

# Shape Recovery on Low-Quality or Missing Images

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**Abstract**—Shape segmentation or recovery is an essential task in image processing, especially in remote sensing imagery. Due to the complicated imaging conditions, satellite or natural images are usually noisy and blurred, which makes it challenging to recognize the actual shapes of ground objects. In this project, we aim at recovering shapes of natural and remote sensing objects (e.g. aircraft) based on an MCMC sampling algorithm and operations learned from the class. We found that the MCMC sampling algorithm often generates artifacts which impact the quality of shape recovery. We propose a post-processing algorithm that recovers the shape without artifacts. According to the test on objects with different noise levels and real-world radar objects, we demonstrate the effectiveness of our method.

**Index Terms**—Shape recovery, radar images, morphological image processing.

## I. INTRODUCTION

Shape modeling is one of the essential tasks in image processing. [1], [2]. Accurate characterization of object shape provides plenty of information for object detection [3], scene understanding [4] and object tracking [5]. Typically, there are two paradigms for modeling object shapes. The first paradigm is object segmentation [6], which aims at separating the contour of the object from its background. By doing this, we can distinguish different objects in a scene by marking it with different colors. This paradigm has promising potentials in autonomous driving industry [7]. Another paradigm is called object detection [8], which draws bounding boxes for each object in the scene and mark it with different labels. By doing this, we are able to recognize even tiny objects in a large scene. And bounding boxes generated by object detection algorithms are widely used as the initial states for object tracking [5]. Both two paradigms process, model and visualize the shape of objects and show promising results with strong potential applications in industry.

Recently, deep models, especially convolutional neural networks [9], achieve great success in object modeling [10]–[13]. For image segmentation, fully connected networks (FCN) [10] shows promising results compared to other models. Instead of segmenting by pixel, FCN takes tiles as input and output segmentation map in an end to end way. Unlike other deep models that contain fully connected layers or shortcuts, FCN only use convolutional layers in its network structure, which may benefit the efficiency of parallel computation. For object detection, YOLO [13] is one of the state-of-the-art object detection models. YOLO uses an innovative one-stage architecture. Unlike traditional deep object detection models, instead of using two networks for object localization and

classification, YOLO divides the image into small subblocks and predict the object classes of each small blocks. Finally, YOLO fit the detected blocks with different bounding boxes. Due to its simplified but effective structure, YOLO is widely applied in real-time object related image systems.

However, deep models have their own shortcomings to overcome in both effectiveness and efficiency. First, deep models, especially deep convolutional neural networks, are effective in circumstances where a large number of training samples are given for training and fine-tuning. Although images are easy to collect, it is a challenging and time-consuming work for us to annotate enough amount of training samples for a customized object related task. Also, in some cases, we have a relatively strong prior or background knowledge on the shape of the object. At this time, even fine-tuning on deep models seem less efficient. Second, it may be challenging for deep discriminative models to perform object modeling on noisy and incomplete data. The popularity of adversarial examples [14] tell us that even a small change in the shape or texture of the object can lead to totally different predictions. Therefore, image processing methods that can compliment deep models on the characterization of object shapes may have promising potential application.

To tackle this issue, [15] proposed an MCMC shape sampling method for shape recovery on incomplete objects. They first constructed a strong shape prior by making 10 training objects, each corresponds to a certain type of shape. Then, they consider that training shapes as a high-dimensional prior. Given a new image with the incomplete shape in it, they calculate the posterior probability of the incomplete shape given the shape priors. The shape prior to the largest probability will be assigned to recover the incomplete shape. Finally, the MCMC sampling algorithm performs sampling on each pixel to calculate the probability of this pixel being the shape. The pixels with probability above the threshold will be marked in the image.

