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Super-resolution restoration of spaceborne HD videos using the UCL MAGiGAN system

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ABSTRACT

We developed a novel SRR system, called Multi-Angle Gotcha image restoration with Generative Adversarial Network (MAGiGAN), to produce resolution enhancement of 3-5 times from multi-pass EO images. The MAGiGAN SRR system uses a combination of photogrammetric and machine vision approaches including image segmentation and shadow labelling, feature matching and densification, estimation of an image degradation model, and deep learning approaches, to retrieve image information from distorted features and training networks. We have tested the MAGiGAN SRR using the NVIDIA® Jetson TX-2 GPU card for onboard processing within a smart-satellite capturing high definition satellite videos, which will enable many innovative remote-sensing applications to be implemented in the future. In this paper, we show SRR processing results from a Planet® SkySat HD 70cm spaceborne video using a GPU version of the MAGiGAN system. Image quality and effective resolution enhancement are measured and discussed.

Keywords: Super-Resolution Restoration, Multi-angle, Generative Adversarial Network, Earth Observation, MAGiGAN, Planet® SkySat® HD Video

1. INTRODUCTION

Very high spatial resolution imaging data is playing an increasing role in many commercial and scientific applications of Earth observation. However, given the physical constraints of the imaging instruments themselves, we always need to trade-off spatial resolution against launch mass, usable swath-width, and telecommunications bandwidth for transmitting data to Earth. One solution to this conundrum is through the use of super-resolution restoration (SRR) to combine image information from repeat observations at multiple viewing angles, and exploit information derived from multiple imaging sources, to generate images at much higher spatial resolutions. SRR can be performed either as post processing on the Earth or potentially via satellite onboard processing using a graphics processing unit (GPU).

Previously, within the EU FP-7 Planetary Robotics Vision Data Exploitation (PRoViDE) and UKSA CEOI 10 SuperRes-EO projects, MSSL developed the Multi-Angle Gotcha image restoration with Generative Adversarial Network (MAGiGAN) method to improve the effective resolution from stacks of overlapping multiple lower resolution images. MAGiGAN combines image information from repeat observations at various viewing angles, and exploits information derived from multiple imaging sources, to generate images at much higher spatial resolutions.

The MAGiGAN SRR system [1] is based on the mutual shape adapted [2] features from accelerated segment test (MSA-FAST) [3] combined with convolutional neural network (CNN) [4] feature matching, adaptive least-squares correlation (ALSC) and region growing (Gotcha) [5], partial differential equation (PDE)-based total variation (TV) regularization (GPT) [6], support vector machine (SVM) and graph cut (GC)-based shadow labelling [7], and the generative adversarial network (GAN) [8] based super-resolution refinement method.

The MAGiGAN system was previously applied to stacks of 4m UrtheCast Corp Deimos-2 (MS band) multi-angle repeat-pass images over several experimental sites to produce SRR results with 3.5–3.75 times (hereafter referred to as "x") resolution enhancement. Since then, MAGiGAN has been tested with 1.1m SSTL Carbonite-2 video frames, the 275m Multi-angle Imaging SpectroRadiometer (MISR) Level 1B1 red band images, and 300m Sentinel 3 OLCI level-1 EFR red band radiance images to produce resolution enhancement at various levels of performance. In this paper, we further explore the MAGiGAN SRR system using as input the Planet® Skysat® HD 70cm videos.

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2. DATASETS

The Planet® SkySat captures sub-metre resolution EO still images or HD videos. Full videos are collected between 30 and 120 seconds (30 frames per second) by the Panchromatic camera from any of the SkySat constellation[1] while the spacecraft pointing follows a target. The size of the video products are 1920x1080 pixels. A raw video product with individual Tiff images with 11bit of radiometric resolution is also available at the full panchromatic detector size of 2560x1080 pixels. The HD video has two types of product, the stabilised (one that all video frames have been co-registered) and the unstabilised without co-registration. In this work, we tested our MAGiGAN SRR system on an unstabilised SkySat video over the San Diego, CA, U.S.A. area. It is mostly urban with tower buildings in the downtown area along with residential blocks. The video length is 54 seconds and 1350 raw panchromatic frames are available at 2560x1080 pixels. An example of the reference frame used in this work is shown in Figure 1.

