SSFD: Self-Supervised Feature Distance as an MR Image Reconstruction Quality Metric

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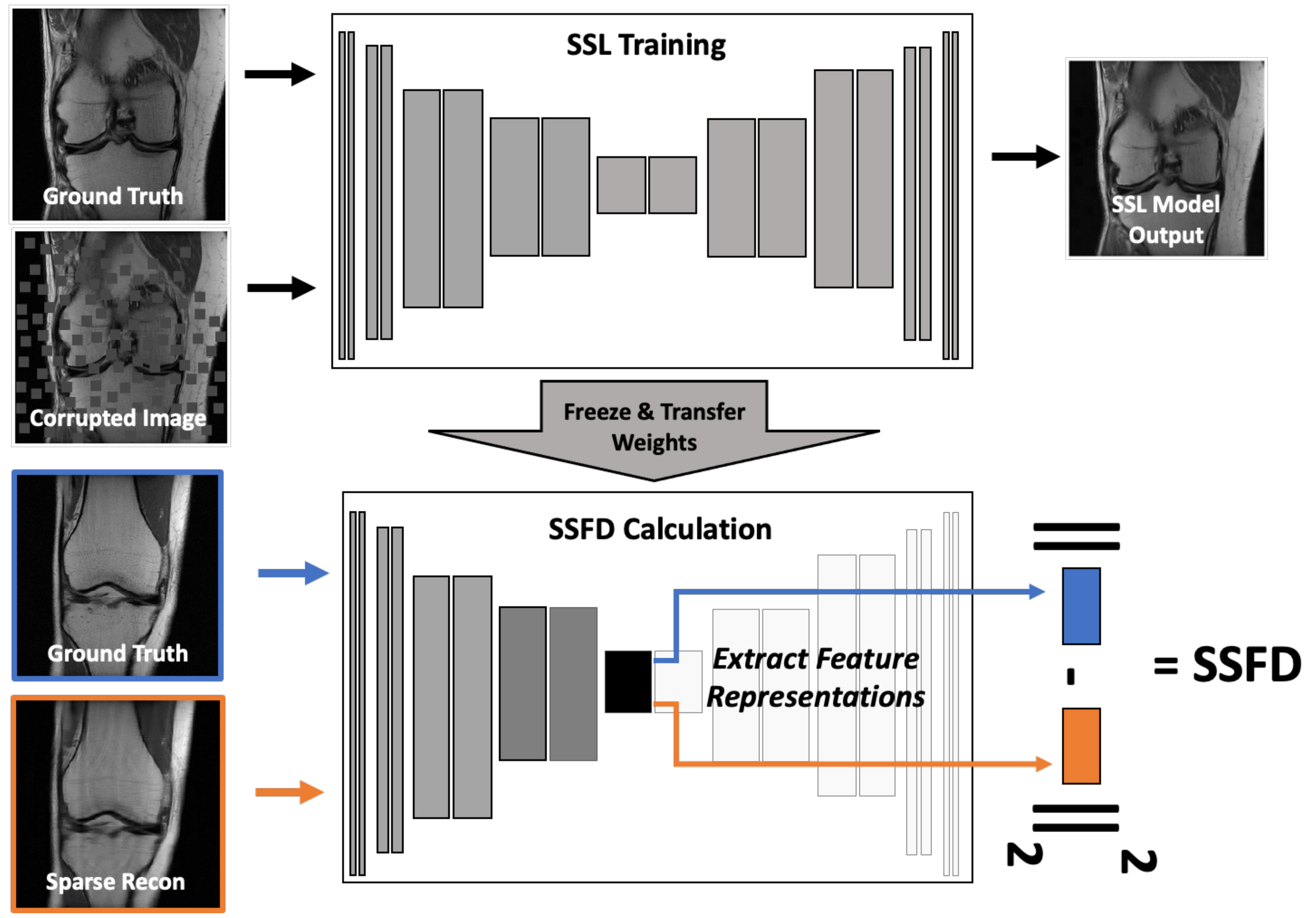
BACKGROUND & MOTIVTAION

