

Supplementary material: A self-supervised and adversarial approach to hyperspectral demosaicking and RGB reconstruction in surgical imaging

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1 Additional Examples from the Results

Figure 1 shows some more examples to compare the RGB visualisations of different demosaicking algorithms, including linear demosaicking, PPID [1], GRMR [2], SGC [3] and our proposed GAN-based algorithm. We have also included three video examples to compare linear demosaicking and our proposed algorithm in the supplementary materials.

2 Per-band pixel differences plot

A plot illustrating the per-band pixel differences for one of the test images is presented in Figure 2. This plot combine with the box plot in the main paper reveal that larger differences tend to occur only in regions where our algorithm enhances spatial details, thereby confirming that these differences are not indicative of any major spectral shift. Note that in this plot, gamma has been adjusted for better visualisation of small pixel value differences.

3 Ablation Study

Table 1 presents the results of an ablation study measuring the quality of the RGB visualisation of the demosaicked hyperspectral images. Detailed ablation study of the SR losses has already been covered in the supplementary material of our previous paper [4], so we won't repeat it and will focus solely on the effects of IPS loss and adversarial losses only. We evaluated our proposed demosaicking algorithm by selectively incorporating either the

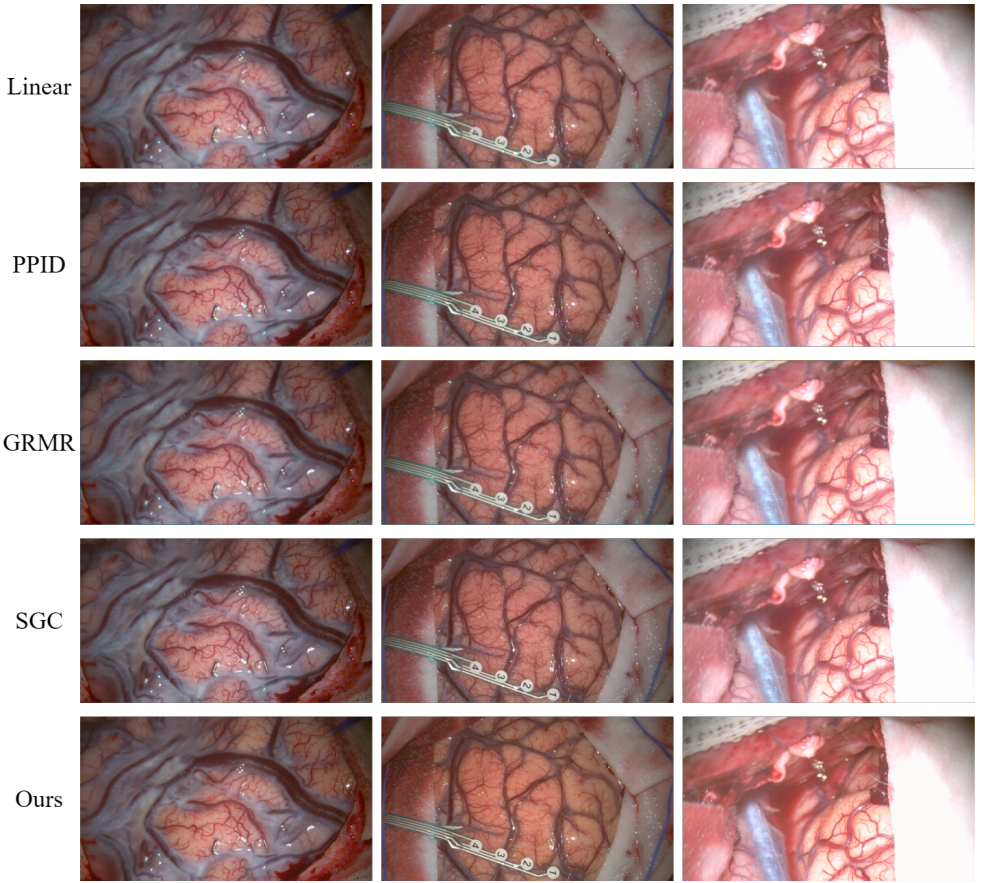


Figure 1: Comparison between different demosaicking methods on example NeuroHSI test images.

IPS loss, the adversarial losses (PatchGAN loss and cycle consistency loss), or both. In all experiments, we retained other loss terms, including total variation and SGC terms, by default. In the experiment with only the IPS loss, the weighting terms were adjusted to $\lambda_{TV} = 1 \times 10^{-3}$, $\lambda_{IPS} = 1$, and $\lambda_{SGC} = 1 \times 10^{-2}$. In the experiment with only the adversarial losses, the weighting terms remained unchanged. An illustrative example of these different experiments can be found in Figure 3. It is evident that both IPS loss and adversarial losses are crucial components of our proposed demosaicking algorithm. When only the IPS loss was used, the weighting for the SGC had to be reduced to avoid artefacts caused by the SGC term over-promoting spatial correlations, which inevitably diminished the ability to recover image sharpness. When only the adversarial losses were applied, the example image clearly shows that although the results exhibit good sharpness, noticeable gridding artefacts appear, which can be mitigated by the IPS loss.