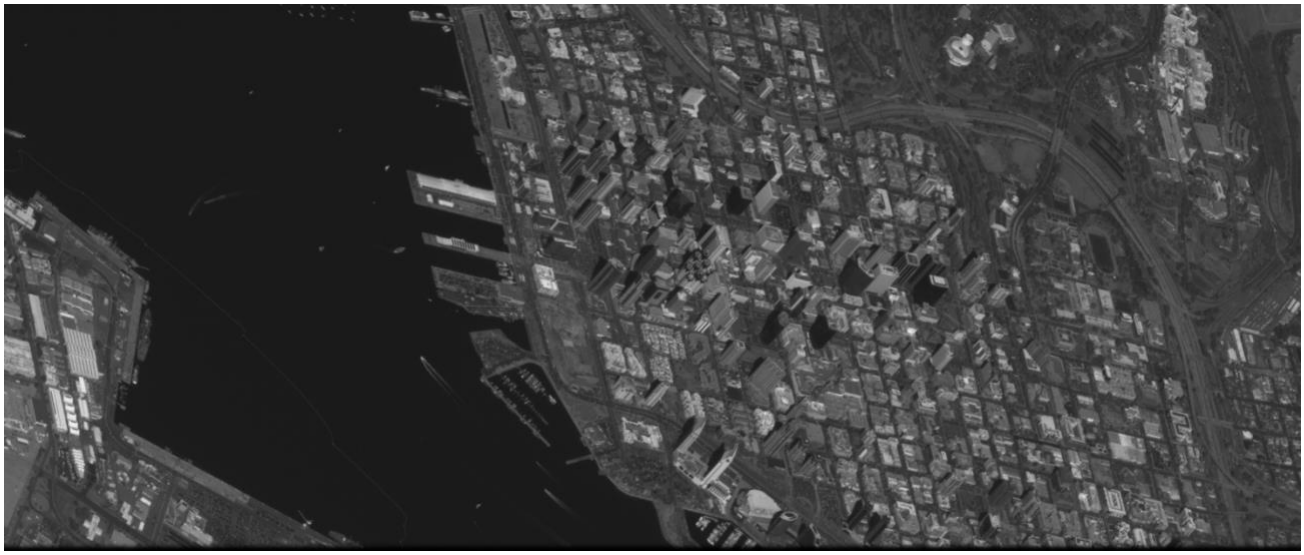

Figure 1 An example of the reference image of the SkySat raw panchromatic frames over the San Diego area.

3. METHOD

The UCL MAGiGAN SRR system is based on multi-angle feature restoration, estimating an observation/degradation model, and using GAN as a further refinement process. A flow diagram is shown in Figure 2. The overall process of the MAGiGAN SRR processing has 5 steps, including: 1) Image segmentation and shadow labelling; 2) Initial feature matching and subpixel refinement; 3) Subpixel feature densification; 4) Estimation of the image degradation model; 5) GAN network training and SRR refinement (prediction).

[1] https://calval.cr.usgs.gov/apps/sites/default/files/jacie/bsmileyJACIE2018approveddraft.pdf

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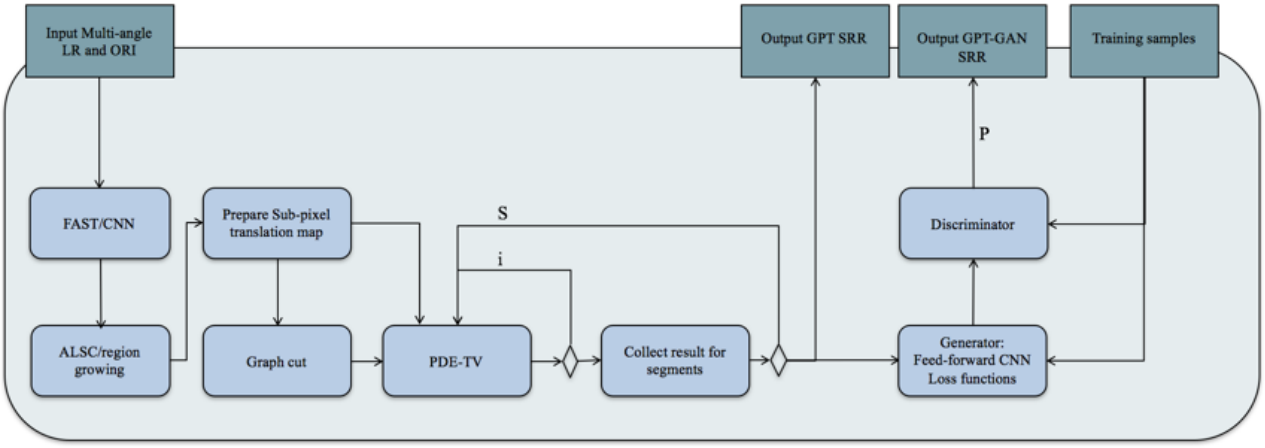