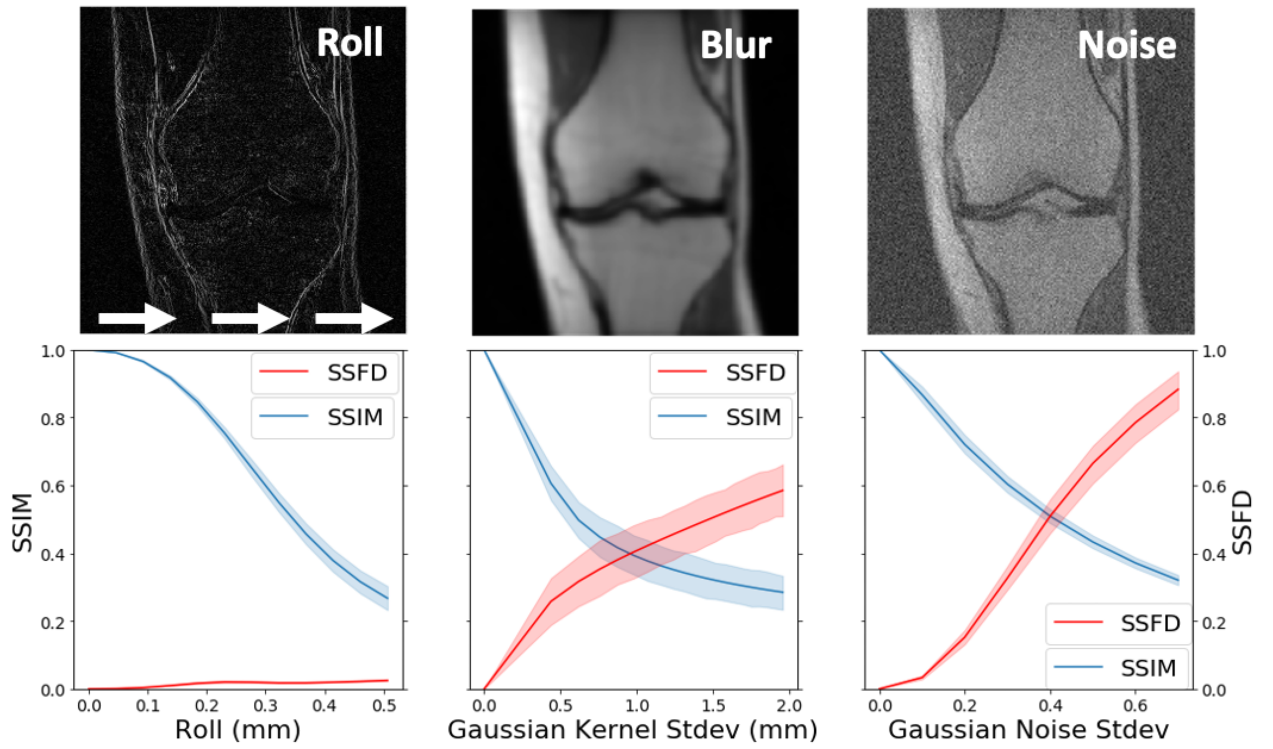
- Evaluation of accelerated magnetic resonance imaging (MRI) reconstruction methods is imperfect due to the discordance between quantitative image quality metrics and radiologist-perceived image quality [1].
- The VGG-16 Perceptual Loss has been proposed as a distance metric for measuring image quality in natural images, but may be sub-optimal for MR images [2][3].
- Self-supervised learning (SSL) has become a popular pre-training tool due to its ability to capture generalizable and domain-specific feature representations of the underlying data for downstream tasks [4].
- **GOAL: Use SSL to extract image-level feature representations of MR images, and use those features to compute a self-supervised feature distance (SSFD) metric to assess MR image reconstruction quality.**

METHODS

- **Dataset:** fastMRI dataset split into training, validation, and testing splits with 27,774 slices (513D scans), 6,968 slices (195 scans), and 7,135 slices (199 scans) respectively. Ground truth reconstruction with JSENSE, and the 4x accelerated reconstructed with a supervised UNet model.
- **SSL:** The pre-text task placed zero-filled image patches of size 16x16 pixels over 25% of the image area via Poisson variable density sampling. A UNet model was trained to in-paint patches and restore original image.
- **Self-supervised Feature Distance:** MSE distance between SSL encoder features.

