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Multi-Series CT Image Super-Resolution by using Transfer Learning and Generative Adversarial Network (TL-GAN)

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Introduction

Multi-series CT (MSCT) scans, including non-contrast CT (NCCT), CT Perfusion (CTP), and CT Angiography (CTA), are widely used in acute stroke imaging. While each scan has its advantage in disease diagnosis, the varying image resolution of different series hinders the ability of the radiologist to discern subtle suspicious findings. Besides, higher image quality requires high radiation doses, leading to increases in health risks such as cataract formation and cancer induction. Thus, it is highly crucial to develop an approach to improve MSCT resolution and to lower radiation exposure.

Hypothesis

MSCT imaging of the same patient is highly correlated in structural features, the transferring and integration of the shared and complementary information from different series are beneficial for achieving high image quality.

Methods

We propose TL-GAN, a learning-based method by using Transfer Learning (TL) and Generative Adversarial Network (GAN) to reconstruct high-quality diagnostic images. Our TL-GAN method is evaluated on 4,382 images collected from nine patients' MSCT scans, including 415 NCCT slices, 3,696 CTP slices, and 271 CTA slices. We randomly split the nine patients into a training set (4 patients), a validation set (2 patients), and a testing set (3 patients). In preprocessing, we remove the background and skull and visualize in brain window. The low-resolution images (1/4 of the original spatial size) are simulated by bicubic down-sampling. For training without TL, we train different series individually, and for with TL, we follow the scanning sequence (NCCT, CTP, and CTA) by finetuning.

Results

The performance of TL-GAN is evaluated by the peak-signal-to-noise ratio (PSNR) and structural similarity (SSIM) index on 184 NCCT, 882 CTP, and 107 CTA test images. Figure 1 provides both visual (a-c) and quantity (d-f) comparisons. Through TL-GAN, there is a significant improvement with TL than without TL (training from scratch) for NCCT, CTP, and CTA images, respectively. These significances of performance improvement are evaluated by one-tailed paired t-tests ($p < 0.05$). We enlarge the regions of interest for detail visual comparisons. Further, we evaluate the CTP performance by calculating the perfusion maps, including cerebral blood flow (CBF) and cerebral blood volume (CBV). The visual comparison of the perfusion maps in Figure 2 demonstrate that TL-GAN is beneficial for achieving high diagnostic image quality, which are comparable to the ground truth images for both CBF and CBV maps.

Conclusion

Utilizing TL-GAN can effectively improve the image resolution for MSCT, provides radiologists more image details for suspicious findings, which is a practical solution for MSCT image quality enhancement.

Statement of Impact

This work is the first-time for transfer learning and GAN being integrated for MSCT image super-resolution. With the shared and complementary information in NCCT, CTP, and CTA images, incorporating the features from different scans are beneficial to achieve high diagnostic imaging quality, which provides a novel solution for image quality enhancement in MSCT imaging instead of a single type of CT scan. This work also offers a potential solution for image quality enhancement in support of radiation dose optimization, assisting a safer MSCT scan strategy for comprehensive brain imaging.