In this work, we aim at recovering shapes of objects on low-quality images or images that some part of objects is missing. We apply the code given by [15], [16] for incomplete images. However, we find that there are holes and noise points in the final output of object shapes, which indicates that the MCMC algorithms alone may not be effective enough for the shape recovery in noisy or incomplete images. To tackle this issue, we propose a post-processing pipeline to remove the artifacts produced by the MCMC sampling algorithm and output promising object shapes. Our contribution is summarized as:

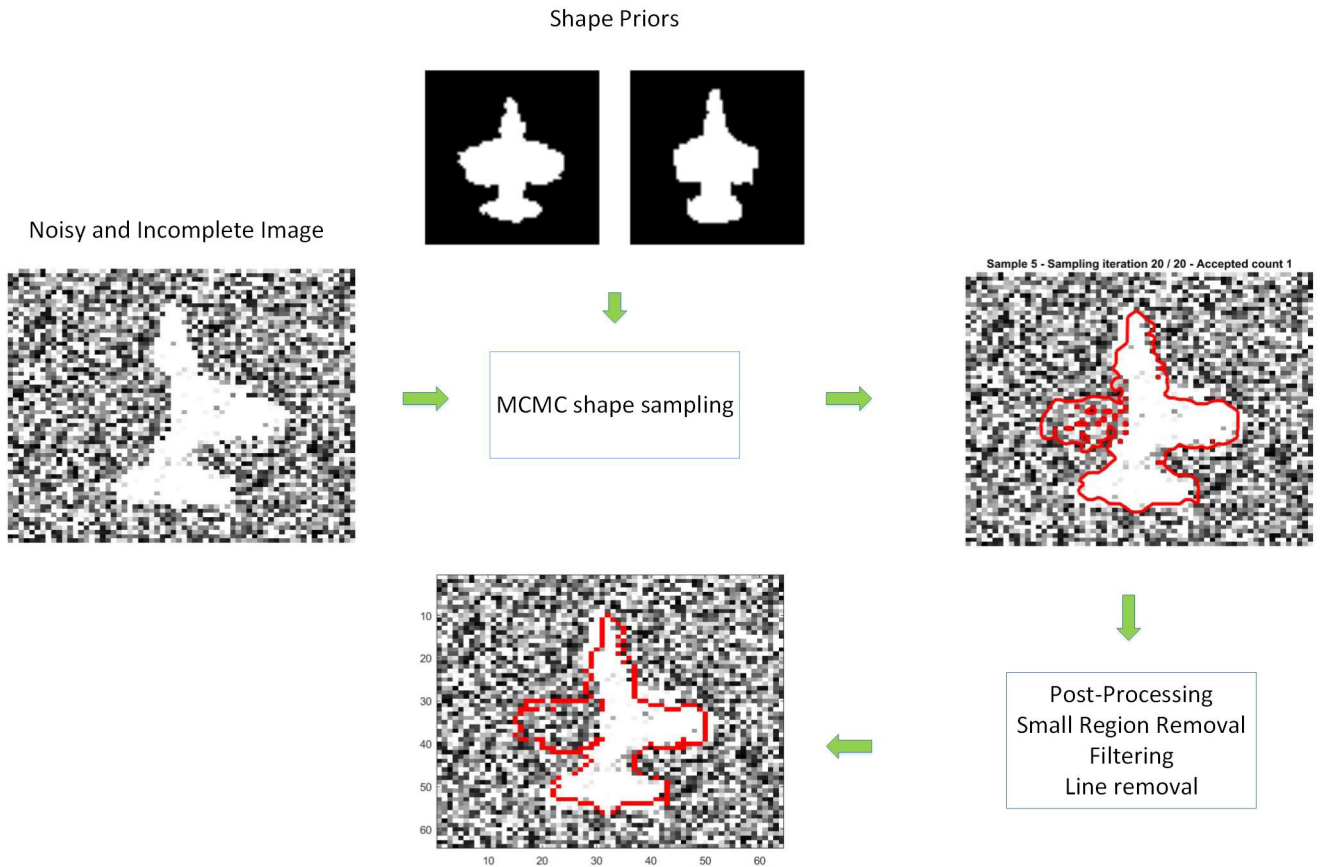


Fig. 1. An overview of the proposed method, shape priors come from visualizing the mat file of [16]

- Propose an image processing scheme that can recover the shape of objects with less noise from noisy or incomplete images.
- Find the problem of MCMC shape recovery algorithm [15] that it generates holes and artifacts in the output shapes. Propose a post-processing method to remove the artifacts.
- Perform our shape recovery algorithm on the different level of noise and real-world incomplete objects imagery obtained by Radar. Empirically demonstrate effectiveness.