Figure 2 Flow diagram of the MAGiGAN SRR system.

In the first processing stage, we use an adaptive non-local means (ANLM) denoising to produce multiple Lower Resolution (LR) inputs from the continuous video frames. The ANLM method is based on the non-local means (NLM) denoising method which takes a mean of all pixels in a sequence of images, weighted by how similar these pixels are to the target pixel. The ANLM denoised value at a given pixel is obtained by a weighted average of the pixels in its temporal neighborhood. The temporal neighbouring pixels are found by minimising the Mean Squared Difference (MSD) of an adaptive sliding window within a constrained step size. Then we segment the denoised LR images based on their image content using the Graph Cut algorithm, and subsequently, segmented image patches for the same region are paired using normalised cross-correlation. If paired segments are found with different illumination, and one segment is much darker (at a given threshold) than the other one, the darker segment is labelled as a shadow patch. Finally, the illumination of the shadow segments is corrected using illumination statistics from the neighbouring non-shadowed pixels. The de-shadowed intermediate images are only used as metadata to provide seed feature points for the shadowed regions and are not used in the follow-on processing stages. The output SRR will keep the shading information from the reference image which are not devoid of shadows.

In the second processing stage, we aim to produce initial feature correspondences between LR images and the reference image and then derive a initial High Resolution (HR) grid (a scaled version of the reference image interpolated by LR images). An accurate, dense, and evenly distributed first estimation of the seed points is essential to the success of interpolating the initial HR grid. The MAGiGAN SRR system uses a MSA-FAST-CNN [2][3][4] based feature matching approach to produce very dense initial feature correspondences. Then we iteratively update the matched seed point locations and orientations from the previous step using forward and backward ALSC within a transformable elliptical window. The feature correspondences are more evenly distributed between different types of image content including recovered shadow regions after the first processing stage.

During the third processing stage, the optimized feature correspondences are then used as seed points in a pyramidal version of ALSC and region growing (Gotcha) process until most pixels in the LR images find their optimal subpixel correspondence with respect to the reference frame. These sub-pixel correspondences are collected to form a series of 2-channel motion maps with encoded subpixel x and y translation vectors. Pixels in any LR image that do not match with any subpixel location in the reference HR grid, are removed from calculation in further steps. If a subpixel location in the HR grid does not have any corresponding motion vector from all motion maps, this HR pixel will be propagated by its neighbouring HR pixels. The Gotcha method progressively refines the existing subpixel correspondences and densifies until we find a matching for all valid pixels. The motion maps provide the initial degradation information in the similarity measurement term of the Maximum a Posteriori (MAP) estimation at the next processing stage.

In the fourth processing stage, we aim to iteratively refine the initial HR grid through estimation of a sequence of degradation matrices by minimizing a similarity cost (calculated from the MSD of each LR image and degraded HR image) and weighted regularization cost. A mathematical representation of this process can be found in [6]. The intermediate HR output image at this processing stage contains restored information from multi-angle distorted features contained in each LR input image. The intermediate HR image generally produces less resolution enhancement for regions that changed in

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each LR input than the regions that are comparably static. This means the effective resolution enhancement for the intermediate HR image (as well as the final SRR image) is not the same for different regions depending on the number of matched pixels from each LR input. Also, the intermediate HR image does not contain high frequency texture details for flat regions given there is no multi-angle information.