Keywords
Image Super-Resolution, Multi-Series CT, Acute Stroke Imaging

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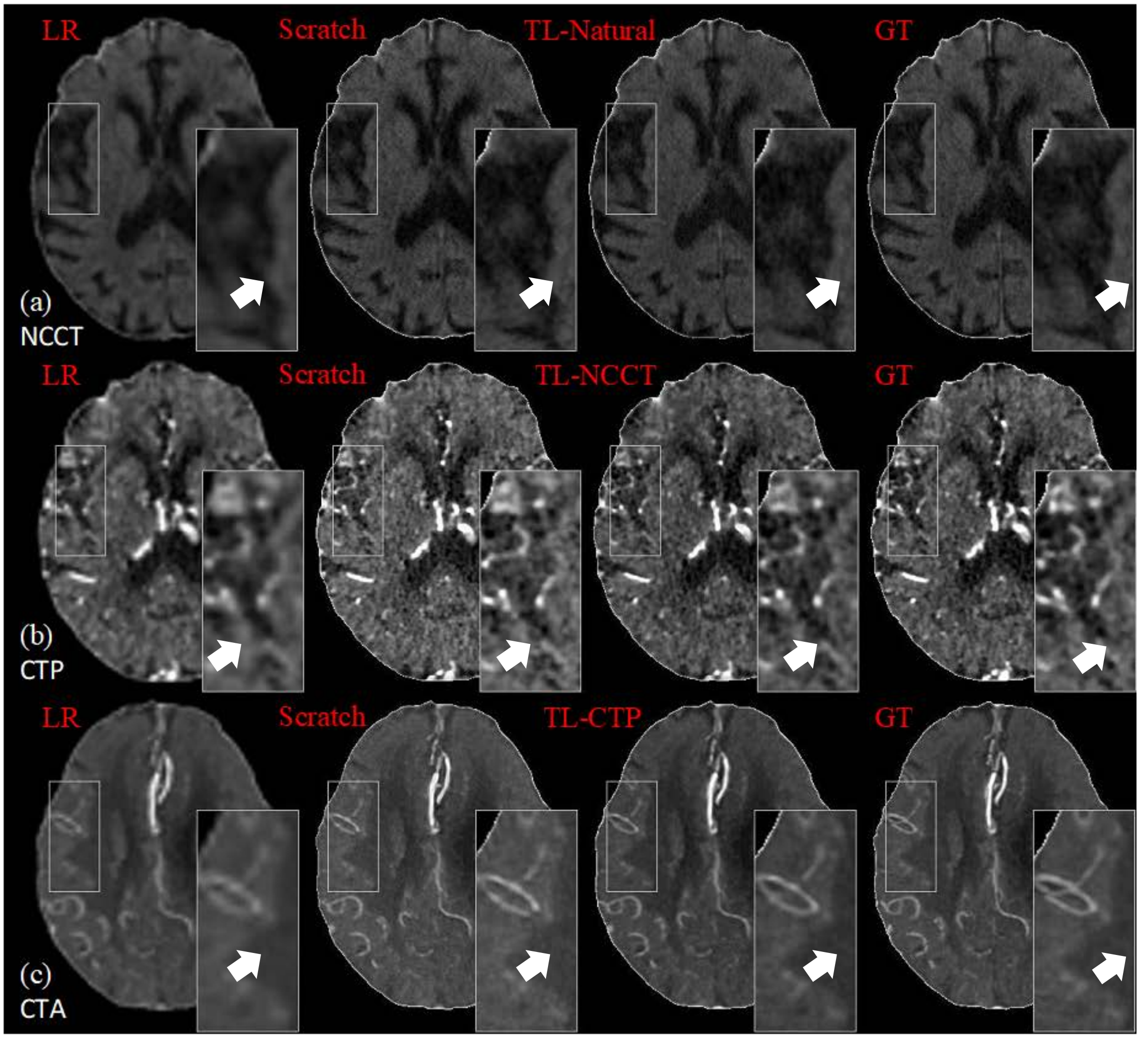

(d) NCCT	Scratch / Var	TL-Natural / Var
PSNR	23.76 / 1.79	**27.99** * / 4.62
SSIM	0.78 / 0.0074	**0.81** * / 0.0089
(e) CTP	Scratch / Var	TL-NCCT / Var
PSNR	23.91 / 1.12	**25.73** * / 1.21
SSIM	0.79 / 0.0036	**0.82** * / 0.0028
(f) CTA	Scratch / Var	TL-CTP / Var
PSNR	25.80 / 1.90	**26.12** * / 2.56
SSIM	0.88 / 0.0014	**0.90** * / 0.00068

Figure 1. Visual (a-c) and quantity (d-f) comparison of NCCT, CTP, and CTA images reconstructed by different methods. The quantity comparison is calculated as an average result from 184 NCCT, 882 CTP, 107 CTA test images. The best performance is highlighted in bold font. LR: The low-resolution image from bicubic interpolation. Scratch: No pretraining and training from random initialization. TL-Natural: Transfer learning from natural images (ImageNet). TL-NCCT: Transfer learning from non-contrast CT images. TL-CTP: Transfer learning from CTP images. GT: The original high-resolution image. * indicates our multimodal transfer learning results are significantly better than the images directly train from scratch.