The organization of this paper is as below: the next section we will introduce the algorithms we use in this work. In Section 3, we perform experiments on two datasets using our proposed methods. Section 4 concludes the paper.

## II. METHOD

### A. Overview

The overview of our method is demonstrated in Figure 1. Given an object image with is incomplete and noisy, we first perform the MCMC shape sampling algorithm described in [15] to draw a raw shape prediction. 10 training shapes are added as priors into the MCMC sampling algorithm. After MCMC shape sampling, as described above, there are small

regions or artifacts generated by their implementation. To tackle this issue, we add a post-processing algorithm after that to get the final output.

### B. Shape Recovery

The MCMC shape sampling algorithm proposed by [15] contains three major steps. First, the algorithm chooses a random class listed in the training set. In other words, choose a shape in the training matrix, where each columns corresponding to a training aircraft. Then, the algorithm calculates the posterior probability of the test set given the shape priors and try to sample the edge points. After, the transition ratio of Metropolis-Hastings Sampling is calculated. If the ratio is bigger than a threshold, the algorithm chooses another shape and do sampling. For each iteration, the MCMC sampling algorithm does it iteratively. After a certain time of iterations, the shape will become stable. Finally, the stable shape will be used as the output.

Generally, the MCMC sampling algorithm considers the image of objects as a high-dimensional distribution. The main problem behind this is that it may not take the relationship of each pixel to its neighbors into consideration. In this sense, it may generate noise points or small holes as shown in Figure 2. Therefore, we think it is promising if we add morphological



Fig. 2. The output of MCMC shape sampling [15], [16]. We can see from the results that there are some holes in the predicted left wing of the aircraft.

operations as post-processing for this task. As learned from class, morphological operations contain a lot of operations that take the neighbor of each pixel into consideration, which captures the texture information for better performance. For implementation of MCMC sampling algorithm, we use work described in [16] for validation that [15] do have problems that requires post-processing.

### C. Post-processing

The ideal output image should contain one unified target shape with clean edges and without holes and noises. Nonetheless, the output shape from the model has many arbitrary and small holes in the missing wing section (see Figure 2). Region-removal and other techniques were applied to recover the original complete shape of the flight.

A region is defined as a set of pixels that are connected, and different types of connections could happen among pixels. An 8-connected region considers pixels as connected if either their edges or corners are touched. A 4-connected region only counts pixels that connected through edges. Small 8-connected regions in the foreground and background were first removed. Large 4-connected regions were changed into outlines.

Due to the edge extraction process, extra lines were frequently produced in the middle of the flight shape. In order to remove these middle lines, for each row in which the distance between the leftmost pixel and the rightmost pixel exceeds a certain amount, only the leftmost pixel and the rightmost pixel are kept in order to have a clean outline.

## III. EXPERIMENTS

### A. Overview

In this section, we conduct two major experiments on shape recovery. The first experiment is an extension of paper [15]. As shown in the paper, the MCMC sampling algorithm can recover the shape of the object such as aircraft in incomplete images. However, there is no demonstration on the MCMC sampling algorithm's effectiveness in recovering shapes from noisy and incomplete images. In our work, we extract the noise from real Synthetic aperture radar (SAR) images and add it on the original aircraft images presented in [15]. Then we perform the proposed scheme to obtain the recovery. The

second experiment is with more practical usage. We obtain a big tile of Synthetic aperture radar (SAR) images with about 30 aircraft in it. We crop some of the aircraft and aim to recover the shape from noisy and blurred SAR imagery.