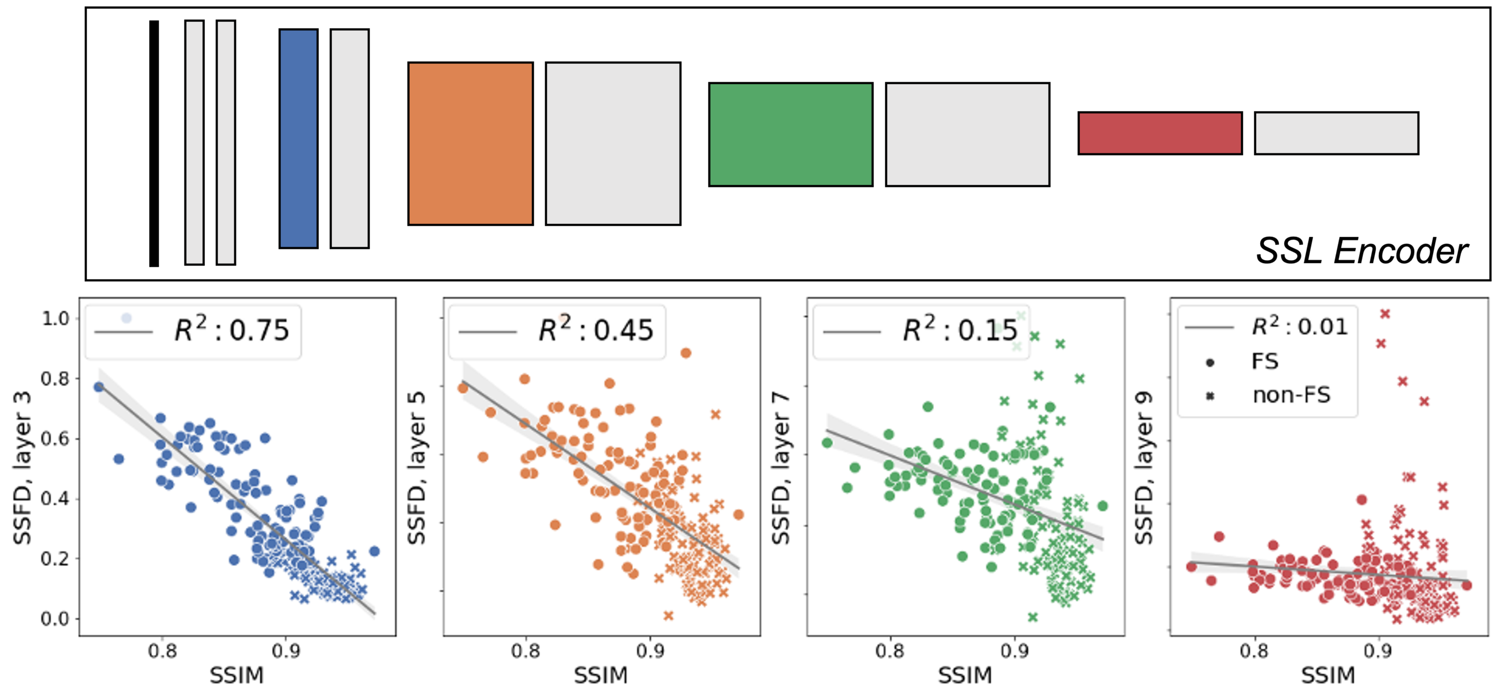


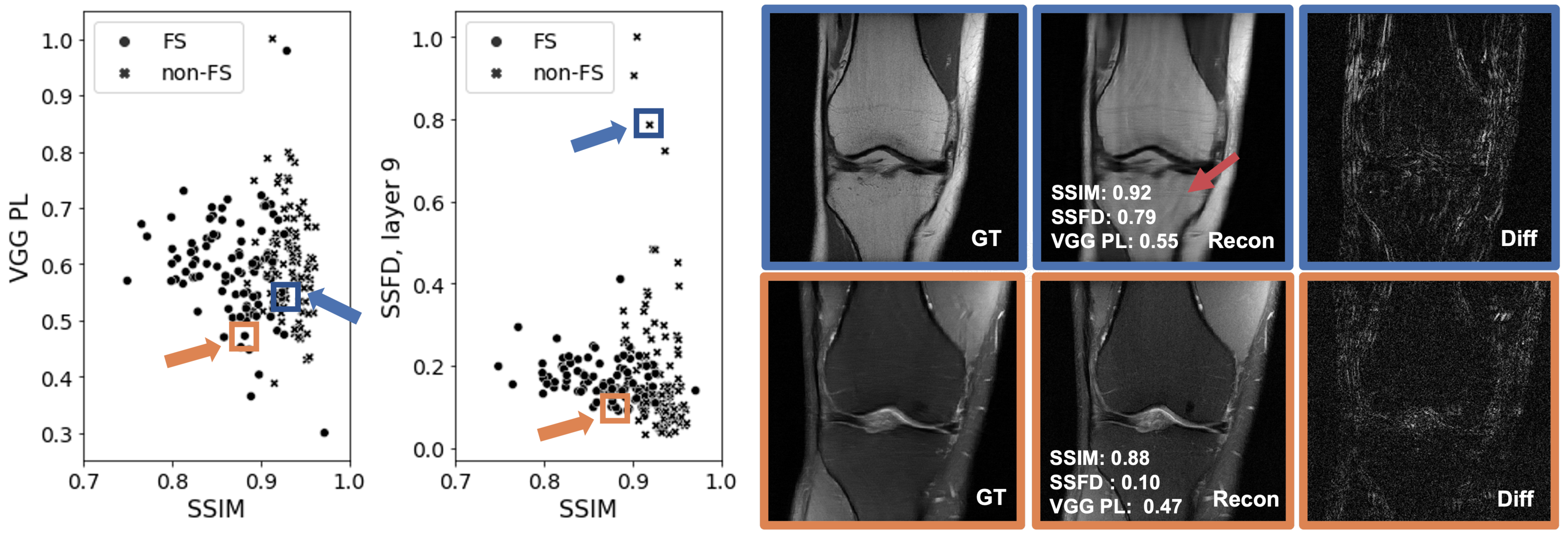
EXPERIMENTS



SSFD under Image Perturbations: Example images at the 50th percentile of perturbations (top). Average SSFD and SSIM with 95% confidence intervals from 199 MR scan test set as a function of image perturbation (bottom). **SSFD is less sensitive to pixel shifts compared to** linearly increasing Gaussian standard deviation for **blurring and noise** for comparable decreases in SSIM.

SSFD vs. Encoder Layer: SSFD vs. SSIM for 4 different encoder layers. SSFD is more highly correlated with SSIM higher up in the encoder network, indicating that **layers earlier in the network learn simpler pixel-level feature representations,** compared to more complex features deeper in the network.





SSFD as a Quality Control Tool: SSIM versus VGG-PL and SSFD plots for the test set (left), with two representative examples of MR. The top image (blue) has a **qualitatively poor reconstruction that is also captured by SSFD, but not other metrics**. The bottom image (orange) has a comparatively good qualitative reconstruction quality, captured by both SSFD and traditional metrics.

CONCLUSION

- This work introduces the SSFD image quality metric based on MR domain-specific feature representations learned from a self-supervised learning task. We demonstrate preliminary results showing the superiority of SSFD to common image quality metrics such as PSNR and SSIM, its robustness to image perturbations, and its ability to capture both pixel-level and global image quality information.

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