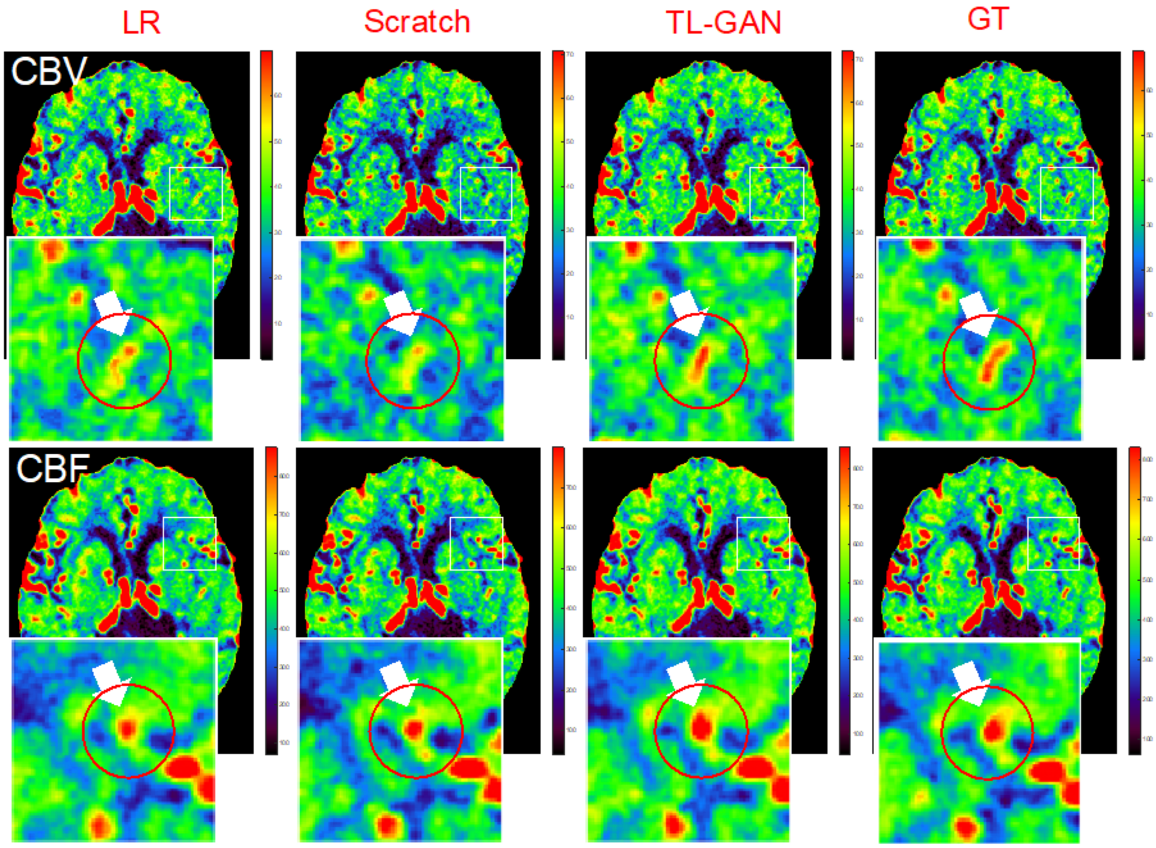

Figure 2. Perfusion maps comparison by different methods.