We also compared the adversarial training with fixed parameters of the RGB models to the training where the RGB models were also trained. Although training with the RGB model achieved a better BRISQUE score, as shown in Table 1, the p-value of 0.21 indicates that this difference is not statistically significant. This result is expected, as BRISQUE primarily

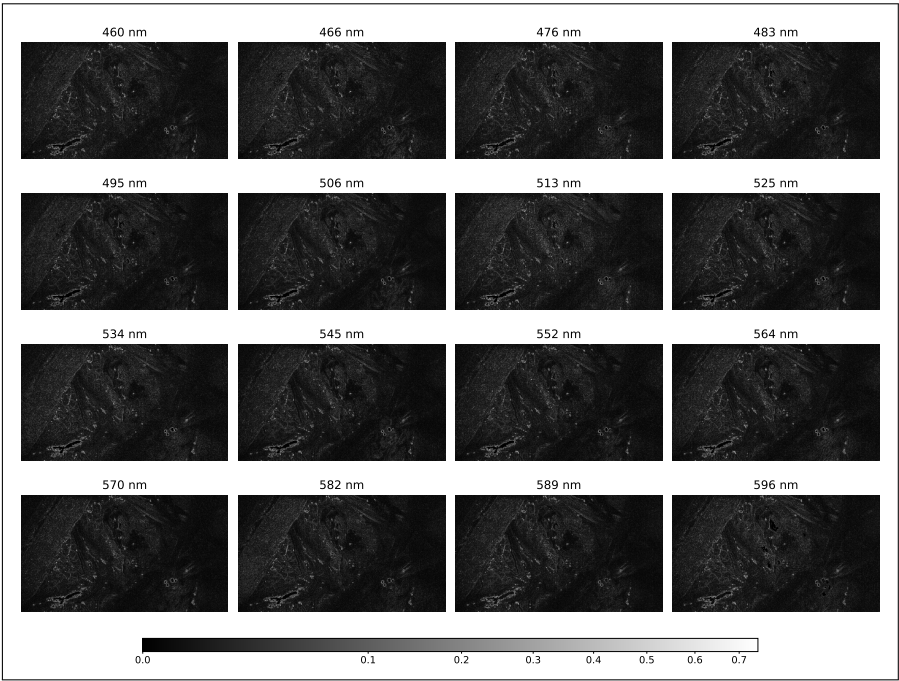


Figure 2: Illustration of per-band pixel difference between our demosaicking results and linear demosaicking on one of the test images.

focuses on assessing the spatial naturalness of images. Our proposed colour model only involves 1×1 convolutions, which do not extract spatial features and thus do not have major contribution to the spatial quality of the images. The main contribution of our proposed RGB model is to improve the colour fidelity of the RGB visualisation of the demosaicked image, which has been evaluated through our user study described in the main paper.

4 More information on the survey

We developed a web application for our user survey, as shown in Figure 4. According to [1], forced-choice pairwise comparison is the fastest and most accurate method for image quality assessment, so we designed a two-alternative forced-choice (2AFC) image quality survey,

Method	BRISQUE	FID Score
IPS only	62.26 ± 6.18	98.02
GAN only (RGB model)	33.04 ± 8.26	86.20
IPS + GAN (fixed RGB model)	19.70 ± 5.91	79.02
IPS + GAN (trained RGB model)	19.35 ± 5.77	75.62

Table 1: Ablation study results measuring the quality of the RGB visualization of the demosaicked hyperspectral images. Lower is better for both BRISQUE and FID.

