# Motion Correction in Digital Subtraction Angiography using Generative Adversarial Networks: An Implementation and Evaluation of the Gradient-Consistency Loss Function

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## INTRODUCTION

- Digital subtraction angiography (DSA) is a commonly used method for the visualization of vasculature throughout the human body; however, artifacts due to patient motion limit this technique's diagnostic utility.
- Generative adversarial networks (GAN) represent a viable solution to the significant problem of motion artifacts in DSA but require additional diagnostic improvements prior to clinical implementation.

## OBJECTIVES

- To investigated the use of a gradient-consistency (GC) loss function to enhance the anatomical accuracy and diagnostic capabilities of GANs for motion correction in DSA

## METHODS

- A dataset containing 29,656 cerebral DSA images with minimal artifacts due to patient motion was collected and split into training, validation, and testing datasets.
- The pix2pix GAN was trained to produce DSAs directly from the post-contrast fluoroscopic image, without the use of a pre-contrast mask.
- Training was performed with both an L1 + adversarial loss and an L1 + GC + adversarial loss.

## RESULTS

- The pix2pix GAN trained with an L1 + GC + adversarial loss had a statistically significant improvement in SSIM on the testing dataset when compared to an L1 + adversarial loss alone (SSIM 0.837 (95% CI 0.835 to 0.839) vs. 0.833 (95% CI 0.831 to 0.835), p-value 0.004).
- Visual review of the images demonstrated notable instances where the addition of the GC loss improved the vessel demarcation and anatomical accuracy of the resultant DSA images.

## CONCLUSIONS

- The inclusion of a GC loss during training improves the ability of the algorithm to accurately demarcate the vasculature of interest when performing motion correction in DSA with a GAN.

## ACKNOWLEDGMENTS

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# Motion correction in digital subtraction angiography can be performed reliably using generative adversarial networks.

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## GRADIENT CONSISTENCY LOSS

The gradient consistency loss is an implementation of the gradient correlation (GC), which is defined by the normalized cross correlation (NCC) between the gradients of two images. Given two images, A and B, the GC is defined as

$$GC(A,B) = \frac{1}{2}\{NCC(\nabla_x A, \nabla_x B) + NCC(\nabla_y A, \nabla_y B)\}$$

where $\nabla_x$ and $\nabla_y$ are the gradient operators in the horizontal and vertical directions, respectively. The $NCC(A,B)$ is defined as

$$NCC(A,B) = \frac{\sum_{(i,j)}(A-\bar{A})(B-\bar{B})}{\sqrt{\sum_{(i,j)}(A-\bar{A})^2}\sqrt{\sum_{(i,j)}(B-\bar{B})^2}}$$

where $\bar{A}$ and $\bar{B}$ represent the mean values of $A$ and $B$, respectively. Using these equations, the gradient consistency loss $L_{GC}$ can be defined as

$$L_{GC}(G) = \mathbb{E}_{x,y,z}[1 - GC(y, G(x,z))]$$

where $G$ is the generative model, $x$ is the input image, $z$ is a random noise vector, and $y$ is the target image.