### B. Dataset

Two datasets, the aircraft dataset, and the SAR remote sensing dataset were used in the current project. The aircraft dataset includes artificially generated binary aircraft images as shown in Figure 4. In the dataset, we have a training set and a test set. The training set has 10 flight instances and each instance represents a unique flight shape category. The test set has another 10 flight images with the missing left wing. To predict the shape of a particular test flight, all 10 training flights were used. This procedure ensured the model to learn from a diverse set of possible flight shapes and to make the prediction on a new flight instance with missing components. In our experiment, for each test image, we add the noise extracted from the background of a SAR imagery. With this procedure, we are able to see if our proposed scheme can recover shapes with different noise levels.

Synthetic aperture radar (SAR) has been widely used for Earth remote sensing due to its capability of penetration, high-resolution imaging and the ability to acquire rich information about targets. The SAR dataset contains 30 aircraft images obtained from radarsat 2 satellite. All aircrafts have the same shapes. An example image is shown in Figure 4. We construct one shape prior to the optics imagery from DigitalGlobe of one of the 30 aircrafts and try to recover the shape of the SAR aircrafts from this shape prior.

### C. Noise Extraction

To test how robust the model is in noisy backgrounds, we modified the aircraft dataset by extracting noises from the SAR dataset and adding to the test images. The modified aircraft test images are shown in Figure 7. Given a true SAR image from radarsat 2, we focus on the dark area. As presented in homework, we extract the dark region to model the SAR noise. After that, we add  $64 \times 64$  noise tile to the test aircraft set as 1-time noise. We can also multiply the noise by 2 or 3 times and added to the test aircraft set. Therefore, we can test our method's robustness in a different level of noise. The aircraft shapes with noise added are also shown in Figure 7.

### D. Shape Prior Construction for SAR aircrafts

To test the performance of our model on shape recovery of SAR aircrafts, we obtain the corresponding Google Earth optics imagery of same location to build the shape priors to each aircraft. We first perform canny edge detection on the optics imagery to get the edge of objects. The detection results are shown in the Figure 5. Then we crop one of the plane at SAR image (shown in Figure 6), and its corresponding shape by canny as a prior pair. We perform erode and dilate on the edge detected to get the same type of priors as aircraft dataset. The final pair of prior is shown in Figure 8.

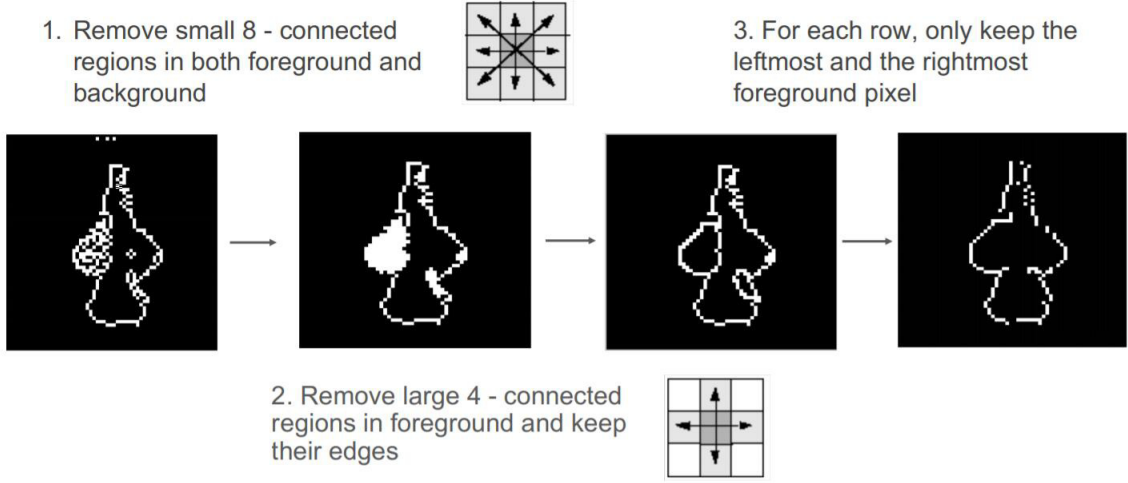


Fig. 3. The post-processing pipeline.

