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A New Compression Sensing Reconstruction Method for Stitching Images Based on Deformable Convolution-Deformable Deconvolution Module

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ABSTRACT

The compression sensing reconstruction of the stitching image is important for the communication of autonomous driving, intelligent vehicles, and unmanned aerial vehicles (UAV). A compression sensing reconstruction method for the stitching image is proposed. The proposed compression sensing reconstruction method contain: image stitching method, deformable convolution module, SCNet, and deformable deconvolution module. The added deformable convolution module can extract the features of the stitching image reasonably due to image distortion. The added deformable deconvolution module can make the stitching image and the reconstructed stitching image maintain consistency. Experimental results show the reconstruction SSIM and PSNR of the proposed method is better than the image stitching method and the SCNet. The reconstruction stitching images also has better visual effects.

INTRODUCTION

The compression sensing reconstruction of stitching images is important for the communication of autonomous driving, intelligent vehicles, and unmanned aerial vehicles (UAV). The compression sensing reconstruction of the normal image has been well researched. The compression sensing reconstruction methods of the normal image can be divided two categories: 1) no-deep-learning-method and 2) deep-learning-method.

To obtain the reconstruction results of larger field-of-view (FoV) images, the images need be stitched. The image stitching methods can also be devided into two categories: 1) no- deep-learning-method and 2) deep-learning-method.

The stitching images can obtain larger field-of-view (FoV) compared with normal images. Therefore, the compresseion sensing reconstruction of stitching images can obtain larger reconstruction images compared with the compression sensing reconstruction of normal images. A compression sensing reconstruction method for the stitching image is proposed. The proposed compression sensing reconstruction method contain: image stitching method, deformable convolution module, SCNet, and deformable deconvolution module. The added deformable convolution module can extract the features of the stitching image reasonably due to image distortion. The added deformable deconvolution module can make the stitching image and the reconstructed stitching image maintain consistency. Experimental results show the reconstruction SSIM and PSNR of the proposed method is better than the image stitching method and the SCNet. The reconstruction stitching images also has better visual effects.

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Keywords: Compression sensing reconstruction, Image stitching, Deformable convolution, SCNet

MATERIALS AND METHODS

1. The Compression Sensing Reconstruction Methods of the Normal Image

no-deep-learning-method

At present, researchers in the field of compressive sensing have proposed many methods that can accurately reconstruct the original data, mainly divided into three categories: convex optimization methods Candès et al. (2006), greedy methods Needell et al. (2010), and combinatorial methods Khan et al. (2018). Among them, greedy methods have been widely used. Common greedy methods include: Orthogonal Matching Pursuit (OMP) Tropp et al. (2007), Regularized OMP (ROMP) Yang et al. (2015), Compressive Sampling Matching Pursuit (CoSaMP) Needell et al. (2009), Subspace Pursuit (SP) Dai et al. (2009), Stagewise OMP (StOMP) Marques et al. (2018), and Sparsity Adaptive Matching Pursuit (SAMP) Ba et al. (2010), etc.

deep-learning-method

Chen et al. (2025) proposed a compression sesning reconstruction method combining SCL and SCNet. Yang and Yuan et al. (2023) designed a ultra-lightweight image compressive sensing reconstruction method based on knowledge distillation. Chen and Zhang Chen et al. (2024) proposed a practical compact deep compressed sensing method.

2. The Image Stitching Methods of Normal Images

no-deep-learning-method

The no-deep-learning-method for the image stitching mainly caontains the step: 1) the feature extraction, 2) feature matching, 3) homograph transformation, and 4) image blending.

deep-learning-method

Zhu et al. (2019) improved a novel panorama generative model for synthesizing realistic and sharp-looking panorama, which does not require a large number of labeled ground-truth data. Sumantri et al. 2020 designed a learning-based approach the reconstructs the scene in 360°×180°from a sparse set of conventional images. Wu et al. 2023 tackled the problem of synthesizing a ground-view panorama image conditioned on a top-view aerial image, which is a challenging problem in this domain.

