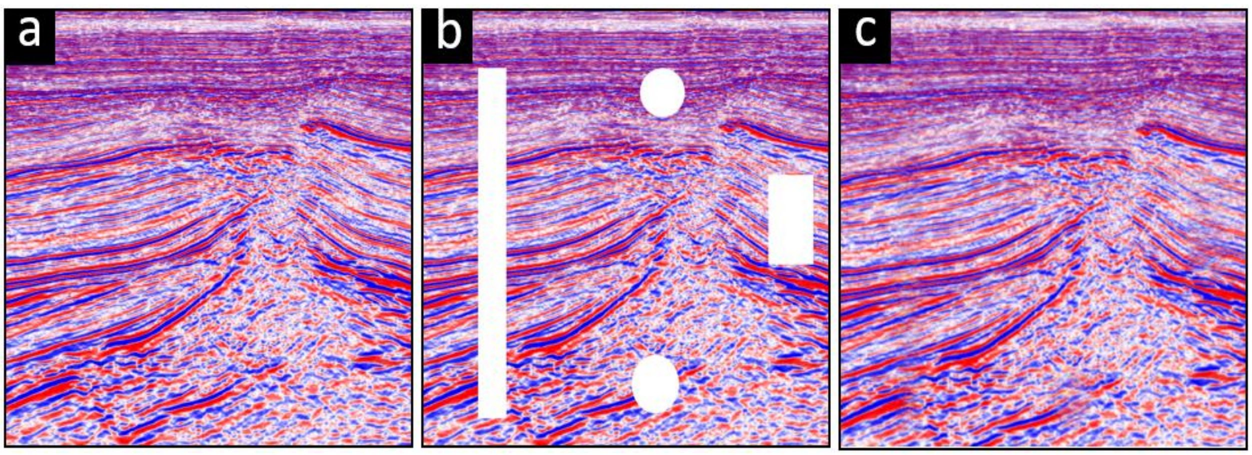

Figure 3. Results of applying exemplar-based inpainting to the seismic section with missing data gaps: (a) original image; (b) image with synthetic data gaps; (c) seismic image restored by inpainting.

References

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