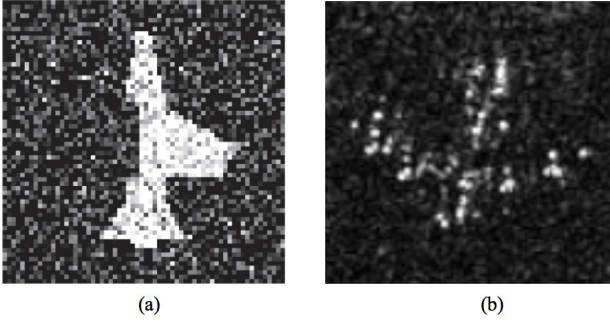


Fig. 4. (a) An example input image from the aircraft dataset. (b) An example input image from the SAR dataset.



Fig. 6. The original SAR imagery of the same location with 5

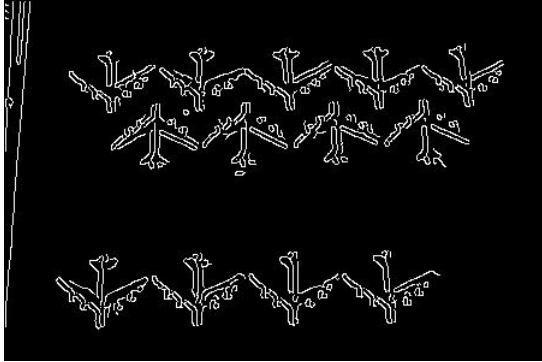


Fig. 5. The results of objects in optics imagery after Canny edge detection.

### E. Results

In this section, we present the results of two experiments. In both experiments, the training set and test set are separated.

- Train on 10 shape priors. Then try to recover the shape of an aircraft from an incomplete image. Different levels of noise from SAR images are added.

- Train on 10 shape priors with 9 from aircraft dataset and one is SAR shape prior constructed as Figure 8. Try to recover the shape of an aircraft from its SAR imagery.

The best results of the first experiment are presented in Figure 9. We can see that our method is able to recover the shape of the aircraft with less holes. Although there are outputs of our method deviate from the actual shape, compared to the MCMC shape sampling algorithm [15], we provide a more precise shape description. The problem of mismatch of shapes may come from the wrong shape priors provided by MCMC algorithm.

The best result of the second experiment are presented in Figure 10. The left is the recovery result of us and the right is the ground truth. We can see that the orientation is still different and there are noise points inside or outside the shape. Because both the training and test set are aligned, this orientation may come from the moderate deviation of MCMC sampling algorithm. The recovery result is generally not as good as aircraft dataset as SAR is really a hard task.

For the processing method, we implement the data pre-processing, augmentation, shape prior construction and post-