During the fifth processing stage, we further refine the intermediate HR image from the previous processing stage using a pre-trained GAN network [8]. GAN uses the perceptual loss calculated from feature maps of a deep learning network to replace the MSE based content loss, and is therefore highly complementary to the multi-angle feature matching and model-based approach in terms of restoring different features. GAN applies a deep network (Generator G) to generate high frequency textures that are highly similar to real images, in combination with an adversarial network (Discriminator D) to distinguish super-resolved images from real images. In this work, we use a previously pre-trained network from 102 non-repeat Deimos-2 4m green band images and 102 corresponding Deimos-2 1m PAN band images [9]. The 102 Deimos-2 green band images (at 4m resolution) formed 18,782 (256 by 256 pixels) LR training samples. The corresponding 102 Deimos-2 PAN band images (1m resolution) formed 18,782 (1024 by 1024 pixels) HR training samples.

4. RESULTS

We tested the MAGiGAN SRR system on the raw panchromatic frames (2560x1080 pixels) of the SkySat video over the San Diego, CA,U.S.A. area. Due to the "zooming effect" of the frames (the target resolution changes when camera moves away), we only used the first 168 (out of 1350) frames for the experiments. In this paper, we demonstrate SRR results of different sub-areas of a cropped region (512x512 pixels). Note that currently, the maximum size we can handle in MAGiGAN SRR is 2048x2048 pixels for the stage (1) to (4) processing. The 1st 2nd 3rd and the last (168th) frame of the cropped region are shown in Figure 3. 11 adjacent frames are used to denoise to 1 input LR frame, hence there are 15 LR inputs used to produce 1 SRR output. The resulting intermediate HR images (size 1024x1024) are then further divided into smaller sample sizes (128x128 pixels) to be used for GAN refinement, resulting in a total of 64 tiles of final SRR images (size 256x256) with an overall up-scaling factor of 4x. The cropping (tiling) is mainly due to memory limitations of computation. Examples of the resulting SRR images (256x256 pixels) in comparison with the original SkySat panchromatic frames for the same region are shown in

Table 1.

Figure 3 The 1st 2nd 3rd and the last (168th) frame of the LR inputs for a cropped region over San Diego