3. A New Compression Sensing Reconstruction Method of the Stitching Image

The image stitching method uses the method propsoed by Ribeiro et al. (2021), which is implemented in python. The proposed compression sensing reconstruction method contain: image stitching method, deformable convolution module, SCNet, and deformable deconvolution module. The added deformable convolution module can extract the features of the stitching image reasonably due to image distortion. The added deformable deconvolution module can make the stitching image and the reconstructed stitching image maintain consistency.

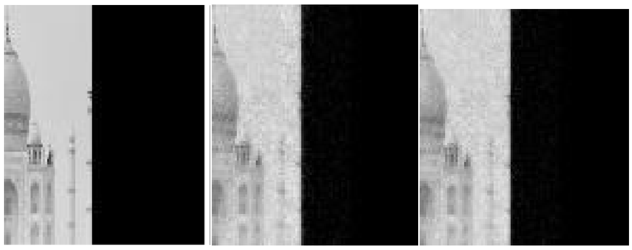
The propsoed method is named DCM-DDM-SCNet.

RESULTS

1. The Ablation Experiments

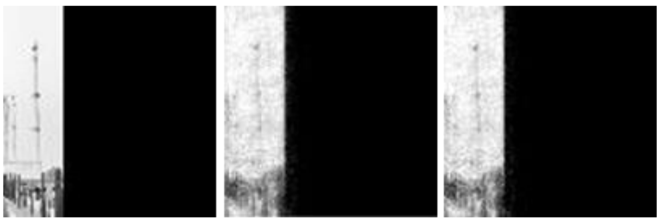
The traning epoch of the SCNet is 200, the learning rate is 0.0001, the block size is 33, and the number of features is 32.

Figure 1: The Reconstruction Image Scene 1



(a) Stitching Image (b) IS+SCNet (c)IS+DCM+SCNet+DDM

Figure 2: The Reconstruction Image Scene 2



(a) Stitching Image (b) IS+SCNet (c)IS+DCM+SCNet+DDM

The reconstruction SSIM and PSNR is shown in Table I. From Table I, the image stitching method+SCNet is named IS+SCNet, and the image stitching method+deformable convolution module+SCNet+deformable deconvolution module is named IS+DCM+SCNet+DDM.

From Table I, in CS ratio 0.01, the SSIM and PSNR of IS+DCM+SCNet+DDM are better than the SSIM and PSNR of IS+SCNet. From Table I, in CS ratio 0.04, the SSIM and PSNR of IS+DCM+SCNet+DDM are also better than the SSIM and PSNR of IS+SCNet.

2. The Reconstruction Time

The reconstruction time and the image stitching time are shown in Table II and Table III respectively. The FPS of SCNet is 11 and the FPS of DCM+SCNet+DDM is 10.

The image stitching time of Scene1 is 0.33s and the image stitching time of Scene2 is 0.34s.

Table 1: The Reconstruction Result

	SSIM (CS Ratio:0.01)	PSNR (CS Ratio:0.01)	SSIM (CS Ratio:0.04)	PSNR (CS Ratio:0.04)
IS+SCNet	58.35	14.17	62.41	16.43
IS+DCM+SCNet+DDM	60.45	15.39	63.26	18.58

Table 2: The Reconstruction Time

	FPS
SCNet	11
DCM+SCNet+DDM	10

Table 3: The Image Stitching Time

	Image Stitching Time (s)
Scene1	0.33
Scene2	0.34

DECLARATIONS

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Author contributions

Xing Hu and Jinwang Cha contribute to the writing of this paper; Weihua Liu and Shuqin Wang contribute to the writing skills' improvment of this paper; Li Xiao, Yi An, Cheng Shao, Jie Ren and Xinjian Li give much improvments on technologies; Ruifeng Pan, Hui Zhang, Mengsheng Wang, Jiapeng Zhu and Hongsheng Tian contribute to the experimental evaluation of this paper.

Competing interests

The authors declare that there is no conflict of interest regarding the publication of this article.

Data Availability

https://download.csdn.net/download/accdgh/90971115

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