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

Hassan H. Hassan and Serguei Goussev*
Multiphysics Imaging Technology, Inc.

Summary

Geophysical data could be corrupted by man-made cultural noise and they could have missing data gaps in their images. Corrupted and missing data degrade the quality of geophysical images and could result in erroneous interpretation, especially for the aeromagnetic data. Airborne magnetic surveys are often flown at low altitudes over areas with wells, pipelines, railroads and power lines. These iron-rich infrastructure generate non-geological magnetic anomalies known as cultural noise. Cultural noise could pose a serious problem for the high-resolution aeromagnetic data due to its interference with and suppression of local-scale magnetic anomalies, especially those generated by relatively shallow geological sources whose anomalous spectra overlap with the cultural noise spectrum. For these reasons, there is a need to restore magnetic images prior to any data processing and interpretation. Ideally, image restoration can be achieved by removing the corrupted area from the magnetic image and filling-in the gaps with data that closely matching the texture and structural trends in the surrounding areas. Traditionally, the affected areas are cut-out manually and the obtained gaps are filled-in by generic interpolation algorithm such as minimum curvature. However, this approach is very tedious, time-consuming and produces poor results when the corrupted area or missing data gap is large. In this study, we tested a novel approach called “inpainting”. It is a digital process of restoring the corrupted and lost parts of images that is based on utilizing the properties of data in the surrounding areas. Inpainting assumes that the data in the corrupted area and in the surrounding areas share the same texture and structure 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. This study, therefore, shows the results of two examples in which inpainting was applied to geophysical images. In the first example, inpainting was applied to a magnetic image 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 preserves the overall texture and coherence between the restored parts of the image and surrounding areas, and it could be applied to fill-in missing data gaps in all kinds of geophysical images.

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. corrupted by culture noise. Its presence could cause a serious problem, because it degrades the quality of aeromagnetic data and reduces their ability to produce an accurate and reliable interpretation result. Therefore, it is important to remove corrupted portion of magnetic images and fill-in the gaps with data matching the texture and structure of the surrounding areas. Traditionally, this is accomplished by manually removing the corrupted areas in magnetic images and filling 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, when the gap area is relatively large. For large gaps, traditional techniques lack the ability to infer data characteristics around the affected areas, so that restored area often show the inconsistency and discontinuity with the surrounding areas. In response to these challenges, we tested a novel technique called 'inpainting' to restore corrupted parts of geophysical images and fill-in the missing data gaps. Image inpainting is used in various applications to restore damaged and missing image parts to a degree that it becomes difficult to tell the difference between the corrupted image and the restored one. In response to its growing applications in many fields of disciplines, several inpainting techniques have been developed. These developed inpainting techniques fall into two popular groups; diffusion-based using partial derivative equation (PDE), and exemplar-based using copy and paste of patches within the treated image. Diffusion-based techniques (Bertalmio *et al*., 2000), use heat equation to fill-in missing data gaps by propagating the Laplacian functions along the image contour lines or trending directions. Heat equation (aka, diffusion equation) describes how the heat diffuses across area and assuming that pixel intensity represents the temperature, modified version of heat equation could be used for image inpainting. Exemplar-based techniques are preferred for our purposes, because they are more efficient in operating within large gap areas. They fill-in gaps by using the copy-and-paste of data patches from unaffected nearby parts of the image to ensure that image texture and structure are well preserved. Exemplar-based inpainting technique developed by Criminisi *et al.* (2004) and illustrated in Figure 1 was used in this study to restore corrupted and missing data gaps in geophysical images.