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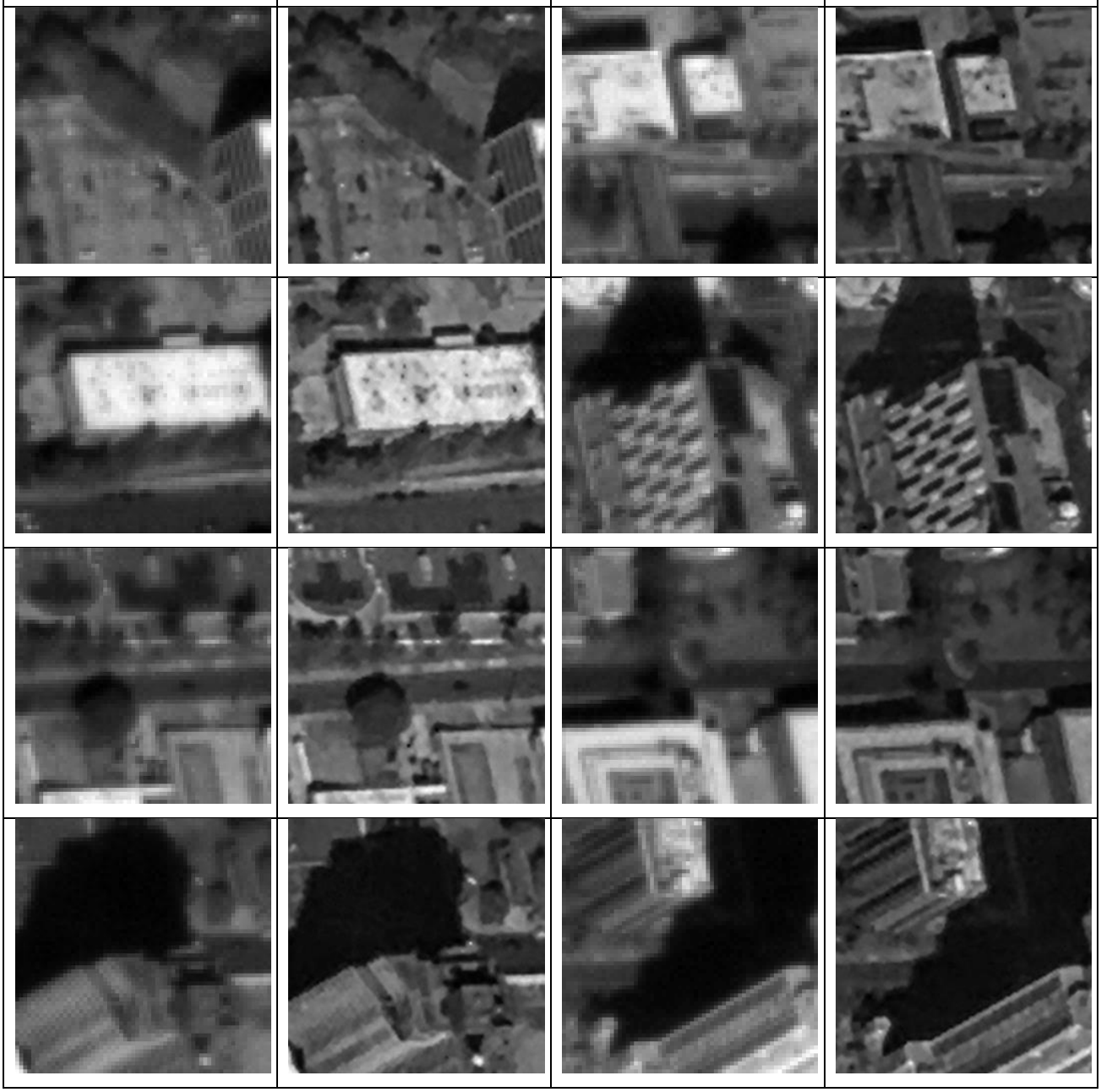
Table 1 Examples of MAGiGAN SRR results in comparison with the original SkySat frames for same regions.

