Reconstructing high-resolution 2D data from low-resolution inputs using a super-resolution conditional generative adversarial network

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ABSTRACT

Super-resolution is an image processing technique that takes a low-resolution image and makes it high-resolution (Nasrollahi and Moeslund, 2014). Recent studies in image processing and medical imaging use Super-Resolution Conditional Generative Adversarial Networks (SRCGANs) to achieve super-resolution, successfully generating high-resolution images that are perceptually indistinguishable from real images (Nasser et al., 2022). We apply the concept of super-resolution to gridded gravity anomalies and train an SRCGAN to learn their complex signal structures and generate high-resolution data from coarsely-sampled grids.

Typical generative adversarial networks (GANs) consist of two neural networks, a generator G and discriminator D, which learn and improve by competing with each other. G generates an image and D attempts to determine if it is a real or generated image. G then updates to make the generated output more realistic, and D updates to better distinguish between real and generated images. We adapt the SRCGAN architecture from Ledig et al. (2017) for use with gridded gravity data. Our generator G takes a low-resolution grid X, coarsely-sampled from a full data set Y, as input, and outputs an up-sampled, high-resolution grid $\hat{Y}$.

Our network is trained and tested using gridded, regional gravity data from Australia (GeoscienceAustralia, 2023). These fully-sampled data Y are resized to a common shape of 128x128 and down-sampled by a factor of 4 to shape 32x32 to obtain the network inputs X. A total of 3546 pairs of fully-sampled and coarsely-sampled grids are used for training, 799 pairs are used for validation during training, and 88 pairs are reserved to test the network after training.

The trained generator is tested with one of the reserved data pairs. Figure 1 shows the fully-sampled grid Y, coarse grid X, and the high-resolution grid $\hat{Y}$ generated from X. We are interested in how well the generator can reconstruct high-resolution signal from just the low-resolution input, so we quantify the increase in information by comparing the differences $Y - X$ and $Y - \hat{Y}$, histograms of which are in figure 1, their mean absolute error (MAE), and their root mean square error (RMSE). These metrics are summarized in table 1. The difference between the fully-sampled data and the coarse data $Y - X$ produces a high MAE and RMSE and is characterized by a noticeably-broad spectrum of differences. The comparison between Y and $\hat{Y}$ yields lower metrics and a sharpening of the histogram.

The improved metrics from the generated high-resolution data show that our trained SRCGAN generator can reconstruct missing signal structure from coarsely-sampled, gridded gravity data. The generated grid is upscaled in size by a factor of 4 in both directions while maintaining the integrity of the input

Table 1: Mean absolute error and root mean square error for the differences between the fully-sampled data Y and both the coarse data X and the generated up-sampled data $\hat{Y}$.

	MAE (mGal)	RMSE (mGal)
$Y - X$	0.705	0.936
$Y - \hat{Y}$	0.140	0.195

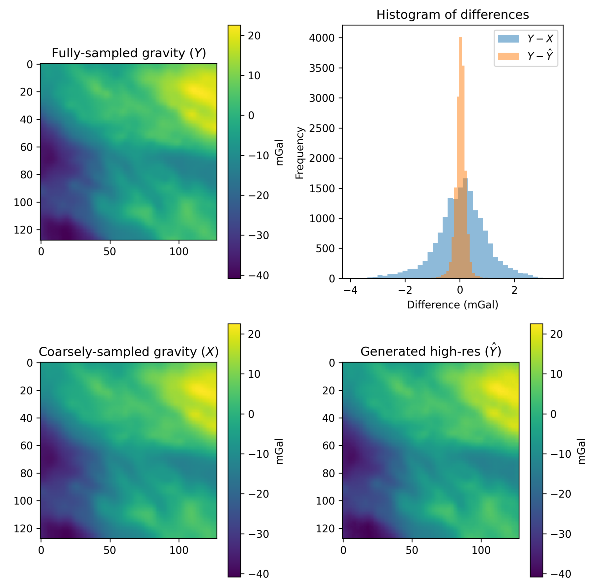

Figure 1: Fully-sampled data Y is down-sampled, X, then input into the trained SRCGAN generator to get a high-resolution output $\hat{Y}$. The differences between Y and the others are plotted in a histogram to visualize the accuracy with which the SRCGAN can reconstruct coarse data.

signal. From the histogram of differences, we understand that the generated high-resolution data closely resembles the full data, discrepancies in which are due to the SRCGAN not completely reconstructing the high-frequency content. This may be improved through further adjusting and tuning of the network and the network training process. These results are a promising look into what may be a robust and versatile data reconstruction method.

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REFERENCES

GeoscienceAustralia, 2023, Data publications.

Ledig, C., L. Theis, F. Huszar, J. Caballero, A. Cunningham, A. Acosta, A. Aitken, A. Tejani, J. Totz, Z. Wang, and W. Shi, 2017, Photo-realistic single image super-resolution using a generative adversarial network.

Nasrollahi, K., and T. Moeslund, 2014, Super-resolution: A comprehensive survey: Machine Vision and Applications, **25**, 1423–1468.

Nasser, S. A., S. Shamsi, V. Bundele, B. Garg, and A. Sethi, 2022, Perceptual cgan for mri super-resolution.