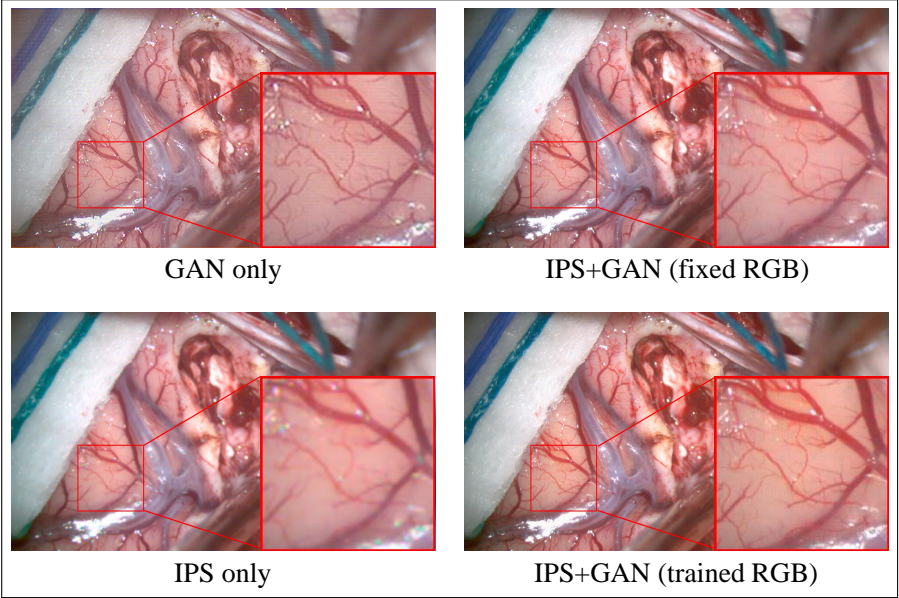


Figure 3: An example from the test set showing the effects of different loss terms in the ablation study.

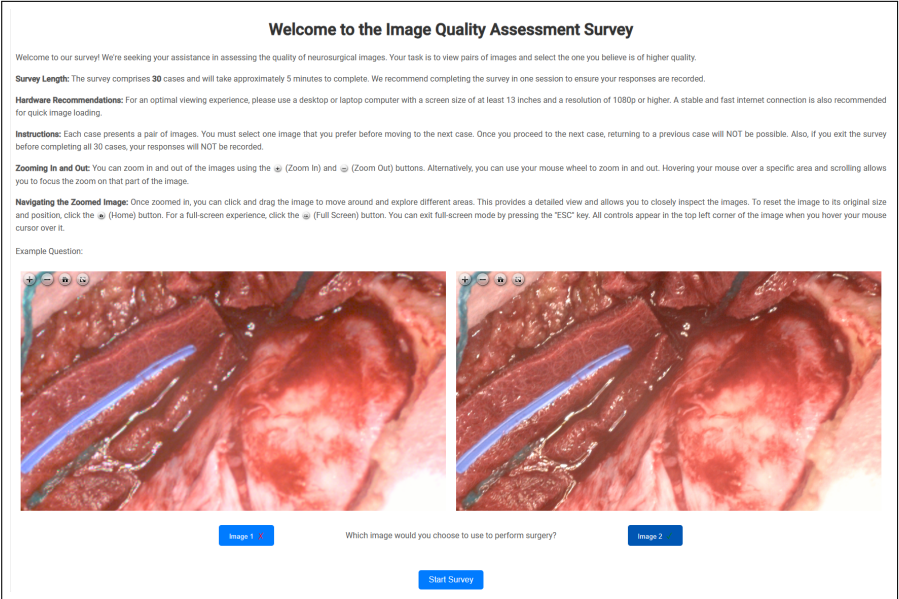


Figure 4: The instruction page of our survey app with an example question. Zoom option is provided to help the participants with observing the images in more details.

where observers were required to compare two images at a time and select the one with better quality without using any rating scales. In this web app, participants were presented with two images per question, allowing them to take their time and zoom in to examine details. They were asked to choose one image with better quality, and once a choice was made, they could not go back and alter their answers. Upon completion of the survey, the data were stored in the backend of the web app for analysis. Using this web app, we collected responses from 23 neurosurgical experts, and the results are presented in the main paper.

References

- [1] Peichao Li, Muhammad Asad, Conor Horgan, Oscar MacCormac, Jonathan Shapey, and Tom Vercauteren. Spatial gradient consistency for unsupervised learning of hyperspectral demosaicking: application to surgical imaging. *International journal of computer assisted radiology and surgery*, 18(6):981–988, 2023.
- [2] Rafał K. Mantiuk, Anna Tomaszewska, and Radosław Mantiuk. Comparison of four subjective methods for image quality assessment. *Computer Graphics Forum*, 31(8): 2478–2491, 2012. doi: <https://doi.org/10.1111/j.1467-8659.2012.03188.x>.
- [3] Sofiane Mihoubi, Olivier Losson, Benjamin Mathon, and Ludovic Macaire. Multispectral demosaicing using pseudo-panchromatic image. *IEEE Transactions on Computational Imaging*, 3(4):982–995, 2017.
- [4] Grigorios Tsagkatakis, Maarten Bloemen, Bert Geelen, Murali Jayapala, and Panagiotis Tsakalides. Graph and rank regularized matrix recovery for snapshot spectral image demosaicing. *IEEE Transactions on Computational Imaging*, 5(2):301–316, 2019. doi: 10.1109/TCI.2018.2888989.