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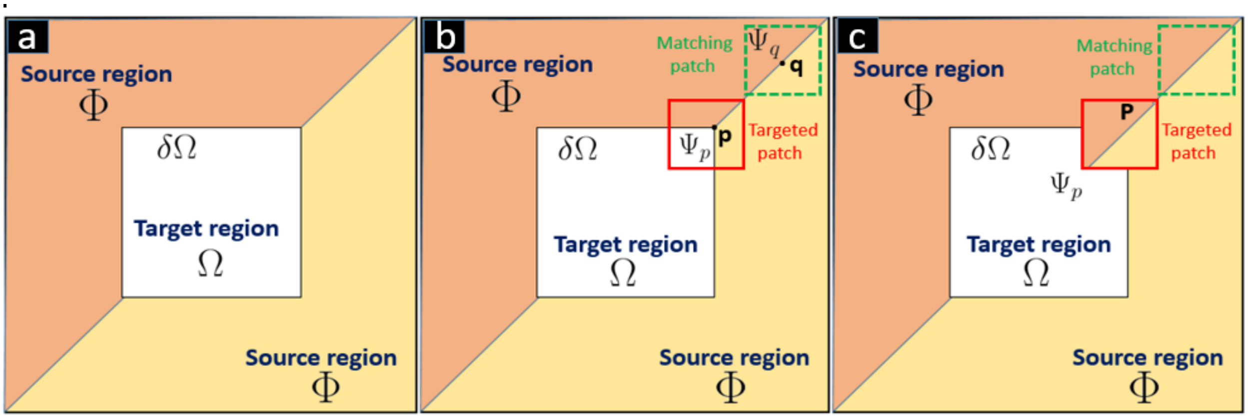

Figure 1. Workflow of exemplar-based image inpainting: (a) input image with target region Ω, its contour δΩ, and source region Φ; (b) target patch Ψ_p for filling-in by data from the matching patch in nearby source region Ψ_q; (c) best matching patch Ψ_q in source region was copied into Ψ_p to insure 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 $\boldsymbol{\Omega}$ and its boundary is denoted by $\boldsymbol{\delta\Omega}$ (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 $\boldsymbol{\Phi}$ and propagated into the target region (Fig. 1b) to replace the corrupted portion of the targeted patch $\boldsymbol{\Psi_p}$ (Fig. 1c).

Inpainting algorithm implements the 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 and process is repeated until the target region is filled-in completely. Priority function *f*(p) is defined by confidence term C(p) and 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, $\boldsymbol{\alpha}$ is a normalization factor equal to 255 for greyscale images, $\mathbf{n_p}$ is the unit vector orthogonal to $\boldsymbol{\delta\Omega}$ at point **p** and its value, or magnitude, is found by computing the gradient of source region this point. $\boldsymbol{\nabla I_P}$ is intensity and direction of a linear structure, or isophote line, at point **p**. Data term *D(p)* propagates the isophote line geometry into the target region, while confidence term *C(p)* describes the relationship between the patch $\boldsymbol{\Psi_p}$ and surrounding pixels in the source region. Equation used to measure the degree of similarity between two patches is expressed as:

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

Here, $d_{SSD}(\boldsymbol{\Psi_p}, \boldsymbol{\Psi_q})$ is 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. Magnetic image is corrupted by cultural noise due to oil pipelines (Fig. 2a). Seismic section (Fig. 3a) was corrupted by several imitated, or synthetic, missing data gaps (Figure 3a). Prior to applying the inpainting, images were pre-conditioned by two filter masks showing the location of affected areas on both 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 masked areas of the magnetic and 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.