Original SkySat frames	MAGiGAN SRR	Original SkySat frames	MAGiGAN SRR
			

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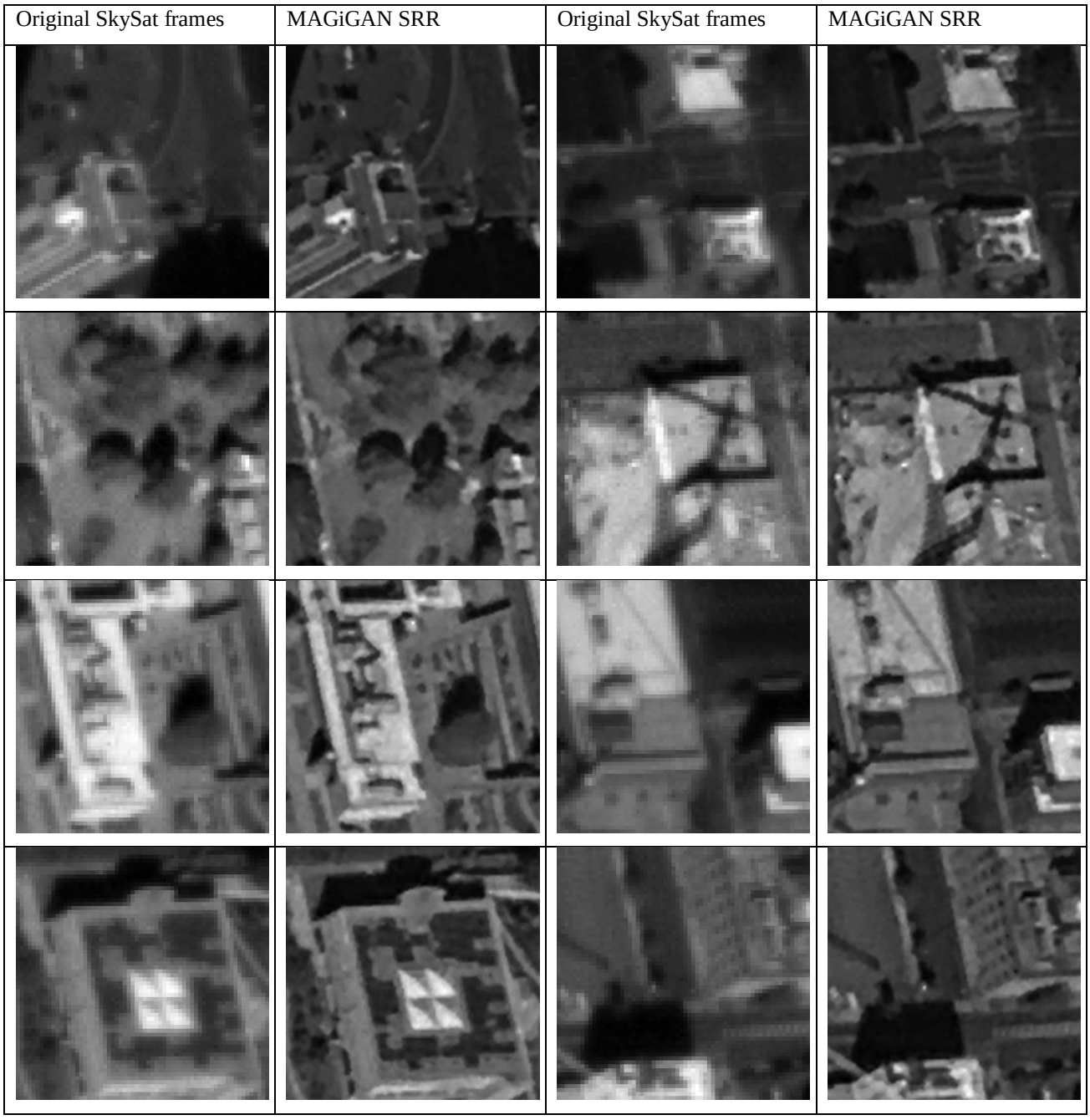

5. CONCLUSIONS AND FUTURE WORK

SRR of EO imagery is challenging due to frequent changes in atmospheric clarity, phase scattering of the Earth's surface, shadowing, and more complex artificial structures. The overall quality of the MAGiGAN SRR results for EO data are generally affected by 4 factors: 1) the quality of the input LR images; 2) the number of LR images; 3) the time difference between each LR image; 4); sufficient volume of training data(sets); 5) image obstacles in terms of smoke, haze, and clouds.

In this paper, we introduce the MAGiGAN SRR system and apply it to spaceborne HR video, developed within the CEOI 10 SuperRes-EO project, designed to address various issues found with EO SRR. The MAGiGAN system not only retrieves

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subpixel information from multi-angle distorted features, but also uses the GAN network to retrieve high-frequency texture details. The multi-angle feature matching and model-based approaches applied in the MAGiGAN SRR system and the GAN single image SRR process are highly complementary to each other in terms of restoring different types of features. If only GAN is applied then there is a risk that artificial features will be "detected" falsely. This was demonstrated in [1]. Therefore, the GAN single image SRR process was integrated as a further refinement step within the MAGiGAN SRR system.

In this paper, we demonstrated SRR results (64 tiles of size 256x256 pixels, total size 2048x2048 pixels) of an urban area of San Diego, CA, U.S.A. using 168 cropped (512x512 pixels) and denoised SkySat panchromatic Tiff image frames. At the GAN refinement processing, we used a previously pre-trained network from 4m and 1m Deimos-2 images. Although the resolution of the target dataset is different (from 70cm to 17.5cm for 4x scale up) to the training images (from 4m to 1m for 4x scale up), the actual achieved resolution enhancement is between 2x to 3x. The MAGiGAN SRR images contain more structural features and texture details which are not observable in the original SkySat panchromatic frames.

Currently, we are working on a GPU porting of the MAGiGAN SRR system. In the future, we will form a much richer LR/HR training datasets for different types of targets using multiple imaging sources and test how far we can use SRR onboard in future EO missions.

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