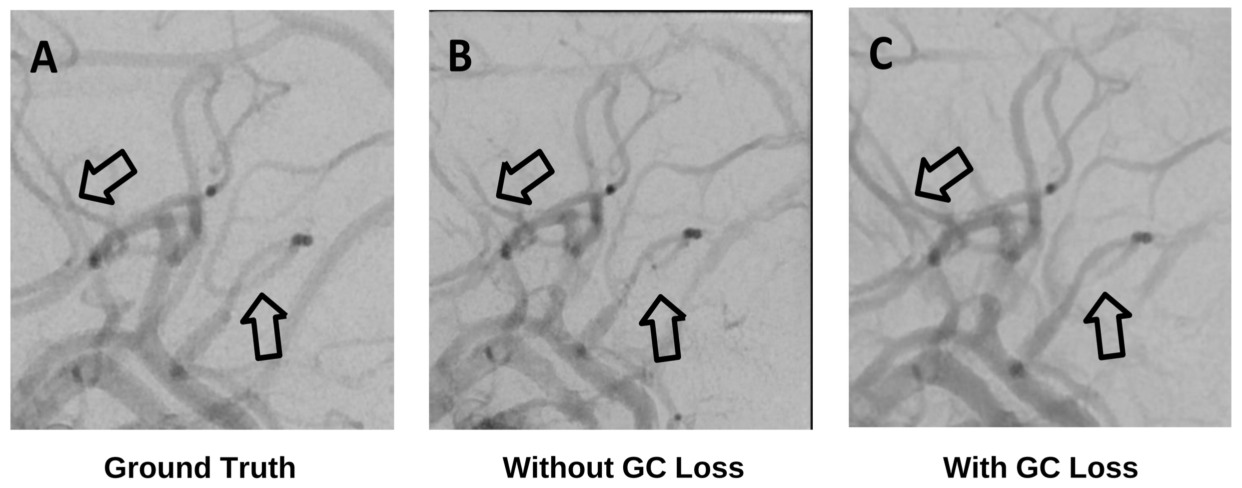


**Figure 1:** An example cerebral DSA generated using the traditional method (ground truth) **(A)**, pix2pix without a gradient consistency (GC) loss **(B)**, and pix2pix with a GC loss **(C)**. As highlighted by the arrow outlines, the inclusion of a GC loss improved the ability of the GAN to accurately identify and demarcate the vasculature of interest.

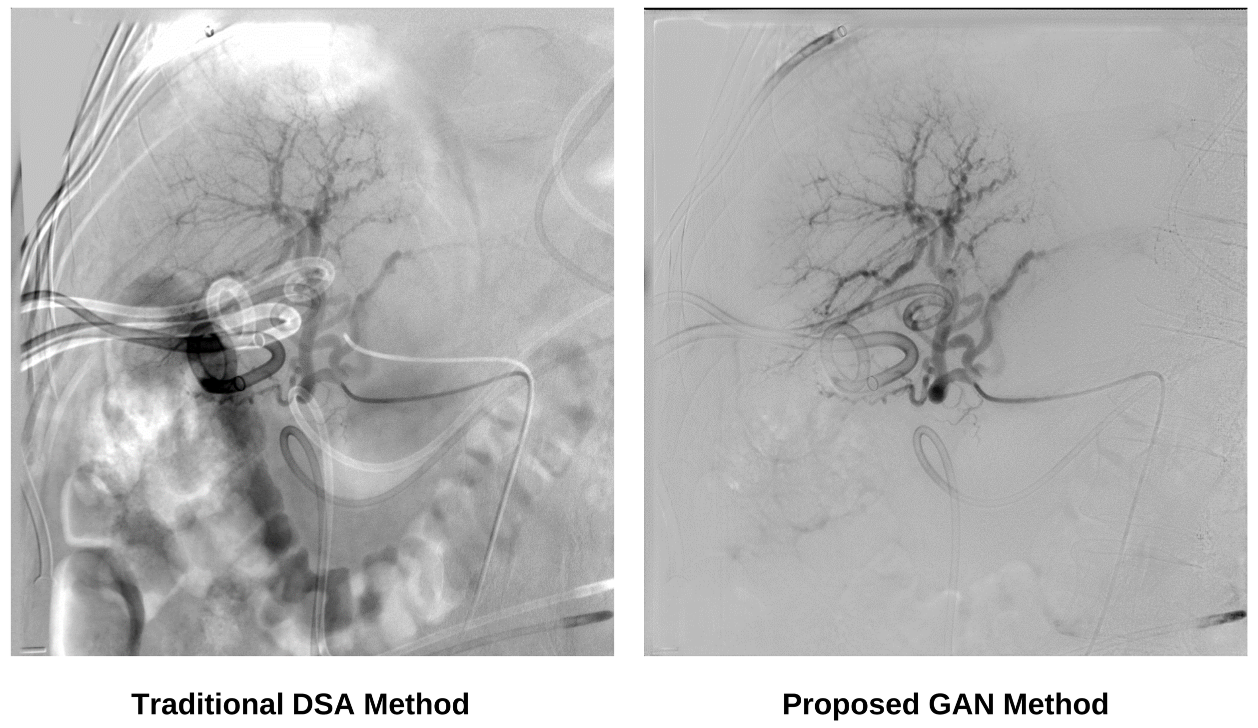


**Figure 2:** Example images from a hepatic case with significant motion artifacts, including a DSA image generated using the traditional method **(Left)** and a DSA image generated using the proposed GAN, showing successful suppression of misalignment artifacts **(Right).**