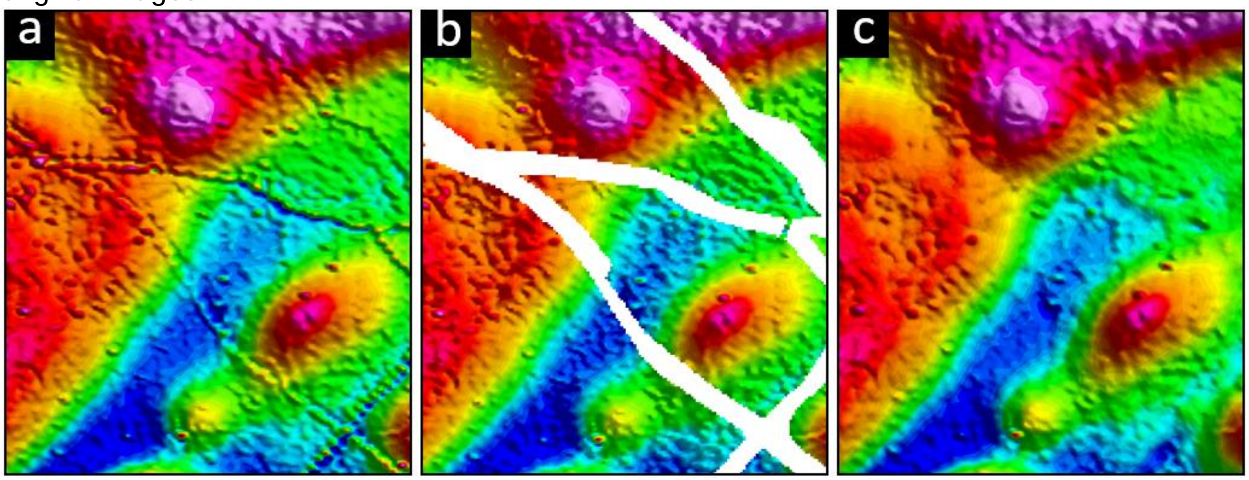

Figure 2. Results of applying exemplar-based inpainting to the reduced to the pole magnetic image: (a) image corrupted by cultural noise; (b) corrupted area removed from image; (c) magnetic image restored by inpainting.

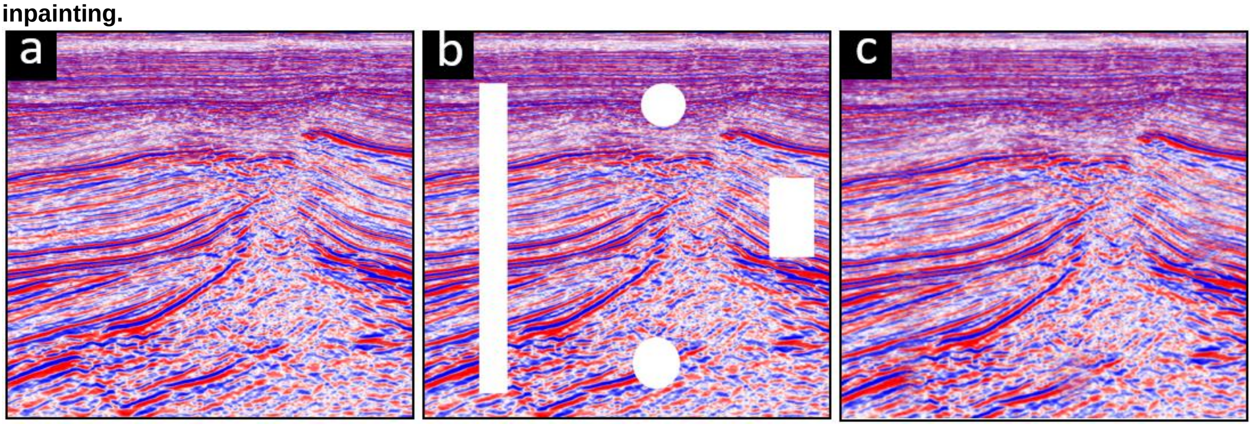

Figure 3. Results of applying exemplar-based inpainting to the seismic section with missing data gaps: (a) original image; (b) image with synthetic data gaps; (c) seismic image restored by inpainting.

Conclusions

In this study, we applied a novel technique called “inpainting” to restore the magnetic image corrupted by cultural noise and seismic section with several missing data gaps. Among known inpainting techniques, we selected the exemplar-based one, because it is better suited for filling-in the large missing data gaps. Obtained results demonstrate the high effectiveness of inpainting in restoration of the corrupted image areas and its ability to maintain the overall texture and structural continuity between the restored parts and surrounding areas of the inpainted image. This technique could be applied to fill-in the missing data gaps in all kinds of geophysical images.

References

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