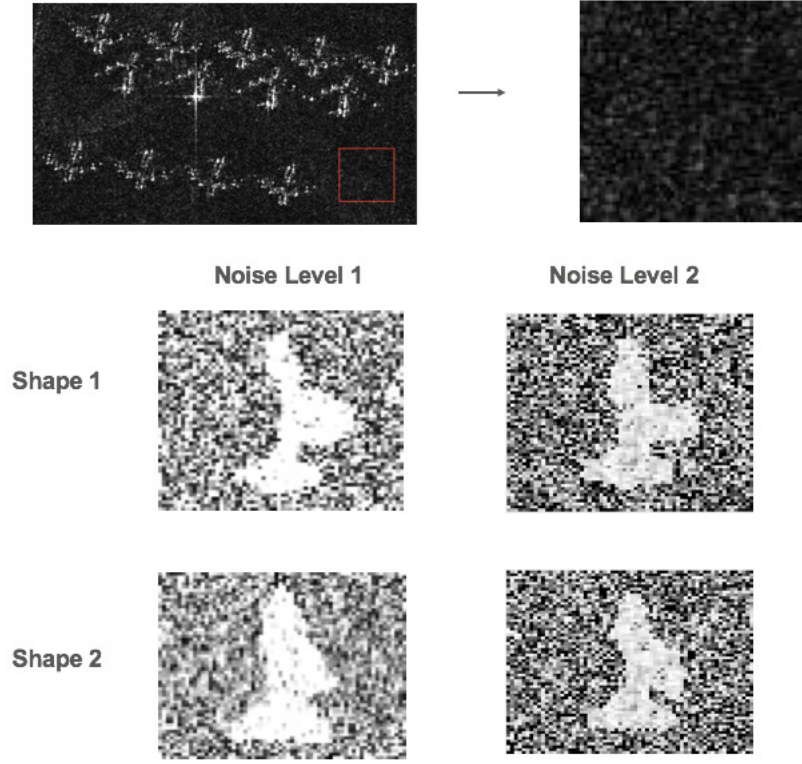


Fig. 7. The top image shows noise extracted from an example image in the SAR dataset. The bottom shows two input shapes after adding 1 level and 2 level noise.

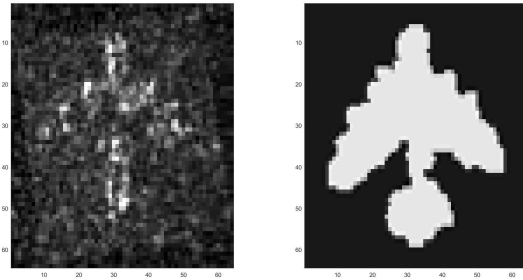


Fig. 8. The shape prior constructed based on the edge detected in the optics imagery.

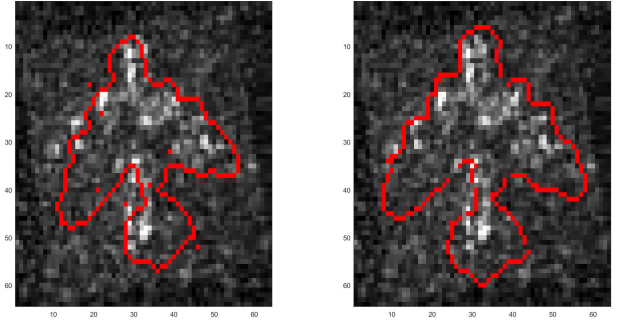


Fig. 10. The resulting of SAR aircraft object. Left is our prediction while the right is the ground truth generated by optics image.

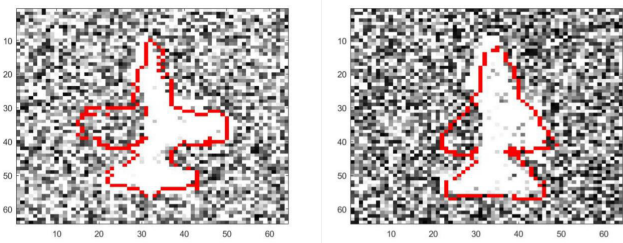


Fig. 9. The resulting output shape from input images with noise level 1.

processing algorithm. We use the code from [15], [16] for MCMC shape sampling. The whole experiments are implemented on Windows Machine with MATLAB.

#### IV. CONCLUSION AND FUTURE WORK

Shape recovery from incomplete and noisy imagery is a challenging task in image processing. In this work, we introduce an image processing paradigm for recovering the shape of aircraft from its incomplete and noisy imagery. We first find the problem of a state-of-the-art shape recovery algorithm

[15] that it generates holes and noise in the output. Then, we propose a series of post-processing method to produce a good final output. On the other hand, we test the algorithm on the noisy radar imaging environment. We find that our algorithm can recover the shape of aircraft in a good way. A further experiment on real-world SAR object recovery also demonstrates the effectiveness of the proposed method, especially post-processing algorithm. The future work will be focused on extending this method for shape recovery on objects with different orientations.

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#### APPENDIX

##### Contribution

- Zhaozhuo Xu: SAR imagery processing, noise extraction, MCMC sampling understanding and testing, writing of slides and report.
- Chenyu You: Pre-processing, noise extraction, MCMC sampling understanding and testing, writing of slides and report.
- Zixian Chai: Post-processing, noise extraction, MCMC sampling understanding and testing, writing of slides and report.