# QSMGAN: Improved Quantitative Susceptibility Mapping using 3D Generative Adversarial Networks with Increased Receptive Field

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**Highlight:**

We propose QSMGAN: a 3D deep CNN based on a 3D U-Net architecture with increased phase receptive field incorporated with the WGAN-GP training strategy, to solve the ill-posed dipole inversion problem in QSM. The method performed better than non-learning algorithms and could be well generalized to unseen pathologies.

**Abstract**

*Introduction*

Quantitative susceptibility mapping (QSM) is a phase-based quantitative MRI technique that enables in vivo quantification of magnetic susceptibility. Despite its broad application, QSM suffers from the ill-posed dipole inverse issue. The COSMOS method could solve this problem but it is time-consuming and impractical to conduct on patients. Many algorithms have been developed (TKD, MEDI, CSC, QSIP, iLSQR…) to tackle this problem but more efficient and accurate methods are still in need. U-Net, an end-to-end Convolutional Neural Networks (CNN) have achieved state-of-the-art performance in many medical imaging related tasks and had been applied to solve QSM. In this abstract, we extended this idea by enforcing physical implications and improved the QSM dipole inversion using GAN.

*Methods*

Figure(a) shows the network structure. The generator is a modified patch-based 3D U-Net with 3x3x3 Conv3d-BatchNorm-LeakyReLU layers with center cropping before the final output to enforce the susceptibility-phase convolutional relationship implied by physics, and the discriminator is a four-block 3D CNN that acts as the critic in GAN. We acquired a cohort of 8 healthy volunteers using a 4-echo GRE sequence with repetition in 3 orientations in a 7T MRI scanner. The tissue phase and target COSMOS susceptibility map were prepared as network input/output. We also acquired data of 12 brain tumor patient with cerebral microbleeds using the same sequence to evaluate the generalization ability of the proposed algorithm.

*Results*

We selected input patch size of $64^3$ and the output patch size of $48^3$ for the generator by comparison of different combinations. After training the 3D U-Net, we continued to train the network using the WGAN-GP strategy where the discriminator provided extra supervision and refined the QSM reconstruction. Figure(b) shows the improvement of QSMGAN over 3D U-Net and traditional non-learning-based methods such as TKD, MEDI and iLSQR. When applying the QSMGAN to brain tumor patients, the algorithm successfully reconstructed the previously unseen CMBs, implying that it didn't suffer from overfitting and managed to learn the physical relationship between susceptibility and phase. In addition, we found that QSMGAN has extra robustness to

artifacts. Figure(c) shows that iLSQR suffered from wrong brain extraction and demonstrated significant artifacts while QSMGAN successfully removed the artifacts.

*Discussion and conclusions*

The QSMGAN we proposed could generate COSMOS-like susceptibility maps accurately and efficiently without repeated scans with different orientation. Although the training took about 48 hours in total, it only needs less than 10 seconds to predict a new scan once the training phase finished. And we also verified that this method could be well generalized to unseen pathologies by evaluation and comparison on brain tumor patients with microbleeds. Future directions include investigating the ability to generalize to other scan parameters (such as TE, TR, and image resolution) and testing the performance of QSMGAN in patients with different pathologies to ultimately improve patient care.

**References**


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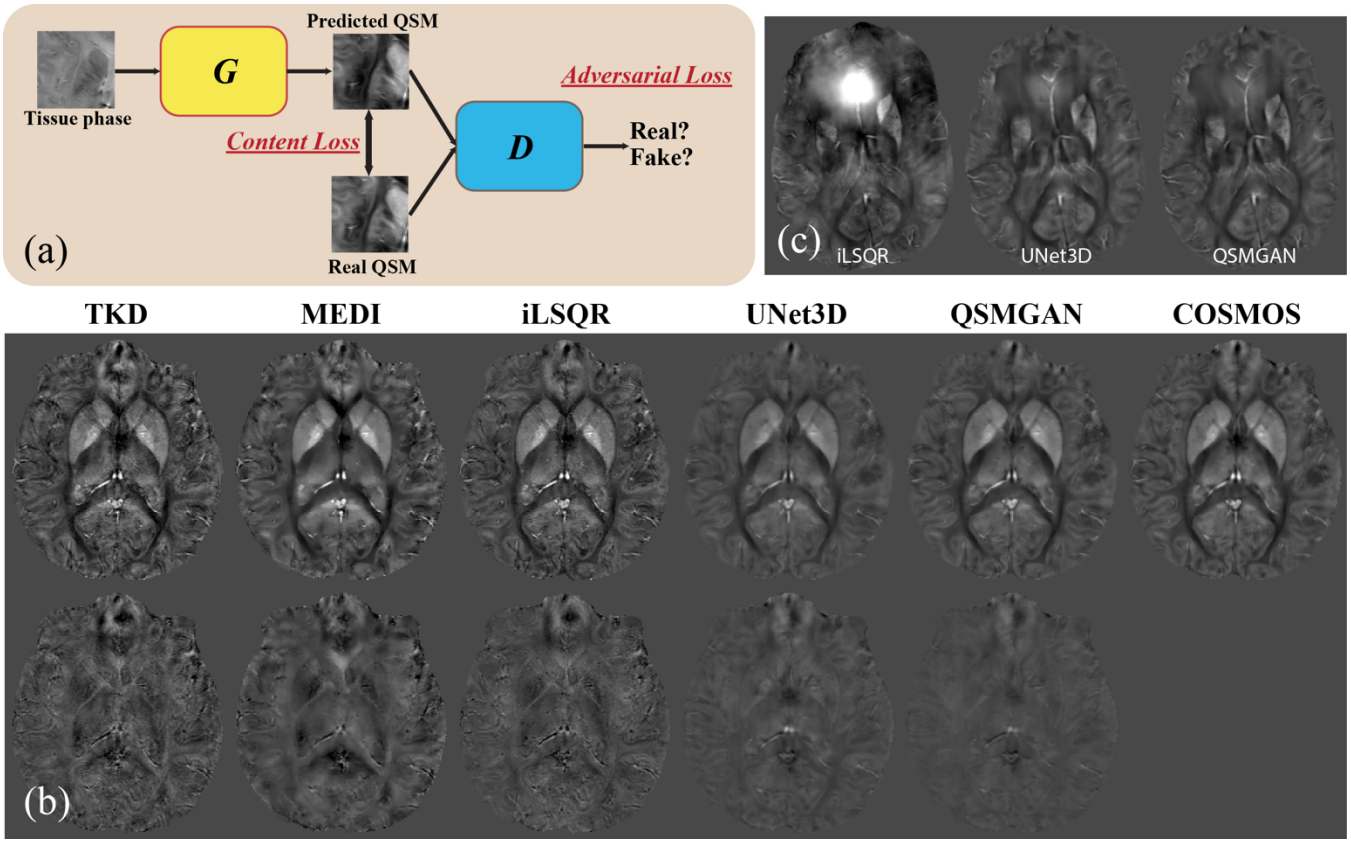
**Figure:**


Predicted QSM
G
Tissue phase
Adversarial Loss
Content Loss
D
Real?
Fake?
Real QSM
(a)
(c)
iLSQR
UNet3D
QSMGAN
TKD
MEDI
iLSQR
UNet3D
QSMGAN
COSMOS
(b)